The Impact of China's Public Investments in Rural Area on Agricultural Productivity and Poverty Reduction

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China's public investments in rural area, as a whole, have been going up for many years as its whole economy develops. These include government investments in: road, land improvement, drinking water facilities, irrigation, education, health, agricultural R&D, energy supply system, and communication system. With the increases of government investments, China's agricultural productivity witnessed steady improvements, along with rural poverty reduction at the same time. It is natural to argue that productivity increases and poverty reduction mainly result from public investment or contributions by other factors such as general economic growth and price increases. While a number of research have reached the common general conclusion that such investment do mater, it is yet to be clarified 1) to what extent total agricultural productivity changes and poverty reduction can be ascribed to public investment; 2) which public investment contribute more effectively; 3) what linkage exist between agricultural productivity and poverty reduction. Getting a clear understanding of the above relationship constitutes the main purpose of this paper.

Due to the data availability, three public investments are studied in this paper, i.e.: government education expenditure in rural elementary and middle school; government expenditure in agricultural science and technology research for all investment objectives except poverty reduction; and Government investment in irrigation construction for farming, forestry, animal husbandry and fishery sectors. The data used in this paper contain information on cross-sectional units (i.e., provinces) observed over time. To deal with this pooled (or panel) data, equations of the form: $y_{it} = \alpha_{it} + \beta_i' x_{it} + \varepsilon_{it}$ are estimated with fixed effects. The study results in this paper point that:

1) The most efficient public investment among the three public investments is government education expenditure in rural elementary and middle school.
2) The second efficient public investment is government expenditure in agricultural science and technology research for all investment objectives except poverty reduction.
3) Government investment in irrigation construction for farming, forestry, animal husbandry and fishery sectors is more efficient than government expenditure in agricultural science and technology research for poverty reduction.
4) Generally, the least efficient public investment among the three public investments is government investment in irrigation construction for farming, forestry, animal husbandry and fishery sectors.

I. Objectives

This paper aims at documenting

1) the impact of public investments on the improvement of total agricultural productivity and of the major agriculture sub-sectors that significantly be livelihood of poor households;
2) the impact of public investments on poverty reduction; and
3) the impact of public investments on poverty reduction through total agricultural productivity.

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II. Data

In order to achieve these objectives, a comprehensive data set relating to this paper is assembled.[2]

1） Public investment

- Government Expenditure in Rural Elementary and Middle School Education (ED).
- Government Expenditure in Agricultural Science and Technology Research (RD).
- Government Investment in Irrigation Construction for Farming, Forestry, Animal Husbandry and Fishery Sectors (IRR).

2） Rural household income and expenditure

- Per Capita Net Income of Rural Households (INCOME).
- Per Capita Living Expenditure of Rural Households (LIVE).

3） Agricultural outputs and inputs

- Grain Production Per Rural Labor (LGRN).
- Pork, Beef, Mutton Production Per Rural Labor (LMEAT).
- Fishery Production Per Rural Labor (LAQU).
- Rural Household's Material Input into Rice Production (CRICE).
- Rural Household's Material Input into Wheat Production (CWHT).
- Rural Household's Material Input into Corn Production (CCORN).
- Rural Household's Material Input into Hog Production (CHOG).[3]
- Rural Household's Material Input into Fishery Production (CFISH).

4） Poverty incidence

- Rural Poverty Population (PVT).
- Rural Labor (LABOR).
- Rural Population (POP).

5） General economic indicators

- Total GDP (GDP).
- Agricultural GDP (AGDP).
- Nonagricultural GDP (NGDP).
- Total Output Value of Farming, Forestry, Animal Husbandry (VAG).
- Total Output Value of Crop Cultivation (VPL).

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[2] The letter in parenthesis is the short name of the variable, which will be used below.

[3] We unprecisely use CHOG as a representative to analyze the impact of material inputs into livestock because 1) the data of material inpute into other livestock production are unavailable, and 2) hog production is the main livestock product in rural China and its importance dominates other livestock's.

III. Approaches and Theoretical Structure

For this paper, a comprehensive concept can categorize total agricultural productivity into yield productivity, labor productivity, and capital productivity. The three measures depict the increase in yield, in output per unit of labor, and in output per unit of capital (material consideration), respectively. In estimating these models, we find that the models of labor productivity regressing on public investments function well. Other models do not, or even give ridiculous results. These perplexing modeling results may be due to the following reasons: 1) Yield productivity and capital productivity of agriculture production in China are mainly affected by agricultural science technology progress, as proven by most agriculture economists. Given the limited land resources and water resources, and with limited public investments into agriculture production, it is difficult for farmers to enlarge the scale of production. Because of the degradation of agricultural production environment, the limited amount of public investments may be just enough to protect normal production activities from suffering from the degradation of agricultural production environment. 2) For the capital productivity, due to the increase in cost of agriculture production inputs, the increase in capital input into agricultural production may also be just enough to break even, and not enough to enhance the capital productivity. 3) As for the labor productivity, however, public investments can help to reduce rural labor in agricultural production, as a result, labor productivity increases, given the amount of output. Nevertheless, the realization of increase in labor productivity heavily depends on capability of the redundant rural labor force being absorbed into nonagricultural sectors. Fortunately, this required migration of rural redundant labor into nonagricultural sectors realizes steadily through market operation as the development of nonagricultural sectors.

