THE IMPACT OF CHINA'S GANSU AND INNER MONGOLIA POVERTY REDUCTION PROJECT ON NET RURAL INCOME PER CAPITA GROWTH

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Abstract:

In 2000, the World Bank conducted its third in a series of bank-assisted, targeted poverty-reduction projects in China to support the Chinese government's Eight-Seven Poverty Reduction Plan. The third project, the Gansu and Inner Mongolia Poverty Reduction Project, aimed to lift the remaining poor counties in Gansu and Inner Mongolia provinces out of poverty by increasing the net rural income in the "treated" area. This paper uses an econometric model to evaluate the impact of this project on the net rural income per capita growth in the treated counties. The major finding of this analysis is that Gansu and Inner Mongolia Poverty Reduction Project has significantly increased the net rural income per capita of the treated counties by 12.00% higher than the non-treated counties.[1]

[1] See Appendix D Model 2

I. Introduction

In the late 1970s, the Chinese government started a nation-wide anti-poverty war, which aimed at solving the basic food and clothing problems of a portion of the rural population that lived below the poverty line. In 1994, the Chinese government announced the Eight-Seven (8-7) Poverty Reduction plan to help the remaining rural poor escape from poverty within a seven-year period. During this period, the Chinese government cooperated with several international organizations; the World Bank was the first multilateral organization to be involved in the anti-poverty campaign in China. During the seven-year period, three projects were implemented through cooperation between the World Bank and the Chinese government including the Southwest Program, the Qinba Program, and Gansu and the Inner Mongolia Poverty Reduction Project (G&MPRP).

This paper seeks to provide empirical analysis of the effect of the Gansu and Inner Mongolia Poverty Reduction Project. The objective and implementation of the project will be outlined in Section 2. In Section 3, I will use a dataset that covers 160 counties in the two provinces from 1997 to 2008 to measure the impact of the project on rural net income growth. In section 4, I will conduct a robustness check to confirm my results from Section 3. Finally, section 5 contains a conclusion and policy recommendations.

II. Gansu and Inner Mongolia Poverty Reduction Project (G&MPRP)

The Gansu and Inner Mongolia Poverty Reduction Project is the third joint, targeted poverty reduction project between the World Bank and the Chinese government, following the Southwest project and the Qinba Project. The project was designed to support the Chinese Government's Eight-Seven Poverty Reduction Plan (ICR, 2006). The objective of this project is to reduce absolute poverty in the remote and inaccessible areas of Gansu Province and Inner

Mongolia Autonomous Region. The project aimed at empowering poor households in selected counties by raising their incomes through increased grain and livestock production to levels sufficient to meet basic food and clothing needs and increasing the living standards of poor rural households through funding alternative income-generation activities in poor rural areas. The main project development objectives (PDO) are the reduction in income poverty (measured as the net income of the target group in RMB per capita) and the reduction in food poverty (measured as grain production below the national poverty line. i.e. below 150 kg per capita) (ICR, 2006).

For G&MPRP, 27 counties of Gansu and Inner Mongolia Provinces and some counties of Qinghai Province were selected in 2000. In 2001, the Qinghai components were dropped due to the verification of its "apparent violation of several provisions" of the World Bank's operational policies. According to the ICR (2006), an investigation was conducted after a complaint was made to the World Bank by the International Campaign for Tibet in 1998. Once it was determined that the Qinghai component would harm the overall feasibility of the program due to the violations of Bank policy, "the Borrower decided to drop the Qinghai Component in order to allow activities in Gansu and Inner Mongolia to proceed" (p.3-4). The Chinese government selected 13 counties in the remaining two provinces (Gansu and Inner Mongolia Provinces) to substitute for the dropped counties of Qinghai Province.[2]

III. Empirical Analysis

Literature Review

There are only a few studies which measure the impact of the Gansu and Inner Mongolia Poverty Reduction Project. The most comprehensive assessment of the impact of this project is the World Bank's Implementation Completion Report (ICR). The ICR claims that the project had