Therefore, based on the data gathered, the following elasticities are modeled and econometrically estimated:

- The elasticities of labor productivity in total agriculture production, in rice production, in wheat production, in corn production, in livestock production, and in fishery production, with respect to public investments, respectively. By these elasticities, objective 1 is achieved, and objective 3 is partly achieved as well.
- The elasticity of poverty incidence with respect to public investments, by which objective 2 will be achieved. Together with the elasticities estimated above, objective 3 is wholly achieved. That is, to achieve object 3, the twos types of regression models are incorporated by using chain derivatives properties.

The data used in this paper contain information on cross-sectional units (i.e., provinces) observed over time. To deal with this pooled (or panel) data, usually we need to estimate equations of the form:

$$y_{it} = \alpha_{it} + \beta_i' x_{it} + \varepsilon_{it}$$

for i = 1, 2, μ, 31 provinces and t = 1, 2, μ, T. Where y_{it} is the dependent variable, and x_{it} and β_i are k-vectors of non-constant regressors and parameters for i = 1, 2, μ, 31 provinces. Each province is observed for dated periods t = 1, 2, μ, T.

We can view these data as a set of province specific regressions so that we have 31 provincial equations:

$$y_i = \alpha_i + \beta_i x_i + \varepsilon_i$$

with T observations, stacked on top of one another. We can refer to the stocked representation:

$$Y = \alpha + X\beta + \varepsilon$$

where α, β and X incorporate any restrictions on the parameters between provinces.

The residual covariance matrix for this set of equations is given by:

$$\Omega = E(\varepsilon\varepsilon') = E\begin{bmatrix} \varepsilon_1\varepsilon_1' & \varepsilon_1\varepsilon_2' & \cdots & \varepsilon_1\varepsilon_{31}' \\ \varepsilon_2\varepsilon_1' & \varepsilon_2\varepsilon_2' & \cdots & \varepsilon_2\varepsilon_{31}' \\ \vdots & \vdots & \vdots & \vdots \\ \varepsilon_{31}\varepsilon_1' & \varepsilon_{31}\varepsilon_2' & \cdots & \varepsilon_{31}\varepsilon_{31}' \end{bmatrix}$$

The basic specification treats the pool specification as a system of equations and estimates the model using system OLS. This specification is appropriate when the residuals are contemporaneously uncorrelated, and time-period and cross-province homoscedastic:

$$\Omega = \sigma^2 I_{31} \otimes I_T.$$

The coefficients and their covariances are estimated using the usual OLS techniques applied to the stacked model.

By checking the pooled data used in this paper, we find that heterogeneities between provinces exist. Bear this in mind, we set α_{it} as fixed effects: $\alpha_{it} = \alpha_i$, and $E(\alpha_i\varepsilon_{it}) \neq 0$. That is, α is allowed to differ across provinces by estimating different constants for each province. These fixed effects are computed by subtracting the "within" mean from each variable and estimating OLS using the transformed data:

$$y_i - \bar{y}_i = \beta_i'(x_i - \bar{x}_i) + (\varepsilon_i - \bar{\varepsilon}_i)$$

where $\bar{y}_i = \Sigma_t y_{it}/31$, $\bar{x}_i = \Sigma_t x_{it}/31$, and $\bar{\varepsilon}_i = \Sigma_t \varepsilon_{it}/31$.

The coefficient covariance matrix estimates are given by usual OLS covariance formula applied to the mean differenced model:

$$\text{var}(b_{FE}) = \hat{\sigma}_W^2 (\tilde{X}'\tilde{X})^{-1}$$

where $\tilde{X}$ represents the mean differenced X, and

$$\hat{\sigma}_W^2 = \frac{e'_{FE}e_{FE}}{31T - 31 - K} = \frac{\sum_{it}(\tilde{y}_{it} - \tilde{x}'_{it}b_{FE})^2}{31T - 31 - K}$$

where $e'_{FE}e_{FE}$ is the SSR from the fixed effects model, K is the total number of estimated parameters.. The estimated fixed effects are computed from

$$\hat{\alpha}_i = \sum_t (\bar{y}_i - \bar{x}'_i b_{FE}) / 31$$

We also find the presence of cross-province heteroscedasticity in the pooled data used in this paper. Therefore, usual OLS techniques are not appropriate and FGLS specifications are estimated instead, that is, each province's estimated residual variance is used as the province's weight. These are so called cross-province weightings. Here, we assume that the residual are still contemporaneously uncorrelated. Hence, we have:

$$\Omega = E\begin{bmatrix} \sigma_1^2 I_T & 0 & \cdots & 0 \\ 0 & \sigma_2^2 I_T & \cdots & 0 \\ \vdots & \vdots & \vdots & \vdots \\ 0 & 0 & \cdots & \sigma_{31}^T I_T \end{bmatrix}$$

where, σ_i^2 is estimated from a first-stage pooled OLS regression. The estimated variances are computed as:

$$\hat{\sigma}_i^2 = \sum_{t=1}^{T_i} (\tilde{y}_{it} - \hat{\tilde{y}}_{it})^2 / T_i$$

where $\hat{\tilde{y}}_{it}$ are the OLS fitted values.

To allow variances within a province to differ across time, covariances that are robust to general heteroscedasticity are estimated by means of white heteroscedasticity covariance. This variance estimator is computed using the stacked model:

$$\text{var}(b) = \frac{31T}{31T - K} (\tilde{X}'\tilde{X})^{-1} \left(\sum_{i,t} u_{it}^2 \tilde{x}_{it} \tilde{x}'_{it} \right) (\tilde{X}'\tilde{X})^{-1}$$

where u_{it} satisfies $\alpha_{it} = \alpha_i + u_{it}$ and $E(u_{it}\varepsilon_{it}) = 0$. It should be noted that this variance estimator dose not account for the possibility of contemporaneous correlation across provinces.

IV. Model Estimation and Results

We use double-log functional forms for all equations in model system of this paper. Since our public investment data are only available for several years (The shortest time series data are rural household's material input into fishery production and government education expenditure in rural elementary and middle school, from 1991 to 2001), all the equations including public investments are restricted in this period.

Usually, public investments can have long lead times in affecting poverty reduction, agricultural production, productivity, etc, and their effects can be long term once they kick in. Thus, one of the thornier problems to resolve when including public investment variables in a function concerns the choice of appropriate lag structure. Most past studies use stock variables, which are usually weighted averages of current and past public investments. But what weights and how many years' lag should be used in the aggregation are under debate. As this regard, we use statistical tools to test and determine the appropriate length of lag for each public investment.

Various procedures have been suggested for determining the appropriate lag length. The adjusted R^2 and Akaike's Information Criteria (AIC) are often used by economists. In this paper, we simply use the adjusted R^2. The optimal length is determined when adjusted R^2 reaches a maximum. As a result, the lags determined by this approach are 0 for government expenditure in rural elementary and middle school education, and government expenditure in agricultural science and technology research, 1 for government investment in irrigation construction for farming, forestry, animal husbandry and fishery sectors, based on the data we use.

Note: All model estimations in this paper are done by using EVIEWS. In the following result tables, sign ? represents panel data.

IV.1 The impact of public investments on the improvement of total agricultural productivity

We use a regression model to estimate the impact of public investment on the improvement of total agricultural productivity (in terms of labor), that is, the regression of per labor VAG on per capita ED, per capita RD, per capita IRR, and five material inputs, i.e., CRICE, CWHT, CCORN, CHOG, and CFISH, as shown in Table IV.1.

Table IV.1 Per Labor Output Value of Farming, Forestry, Animal Husbandry Model

Dependent Variable: LOG(VAG?/LABOR?)
Method: GLS (Cross Section Weights)

Sample: 1991 2001				
Included observations: 11				
Total panel (balanced) observations 341				
Convergence achieved after 14 iteration(s)				
White Heteroskedasticity-Consistent Standard Errors & Covariance				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
LOG(ED?/POP?)	0.222321	0.018953	11.73037	0.0000
LOG(RD?/POP?)	0.186506	0.011510	16.20426	0.0000
LOG(IRR?(-1)/POP?(-1))	0.006717	0.003622	1.854196	0.0645
LOG(CRICE?)	0.122038	0.012295	9.925465	0.0000
LOG(CWHT?)	0.330794	0.023676	13.97153	0.0000
LOG(CCORN?)	0.164162	0.012237	13.41492	0.0000
LOG(CHOG?)	0.192323	0.015793	12.17753	0.0000
LOG(CFISH?)	0.163935	0.016811	9.751846	0.0000
Fixed Effects				
Beijing	-4.354477		Hubei	-4.635168
Tianjin	-4.275486		Hunan	-5.013208
Hebei	-4.652921		Guangdong	-4.838045
Shanxi	-5.389662		Guangxi	-5.323353
Inner Mongolia	-4.700378		Hainan	-4.560101
Liaoning	-4.495062		Chongqing	-4.785966
Jilin	-4.860003		Sichuan	-4.843361
Heilongjiang	-4.571451		Guizhou	-5.426347
Shanghai	-4.261819		Yunnan	-5.606053
Jiangsu	-4.435691		Tibet	-5.366657
Zhejiang	-4.655702		Shaanxi	-5.121909
Anhui	-4.746625		Gansu	-5.247391
Fujian	-4.488666		Qinghai	-5.466139
Jiangxi	-4.938541		Ningxia	-5.497016
Shandong	-4.634883		Xinjiang	-4.525607
Henan	-5.134384			
Weighted Statistics				
R-squared	0.985479	Mean dependent var		-0.826592
Adjusted R-squared	0.983652	S.D. dependent var		1.486637
S.E. of regression	0.190079	Sum squared resid		10.91122
F-statistic	2928.008	Durbin-Watson stat		1.375537
Prob(F-statistic)	0.000000			
Unweighted Statistics				
R-squared	0.937644	Mean dependent var		-0.509666
Adjusted R-squared	0.929797	S.D. dependent var		0.717410
S.E. of regression	0.190083	Sum squared resid		10.91175
Durbin-Watson stat	1.635995			