[2] See Appendix A

a substantial impact on poverty, citing survey data that indicated average per capita incomes increased by 78 percent and poverty headcount dropped by 14 percentage points. However, this evaluation is questionable because the evaluative claims of the ICR only reflect the true impact of the project under the assumption that there would have been no progress against poverty in the absence of the G&MPRP. That assumption is highly implausible in this setting (Ravallion, 2006). I have not found any literature that provides econometric evaluation of this project; therefore, this study will be the first to use econometric techniques evaluating the project. Fortunately, there are some papers which provide empirical analysis of other poverty reduction projects that can guide our methodology in this analysis. Martin Ravallion used a “difference-in-difference” fixed effects analysis to evaluate the impact of the Southwest Poverty Reduction Project of World Bank (SWP) by comparing the SWP area (treat group) and the non-SWP area (control group). He also used a propensity scoring technique to balance the treatment and control units in terms of the initial conditions that may have influenced program placement. This method addresses time-varying selection bias based on observable factors, which is an advanced method utilized in econometric analysis (Ravallion, 2006). Albert Park, author of “Regional poverty targeting in China” utilized 3SLS to evaluate the impact of China’s large-scale poverty alleviation program in three periods from 1986 to 1995. Park includes lagged income as an independent variable while using income as dependent variable, which may cause an autocorrelation problem. To mitigate the problem of autocorrelation, Park used 3SLS. Based on the previous techniques used in these literatures, I will evaluate the impact of the project by correcting for some of their mistakes and by utilizing some of the techniques that they used to address the endogeneity problems.

Data

I collected county-level data for Gansu and Inner Mongolia from 1997 to 2008. Data on grain output, rural population, and rural labor were collected from “China Data Online” which is a website authorized by the National Bureau of Statistics of China. Data on rural income per capita was collected from Chinese county statistical yearbooks. Data on project designation was collected from the World Bank database. Within the 160 counties that are included in the sample, 27 counties were selected into the project in 2000, 13 counties were selected into the project in 2001. This project was completed in 2006.[3]

I use log (rural net income per capita) as the dependent variable, which is calculated from rural net income per capita from 1997 to 2006. Project participation ($Treat_{it}$) is my key independent variable, which is treated as a dummy—counties which were selected into the project at year t and after were labeled as one. All of the treated counties entered into the project at either the beginning of 2000 or 2001. Thus, I assume that the project would impact the rural net income of the same year.

Econometric Models

I utilized a two-way fixed effects model to evaluate the impact of the program. Two-way fixed effects models are able to knock out all the influence from time-invariant characteristics of every individual county, correcting the problem of omitted variable bias efficiently. The year dummies also rule out the trend of net rural income growth. During the time of the project, China also experienced a boom in economic growth. Thus, including year dummies is able to mitigate the effect of the broad-based economic growth trends. Log (rural net income) is my dependent variable. The baseline model is

$$Log(inc)_{it}=\beta_0+\beta 1 Treat_{it}+\sum\delta year_t+\alpha_i+u_{it}(i=1,\ldots N;t=1997,1998,\ldots 2006)$$

Here "i" stands for the id of all of the 160 individual counties in the sample, "t" stands for the time, or years, in the sample. α_i is the county level fixed effects. The two provinces, Gansu and

[3] See Appendix A

Inner Mongolia, are very close to each other geographically, sharing a long border. I declined to use province-level fixed effects for a couple of different reasons. First, the economic growth project was implemented on a county level, not a provincial level. A second reason for not using the fixed effects at the province level is that Gansu and Inner Mongolia share similar characteristics, such as both are located in western China, a poverty-concentrated area, in close proximity to one another.

Selection of control variables: Some variables, such as grain output, medical center quality and school enrollment, may have been influential factors considered by the government when they selected counties into the project. By using these variables as my control variables, the problem of endogeneity would arise because these variables are the very objectives of the project itself. Thus, while controlling for all the time-constant variables in the fixed effects (α_i), I only used one time-varying control variable--rural labor participation rate, or RLPR (rural labor/rural population), based on the assumption that a higher rural labor participation rate will lead to higher rural labor income per capita.

$$\text{Log(inc)}_{it}=\beta_0+\beta_1\text{Treat}_{it}+\sum\delta\text{year}_t+\beta_2\text{RLPR}_{it}+\alpha_i+u_{it}(i=1,\ldots N;t=1997,1998,\ldots 2006)$$

Regression Results

Using the aforementioned models, the regression result shows that the "treated" counties' net rural income increased by 12.00%[4] more than the incomes of "non-treated" counties' net rural income and this finding is highly statistically significant. These results demonstrate that the poverty-reduction project is very effective at increasing net rural incomes, although this result is much lower than the World Bank's ICR findings demonstrate. As mentioned, the ICR does not

[4] See Appendix D Model 2

rule out the effect of broad-based boom of Chinese economy, and this likely largely explains the differences between the two analyses.