Table IV.1 shows that elasticities of total agricultural productivity are: 0.222 with respect to (w.r.t) per capita ED, 0.187 w.r.t per capita RD, 0.007 w.r.t per capita IRR, 0.122 w.r.t CRICE, 0.331 w.r.t CWHT, 0.164 w.r.t CCORN, 0.192 w.r.t CHOG, 0.164 w.r.t CFISH. Therefore, among three public investments, ED can contribute labor productivity of total agricultural the most, RD the second, and IRR the least. Among five material inputs, CWHT can contributes total agricultural productivity the most, and CRICE the least. This may result from the fact that, in China, rice production is more efficient than other agriculture products due to the extension of hybrid rice technology which is at the top level in the world.

Comparing these two types of factors, we see that, averagely, material inputs can contribute total agricultural productivity more than public investment, which also shows public investments are not enough so that their importance is still dominated by material inputs in agriculture sector.

The mean of Fixed effects in Table IV.1 is -4.8662, standard deviation is 0.1549 which shows relative homogenous of total agricultural productivity among provinces. Nevertheless, the fixed effects show that this kind of labor productivity in east region (-4.5139) is averagely higher than those in central (-4.9111) and west region (-5.1592), and the labor productivity in west region ranks the last.[4]

IV.2 The impact of public investments on the improvement of Crop Cultivation productivity

We use the same structure model as in IV.1 to estimate the impact of public investment on the improvement of crop cultivation productivity (in terms of labor), that is, a regression of per labor VPL on per capita ED, per capita RD, per capita IRR, and five material inputs, i.e., CRICE, CWHT, CCORN, CHOG, and CFISH. Because material inputs into livestock (CHOG) and fishery (CFISH) will affect the developments of these two sectors, and will in turn affect the development of crop production through changes in the demand for feed, CHOG and CFISH are kept as regressors in this model.

Table IV.2 Per Labor Output Value of Crop Cultivation Model

Dependent Variable: LOG(VPL?/LABOR?)				
Method: GLS (Cross Section Weights)				
Sample: 1991 2001				
Included observations: 11				
Total panel (balanced) observations 341				
Convergence achieved after 11 iteration(s)				
White Heteroskedasticity-Consistent Standard Errors & Covariance				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
LOG(ED?/POP?)	0.262851	0.020447	12.85509	0.0000
LOG(RD?/POP?)	0.082183	0.010000	8.218094	0.0000
LOG(IRR?(-1)/POP?(-1))	0.015213	0.006752	2.253039	0.0249
LOG(CRICE?)	0.204631	0.023956	8.541813	0.0000

4 Unit: VAG per labor, 10,000 Yuan; ED per capita, 100Yuan; RD per capita, 0.1 Yuan; IRR per capita, Yuan; CRICE, CWHT, CCORN, CPIG, CFISH, Yuan/50kg.
East region: Beijing, Tianjin, Hebei, Liaoning, Shanghai, Jiangsu, Zhejiang, Fujian, Shangdong, Guangdong, Hainan.
Central region: Shanxi, Jilin, Heilongjiang, Anhui, Jiangxi, Henan, Hubei, Hunan.
West region: Chongqing, Sichuan, Guizhou, Guangxi, Yunnan, Tibet, Shaanxi, Inner Mongolia, Gansu, Qinghai, Ningxia, Xinjiang.

LOG(CWHT?)	0.296811	0.029381	10.10204	0.0000
LOG(CCORN?)	0.125034	0.024408	5.122619	0.0000
LOG(CHOG?)	0.251799	0.028002	8.992084	0.0000
LOG(CFISH?)	0.102287	0.018962	5.394323	0.0000
Fixed Effects				
Beijing	-4.470093		Hubei	-4.782216
Tianjin	-4.456584		Hunan	-5.337018
Hebei	-4.914629		Guangdong	-5.125437
Shanxi	-5.406931		Guangxi	-5.584875
Inner mongolia	-4.907155		Hainan	-5.025579
Liaoning	-4.751419		Chongqing	-5.083818
Jilin	-4.869363		Sichuan	-5.059484
Heilongjiang	-4.470946		Guizhou	-5.554679
Shanghai	-4.577405		Yunnan	-5.710906
Jiangsu	-4.731599		Tibet	-5.747938
Zhejiang	-5.079347		Shaanxi	-5.17768
Anhui	-5.038544		Gansu	-5.215931
Fujian	-5.037039		Qinghai	-5.87203
Jiangxi	-5.227734		Ningxia	-5.411914
Shandong	-4.911769		Xinjiang	-4.358546
Henan	-5.318442			
Weighted Statistics				
R-squared	0.985792	Mean dependent var		-1.958657
Adjusted R-squared	0.984004	S.D. dependent var		1.483759
S.E. of regression	0.187658	Sum squared resid		10.63514
F-statistic	2993.345	Durbin-Watson stat		1.398854
Prob(F-statistic)	0.000000			
Unweighted Statistics				
R-squared	0.933123	Mean dependent var		-1.141128
Adjusted R-squared	0.924708	S.D. dependent var		0.683913
S.E. of regression	0.187661	Sum squared resid		10.63547
Durbin-Watson stat	1.641032			

Table IV.2 shows that elasticities of crop cultivation productivity are: 0.263 with w.r.t per capita ED, 0.082 w.r.t per capita RD, 0.015 w.r.t per capita IRR, 0.205 w.r.t CRICE, 0.297 w.r.t CWHT, 0.125 w.r.t CCORN, 0.252 w.r.t CHOG, 0.102 w.r.t CFISH. Among three public investments, same as in IV.1, ED can contributes crop cultivation productivity the most, RD the second, and IRR the least. Because CHOG and CFISH have impacts on crop cultivation productivity indirectly through the changes in feed demand, elasticity of crop cultivation productivity w.r.t CHOG increase and that w.r.t CFISH decrease, compared with the case in IV.1. As for material inputs into three crops' production, CWHT can contributes crop cultivation productivity the most, and CCORN the second, and CRICE the least, same rank as in IV.1, and same explanation can be given here.

Comparing these two types of factors, we see the same picture that, averagely, material inputs can contribute crop cultivation productivity more than public investment, and same explanation can be given here.

The mean of Fixed effects in Table IV.2 is -5.0715, standard deviation is 0.3959 which also shows relative homogenous of crop cultivation productivity among provinces. Nevertheless, the fixed effects show that crop cultivation productivity in east region (-4.8255) is averagely higher than those in central (-5.0564) and west region (-5.3071), and the labor productivity in west region ranks the last.[5]

IV.3 The impact of public investments on the improvement of major agriculture sub-sectors

To evaluate this impact, we consider labor productivity in the following three productions: Per Labor Grain Production (LGRN), Per Labor Pork, Beef, Mutton Production (LMEAT), and Per Labor Fishery Production (LAQU).

IV.3.1 The impact of public investments on the improvement of Grain Production

The model constructed to estimate this impact is the regression of grain production productivity (in terms of labor) on per capita ED, per capita RD, per capita IRR, and three material inputs, CRICE, CWHT, and CCORN.

Table IV.3.1 Per Labor Grain Production Model

Dependent Variable: LOG(LGRN?)				
Method: GLS (Cross Section Weights)				
Sample: 1990 2001				
Included observations: 12				
Total panel (balanced) observations 372				
Convergence achieved after 8 iteration(s)				
White Heteroskedasticity-Consistent Standard Errors & Covariance				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
LOG(ED?/POP?)	0.043092	0.013439	3.206540	0.0015
LOG(RD?/POP?)	0.016979	0.006784	2.502872	0.0127
LOG(IRR?(-1)/POP?(-1))	0.016007	0.003964	4.038422	0.0001
LOG(CRICE?)	0.087824	0.016324	5.379918	0.0000
LOG(CWHT?)	0.071725	0.015972	4.490588	0.0000
LOG(CCORN?)	0.022828	0.012498	1.826492	0.0685
Fixed Effects				
Beijing	7.623619		Hubei	7.129527
Tianjin	7.286971		Hunan	6.781149
Hebei	6.899032		Guangdong	6.691356
Shanxi	6.843979		Guangxi	6.446985
Inner mongolia	7.373084		Hainan	6.558256

[5] Unit: VPL per labor, 10,000 Yuan.

Liaoning	7.385415		Chongqing	6.755487
Jilin	7.841553		Sichuan	6.723493
Heilongjiang	8.031176		Guizhou	6.279421
Shanghai	7.504021		Yunnan	6.296463
Jiangsu	7.272524		Tibet	6.377675
Zhejiang	6.757076		Shaanxi	6.639502
Anhui	6.791102		Gansu	6.63917
Fujian	6.674652		Qinghai	6.356215
Jiangxi	6.97832		Ningxia	7.027316
Shandong	6.992905		Xinjiang	7.341196
Henan	6.730896			
Weighted Statistics				
R-squared	0.999733	Mean dependent var		11.67133
Adjusted R-squared	0.999704	S.D. dependent var		7.240157
S.E. of regression	0.124462	Sum squared resid		5.189440
F-statistic	251020.0	Durbin-Watson stat		1.321839
Prob(F-statistic)	0.000000			
Unweighted Statistics				
R-squared	0.938635	Mean dependent var		7.302504
Adjusted R-squared	0.932040	S.D. dependent var		0.477442
S.E. of regression	0.124465	Sum squared resid		5.189640
Durbin-Watson stat	0.894058			

Table IV.3.1 shows that elasticities of grain production productivity are: 0.043 with w.r.t per capita ED, 0.017 w.r.t per capita RD, 0.016 w.r.t per capita IRR, 0.088 w.r.t CRICE, 0.072 w.r.t CWHT, 0.023 w.r.t CCORN. Among three public investments, ED can contributes grain production productivity the most, RD the second, and IRR the least. The rank in three material inputs is CRICE, CWHT, CCORN. These elasticities tell us that the impacts of both public investment and material inputs on grain production productivity are very limited. All elasticities are less than 0.009.

Comparing these two types of factors, we see the same picture that, averagely, material inputs can contribute grain production productivity more than public investment.