IV. Robustness Checks

Targeting

Selection biases always exist in the process of policy implementation. The targeted counties are chosen based on some of their unique characteristics, meaning that the Chinese government may purposely pick some counties to join the World Bank project. As a poverty reduction project, poorer counties are more likely to be selected into it. To see what factors determine which counties were selected, I ran a cross-sectional probit model by collapsing the pretreatment data from 1996 to 1999. The regression result shows that income growth and grain output are two key factors for targeting under this program. As the results show, a 1% increase in rural income per capita reduces the probability of being targeted by 0.53%; a 1% increase in grain output increases the probability of being targeted by 0.15%.[5] This means that the more rural income per capita, the less the grain output per capita, the less likely the counties to be selected. Based on the Chinese government's targeting history in Eight-Seven Poverty Reduction Plan, the revolutionary history of several counties should also have been a significant factor for these counties to be chosen to receive the poverty reduction program. However, the regression result shows that the variable revolutionary is not significant in the G&MPRP targeting; this finding may be due to the small scale of G&MPRP and lack of observations for testing. Thus, we find that "treated" counties demonstrate some different characteristics from the "untreated" counties. Fortunately, if this selection bias is constant over time, outcome changes are not correlated with initial differences between the participating and non-participating areas, these biases could be eliminated by two-way fixed effects.

[5] See Appendix E

Discussion of Time-Varying Selection Bias

Recall that counties with lower rural income per capita are more likely to be selected into the project. I compare the log rural income per capita between treated counties and non-treated counties. The treated counties have significantly lower rural income per capita than the counties not treated[6]. From this result we can see that counties treated are "poorer" than the non-treated counties. The targeted counties may lack infrastructure and other initial endowments, which could (in turn) affect the subsequent income growth rates (Ravallion, 2006). Simply stated, poorer counties may grow at a slower rate than the relatively rich counties. This is also the source of the time-varying selection bias, which always exists in the policy evaluation literature when we use a "difference-in-difference" model. The model I used in the previous section is based on the assumption that there is no time-varying selection bias exist, meaning the "treated" group should grow at the same rate as the "control" group in the absence of the project. As I mentioned in the literature review, Ravallion uses the propensity score technique to address the time-varying selection bias. He addresses this issue by balancing treatment and comparison units in terms of the initial conditions that may have influenced program placement. These initial conditions are represented by a series of observed variables that constitute a vector X. Ravallion's assumption is that the selection bias is time-invariant conditional on the vector X. This method removes the time-varying selection bias only based on the observable factors. The bias remains if there are any unobservable time-varying factors that correlated with the change of the outcomes (Ravallion, 2006). I did not use propensity scoring in my model based on the limitation of the data and the econometric techniques that I learned. However, if the "treatment" group and "control" group in my sample grew at the same rate in the absence of the project, I would not take the time-varying selection bias as a significant problem.

[6] See Appendix F

Change Test

In order to test the above identifying assumption of the validity of fixed effects using the pre-treatment data before 2000, this can be deemed as "in the absence of the project". I split my sample into three groups: Group 1 includes the counties that were treated in 2000, Group 2 includes the counties that were treated in 2001, and Group 3 includes all of the counties that were not treated at all. First, I test if Group 1 grew at the same rate as Groups 2 and 3 by using data from 1997 to 1999. Then, I test if Group 2 grew at the same rate as Group 3 by using data from 1997 to 2000. The result shows that both the coefficients of "treat" are insignificant. That means whether the county was treated or not has no correlation with their changes in the absence of the project.[7] Thus I can safely use two-way fixed effects to evaluate the impact of the project to the income growth.

"Tau" Test[8]

In this sample, there are 27 counties that entered into the project in 2000 and 13 counties that entered into the project in 2001. I collapsed their "first year entering the project" into the same point in order to creating a "tau" variable. By graphing log rural income according to the variation of "tau", I can see the tendency of income growth before and after they enter the project of the two groups together. The graph does not show any trend indicating an Ashenfelter's dip before the "treated "counties entered the project. From the tendency of the log net rural income as the graph shows, we can see that there is no obvious increase in log net rural income in the first year they entered into the project, the slope become steeper from the second year to the fifth year

[7] See Appendix G

[8] "Tau Test" is used when "treated" counties entered the project at different time by collapsing the different enter time into the same point.

after the counties entered into the project. Additionally, the slope becomes a little bit flatter from the sixth year after entering the project. In year six, G&IPRP came to its conclusion.[9]

Heteroskedasiticity & Autocorrelation Check

Next I will conduct a robustness check of the error term. First, I will check whether a heteroskedasticity problem will substantially influence the regression results. Secondly, I will run the final regression with "robust" standard errors to control for autocorrelation.