The mean of Fixed effects in Table IV.3.1 is 6.9364, standard deviation is 0.2013 which also shows relative homogenous of grain production productivity among provinces. Nevertheless, the fixed effects show that labor productivity of grain production in central region (7.1410) is averagely higher than those in east (7.0587) and west region (6.6880). That central region is the highest stems from the fact that this region is China's grain production zone.[6]

IV.3.2 The impact of public investments on the improvement of Pork, Beef, Mutton Production

[6] Unit: LGRN, kg per labor.

The model constructed to estimate this impact is the regression of meat production productivity (in terms of labor) on per capita ED, per capita RD, per capita IRR, and one material input, CHOG.

Table IV.3.2 Per Labor Meat Production Model

Dependent Variable: LOG(LMEAT?)				
Method: GLS (Cross Section Weights)				
Sample: 1990 2001				
Included observations: 12				
Total panel (balanced) observations 372				
Convergence achieved after 11 iteration(s)				
White Heteroskedasticity-Consistent Standard Errors & Covariance				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
LOG(ED?/POP?)	0.250562	0.014360	17.44864	0.0000
LOG(RD?/POP?)	0.075946	0.011800	6.436114	0.0000
LOG(IRR?(-1)/POP?(-1))	0.018346	0.009018	2.034444	0.0426
LOG(CHOG?)	0.223587	0.021106	10.59330	0.0000
Fixed Effects				
Beijing	4.386314		Hubei	3.840027
Tianjin	3.832632		Hunan	3.746201
Hebei	3.772667		Guangdong	3.350787
Shanxi	3.072764		Guangxi	3.434041
Inner mongolia	3.896061		Hainan	3.237489
Liaoning	4.011528		Chongqing	3.861877
Jilin	3.704706		Sichuan	3.813549
Heilongjiang	3.746853		Guizhou	3.319158
Shanghai	4.105244		Yunnan	3.099832
Jiangsu	3.601527		Tibet	3.541175
Zhejiang	3.194021		Shaanxi	3.087238
Anhui	3.40822		Gansu	3.231273
Fujian	3.505179		Qinghai	3.686155
Jiangxi	3.765866		Ningxia	2.955798
Shandong	3.596584		Xinjiang	3.601534
Henan	3.464379			
Weighted Statistics				
R-squared	0.996818	Mean dependent var		6.299934
Adjusted R-squared	0.996497	S.D. dependent var		2.602659
S.E. of regression	0.154038	Sum squared resid		7.996286
F-statistic	35192.07	Durbin-Watson stat		1.050038
Prob(F-statistic)	0.000000			
Unweighted Statistics				
R-squared	0.914021	Mean dependent var		4.811977
Adjusted R-squared	0.905347	S.D. dependent var		0.500702
S.E. of regression	0.154045	Sum squared resid		7.996947
Durbin-Watson stat	0.817539			

Table IV.3.2 shows that elasticities of meat production productivity are: 0.251 with w.r.t per capita ED, 0.076 w.r.t per capita RD, 0.018 w.r.t per capita IRR, 0.224 w.r.t CHOG. Among three public investments, ED can contributes meat production productivity the most, RD the second, and IRR the least. Material input CHOG can contribute meat production productivity more than RD and IRR, but less than ED.

The mean of Fixed effects in Table IV.3.2 is 3.5765, standard deviation is 0.1111 which also shows relative homogenous of meat production productivity among provinces. Nevertheless, the fixed effects show that labor productivity of pork, beef, mutton production in east region (3.6904) is averagely higher than those in central (3.5936) and west region (3.4606), and labor productivity in west region ranks the last.[7]

IV.3.3 The impact of public investments on the improvement of Fishery Production

The model constructed to estimate this impact is the regression of fishery production productivity (in terms of labor) on ED per capita, RD per capita, IRR per capita, and one material input, CFISH.

Table IV.3.3 Per Labor Fishery Production Model

Dependent Variable: LOG(LAQU?)				
Method: GLS (Cross Section Weights)				
Sample: 1991 2001				
Included observations: 11				
Total panel (balanced) observations 338				
Convergence achieved after 14 iteration(s)				
White Heteroskedasticity-Consistent Standard Errors & Covariance				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
LOG(ED?/POP?)	0.612468	0.026107	23.45993	0.0000
LOG(RD?/POP?)	0.202383	0.017621	11.48525	0.0000
LOG(IRR?(-1)/POP?(-1))	0.019371	0.004914	3.942130	0.0001
LOG(CFISH?)	0.191443	0.026488	7.227525	0.0000
Fixed Effects				
Beijing	2.293485		Hubei	3.541978
Tianjin	3.577145		Hunan	2.612855
Hebei	2.236723		Guangdong	3.788737
Shanxi	-0.3922		Guangxi	2.943114
Inner mongolia	0.921159		Hainan	3.754257
Liaoning	4.228599		Chongqing	2.129503
Jilin	1.273634		Sichuan	1.419924
Heilongjiang	2.256165		Guizhou	0.21779
Shanghai	3.370885		Yunnan	0.290986
Jiangsu	3.569862		Tibet	-1.777859
Zhejiang	4.435383		Shaanxi	0.292648
Anhui	2.913272		Gansu	-0.908322
Fujian	4.563131		Qinghai	-0.863533
Jiangxi	3.160616		Ningxia	1.104625

[7] Unit: LMEAT, kg per labor.

Shandong	3.847678		Xinjiang	0.744675
Henan	0.838557			
Weighted Statistics				
R-squared	0.996722	Mean dependent var		6.364764
Adjusted R-squared	0.996354	S.D. dependent var		5.017204
S.E. of regression	0.302935	Sum squared resid		27.80619
F-statistic	30711.95	Durbin-Watson stat		1.037809
Prob(F-statistic)	0.000000			
Unweighted Statistics				
R-squared	0.975664	Mean dependent var		3.453965
Adjusted R-squared	0.972933	S.D. dependent var		1.841382
S.E. of regression	0.302944	Sum squared resid		27.80782
Durbin-Watson stat	0.910613			

Table IV.3.3 shows that elasticities of fishery production productivity are: 0.612 with w.r.t per capita ED, 0.202 w.r.t per capita RD, 0.019 w.r.t per capita IRR, 0.191 w.r.t CFISH. Among three public investments, ED can contributes fishery production productivity the most, RD the second, and IRR the least. Material input CFISH can contribute fishery production productivity more than IRR, but less than ED and RD.

The mean of fixed effects in Table IV.3.3 is 2.0124, standard deviation is 3.0484 which shows heterosgenous of fishery production productivity among provinces, from -1.7779 in Tibet to 4.5671 in Fujian. The fixed effects show that labor productivity of fishery production in east region (3.60599) is averagely higher than those in central (2.0256) and west region (0.5429), and labor productivity in west region ranks the last. This heterosgenous mainly stems from the regional characteristics of fishery production in China.[8]

IV.4 The Impact of Public Investments on Poverty Reduction

The model constructed to estimate this impact is the regression of poverty incidence, PVT/POP, on per capita ED, per capita RD, and per capita IRR.

Table IV.4 Poverty Incidence Model

Dependent Variable: LOG(PVT?/POP?)
Method: GLS (Cross Section Weights)
Sample: 1990 2001
Included observations: 12
Total panel (balanced) observations 365
Convergence achieved after 7 iteration(s)
White Heteroskedasticity-Consistent Standard Errors & Covariance

[8] Unit: LAQU, kg per labor.

Variable	Coefficient	Std. Error	t-Statistic	Prob.
LOG(ED?/POP?)	-0.504271	0.025192	-20.01691	0.0000
LOG(RD?/POP?)	-0.092620	0.025448	-3.639561	0.0003
LOG(IRR?(-1)/POP?(-1))	-0.100638	0.012829	-7.844722	0.0000
Fixed Effects				
Beijing	-4.918362		Hubei	-3.678776
Tianjin	-5.47092		Hunan	-4.071049
Hebei	-3.88047		Guangdong	-6.080403
Shanxi	-2.897173		Guangxi	-3.431435
Inner mongolia	-2.852656		Hainan	-3.158858
Liaoning	-3.580477		Chongqing	-3.656998
Jilin	-3.149844		Sichuan	-3.483938
Heilongjiang	-2.892006		Guizhou	-2.981577
Shanghai	-7.073111		Yunnan	-2.512415
Jiangsu	-5.103476		Tibet	-2.098305
Zhejiang	-5.170221		Shaanxi	-2.954538
Anhui	-3.847843		Gansu	-2.597435
Fujian	-5.386126		Qinghai	-2.265484
Jiangxi	-4.08683		Ningxia	-2.162212
Shandong	-4.598956		Xinjiang	-2.021552
Henan	-3.552644			
Weighted Statistics				
R-squared	0.958120	Mean dependent var		-4.722829
Adjusted R-squared	0.953944	S.D. dependent var		2.551083
S.E. of regression	0.547478	Sum squared resid		99.21126
F-statistic	3786.233	Durbin-Watson stat		1.083113
Prob(F-statistic)	0.000000			
Unweighted Statistics				
R-squared	0.847907	Mean dependent var		-3.085785
Adjusted R-squared	0.832743	S.D. dependent var		1.338690
S.E. of regression	0.547485	Sum squared resid		99.21373
Durbin-Watson stat	0.747118			

Table IV.4 shows that elasticities of poverty incidence are: -0.504 with w.r.t per capita ED, -0.093 w.r.t per capita RD, -0.101 w.r.t per capita IRR. Among three public investments, per capita ED can contribute poverty reduction the most, per capita IRR the second, and per capita RD the least.

The mean of fixed effects in Table IV.3.2 is -3.7296, standard deviation is 1.5344 which shows relative heterosgenous of poverty incidence among provinces, from -7.0731 in Shanghai to 4.5671 to -2.0216 in Xinjiang. The fixed effects show that poverty incidence in east region (-4.9474) is averagely lower than those in central (-3.5220) and west region (-2.7516). This heterosgenous reflects the difference in the level of rural economic development between provinces in China.[9]

IV.5 The Impact of Public Investments on Poverty Reduction through Total Agricultural

9 Unit: poverty incidence, %.

Productivity

The following regression model is incorporated with the models in V.1 and V.4 in order to estimate the impact of public investments on poverty reduction through total agricultural productivity by using chain derivatives properties.

The model constructed to estimate the impact of total agricultural productivity (in terms of labor) on poverty incidence is the regression of poverty incidence on per labor output value of farming, forestry, animal husbandry (VAG/LABOR).

Table V.5.1 The Impact of Total Agricultural Productivity on Poverty Reduction Model

Dependent Variable: LOG(PVT?/POP?)				
Method: GLS (Cross Section Weights)				
Sample: 1985 2001				
Included observations: 17				
Total panel (unbalanced) observations 511				
Convergence achieved after 6 iteration(s)				
White Heteroskedasticity-Consistent Standard Errors & Covariance				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
LOG(VAG?/LABOR?)	-0.571719	0.019764	-28.92685	0.0000
Fixed Effects				
Beijing	-5.009489		Hubei	-3.553842
Tianjin	-5.206959		Hunan	-4.010315
Hebei	-3.5349		Guangdong	-5.918142
Shanxi	-3.1101		Guangxi	-3.364851
Inner mongolia	-2.763179		Hainan	-2.980239
Liaoning	-3.30276		Chongqing	-2.94133
Jilin	-2.961842		Sichuan	-3.014272
Heilongjiang	-2.648409		Guizhou	-2.681376
Shanghai	-7.012671		Yunnan	-2.704844
Jiangsu	-4.327065		Tibet	-2.596696
Zhejiang	-4.603177		Shaanxi	-2.732258
Anhui	-3.542153		Gansu	-2.481137
Fujian	-4.850005		Qinghai	-2.674517
Jiangxi	-3.688749		Ningxia	-2.259723
Shandong	-4.211833		Xinjiang	-2.002461
Henan	-3.13563			
Weighted Statistics				
R-squared	0.851723	Mean dependent var		-3.698374
Adjusted R-squared	0.842126	S.D. dependent var		1.516306
S.E. of regression	0.602479	Sum squared resid		173.8677
Durbin-Watson stat	0.831363			
Unweighted Statistics				
R-squared	0.817658	Mean dependent var		-2.921112
Adjusted R-squared	0.805858	S.D. dependent var		1.367387
S.E. of regression	0.602493	Sum squared resid		173.8757

Durbin-Watson stat	0.756431			

Table IV.5.1 shows that elasticity of poverty incidence w.r.t total agricultural productivity in terms of labor is -0.572 .

Therefore, the elasticities of poverty incidence through total agricultural productivity are: -0.572*0.222 = -0.127 w.r.t per labor ED, -0.572*0.187 = -0.107 w.r.t per labor RD, -0.572*0.007 = -0.004 w.r.t per labor IRR.

V. Conclusion

Based on the results from the models we use in this paper listed above, we see that government education expenditure in rural elementary and middle School can works the most efficiently among the three public investments.

The statistics in all tables above pass statistical test except Durbin-Watson statistic. Weighted Durbin-Watson statistic is relatively low, from 1.083113 to 1.398854, all of them are less than 2, which show that there are relatively negative series correlations in time period in the data. Taking into account the fact that the length of time modeled in this paper is short, however, the series correlation here dose not make much sense to the results' validities.

Table V. Elasticities estimated

	VAG/L	VPL/L	LGRN	LMEAT	LAQU	PVT/P
ED/P	0.222321	0.262851	0.043092	0.250562	0.612468	-0.504271
RD/P	0.186506	0.082183	0.016979	0.075946	0.202383	-0.092620
IRR/P	0.006717	0.015213	0.016007	0.018346	0.019371	-0.100638
CRICE	0.122038	0.204631	0.087824			
CWHT	0.330794	0.296811	0.071725			
CCORN	0.164162	0.125034	0.022828			
CHOG	0.192323	0.251799		0.223587		
CFISH	0.163935	0.102287			0.191443	

In terms of the elasticities in Table V, we conclude:

1） The most efficient public investment among the three public investments is government education expenditure in rural elementary and middle school.

2） The second efficient public investment is government expenditure in agricultural science and technology research for all investment objectives except poverty reduction.

3） Government investment in irrigation construction for farming, forestry, animal husbandry and fishery sectors is more efficient than government expenditure in agricultural science and technology research for poverty reduction.

4） Generally, the least efficient public investment among the three public investments is government investment in irrigation construction for farming, forestry, animal husbandry and fishery sectors.

5） Labor productivity of grain production is less affected by the three public investments, and by rural household’s material inputs as well, while labor productivity of fishery production is more affected by the three public investments.

6） Averagely, rural household’s material inputs are more important to agriculture production than public investments.

7） government education expenditure in rural elementary and middle school contributes poverty reduction the most, government investment in irrigation construction for farming, forestry, animal husbandry and fishery sectors the second, and government expenditure in agricultural science and technology research the last.

8） The rank of the impacts of public investments on poverty incidence through total agricultural productivity is: government education expenditure in rural elementary and middle school, government expenditure in agricultural science and technology research, and government investment in irrigation construction for farming, forestry, animal husbandry and fishery sectors, in turn.