When controlling for heteroskedasticity, the coefficient of "$Treat_{it}$" is still highly significant; this means that the heteroskedasticity will not impact the result of the model.[10] When controlling for autocorrelation of the error term by regressing the residuals on their lags, a strong autocorrelation was found between the residual and its first lag. [11]To deal with this problem, I ran a model by using bi-annual data (1998, 2000, 2002, 2004, 2006) by dropping the intermediate years. The $Treat_{it}$ dummy is still highly significant and the coefficient almost does not change.[12] I also resort to using Newey-West standard errors to test whether the autocorrelation can influence my conclusion. After runing the regression with Newey-West standard errors, the coefficient is still highly significant. Therefore, the problem of autocorrelation will not influence the result of the model.[13]

The Impact after the Completion of the Project

To see if the project has sustainable impact after the project finished, I generated the interaction between "P_{it}" with year 2007 and year 2008. The coefficient of the interaction of 2007 is insignificant, while the coefficient of the interaction of 2008 is significant at a 10% level. One

[9] See Appendix H
[10] See Appendix D Model 3
[11] See Appendix I
[12] See Appendix J
[13] See Appendix D

of the reasons for the insignificance found in 2007 would be that the "treated" counties repaid a large amount of their loan to the World Bank, which reduced their net rural income growth significantly. In 2008, the "treated" counties' income grows more than the "non-treated" counties, of which the finding is significant at the 90% confidence level. However, to see the long-run impact of the project after it finished, we still need the data after 2009, which is not yet available.[14]

Further Testing the Subgroup

To further test the results of the model, I split the "treated" counties into two sub-groups. Group one includes the counties which enter the project in 2000, while group two includes the counties which enter the project in 2001. I evaluated the impact of the project on the two groups separately. In the new model, I created the interaction of "$Treat_{it}$" with the dummy variable: Treat2001: equal to 1 if the counties are treated in 2001. The regression result shows that the counties who were treated in 2000 see 10.26% more growth of their income than the non-treated group. The counties who were treated in 2001 see a 15.7% more income growth than the non-treated group. From this result, we can see that the project did increase the income of the counties initially treated in both years. [15]

□. Conclusion

Based on the evidence shown in the previous analysis, I am confident enough to draw the conclusion that the Gansu and Inner Mongolia Poverty Reduction Project has significantly increased the net rural income per capita growth of selected counties in the two provinces. The

[14] See Appendix K
[15] See Appendix L

"treated" counties' net rural income per capita increased by an average of 12.04% compared to the non-treated counties, though this impact is much smaller than the ICR claimed.

However, there are also many problems in the process of the implementation of the project. The net rural income growth of the treated counties became insignificant right after the disbursement period. This insignificance is not only due to the repayment of the loans in 2007; it is also due to the inefficiency of the management of the project. The treated counties were required to report their bill of expense to the World Bank before June 30, 2006. After that, late reporting would lead to extra fees paid to the World Bank. Because of the inefficiency of the reporting mechanism, an extra lost burden would fall on the farmers in those counties resulting in decreased benefits of the program.

On the basis of our understanding of the hierarchal political system in China, there is reason to believe that the project may not have been implemented efficiently. An example of this is that part of the money was not used properly according to the designated program. If the loans could be placed into the right places, the impact of this project could have had an even greater effect on increasing the net rural income. Every poverty-reduction project has the long-term goal of lifting the treated area out of poverty. To see the long-run impact of this project, we would still need to consider the future data. This project will be deemed even more successful when it has a sustainable impact on the treated area in the long-run.

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Appendix:

A: Project provinces and Number of Treated counties

province	Gansu	Inner Mongolia
Number of counties	**76**	**84**
Treat in 2000	**14**	**13**
Treat in 2001	**6**	**7**

B: Description of Main Variables

Log(inc)	Log of net rural income per capita
Treat	**0-1 dummy of treated or not**
RLPR	**Rural labor rate (rural labor/rural population)**
Treatever	**Equal to 1 if the county was treated**
Log(grain)	**Log (grain per capita)**
Treat 2000	**=1 if the county treated in 2000**
Treat 2001	**=1 if the county treated in 2001**
Year 2007	**Year==2007**
Year 2008	**Year==2008**

C: Regression Models:

Two Way Fixed Effects:

$Log(inc)_{it}=\beta_0+\beta_1 Treat_{it}+\sum\delta year_t+\beta_2 RLPR_{it}+\alpha_i+u_{it}(i=1,\ldots N;t=1997,1998,\ldots 2006)$

Probit Model on Targeting:

$Treatever= \beta_0+\beta_1 Log(inc)+ \beta_2 Log(grain)+\varepsilon_i$

(*Cross-sectional Regression by collapsing pretreatment data from 1997 to 1999*)

Test pre-Treatment Change

$\square Log(inc)_{it}= \beta_0+ \beta_1 treat2000+ \beta_2 \square RLPR_{it}+ \varepsilon_i$

$\square Log(inc)_{it}= \beta_0+ \beta_1 treat2001+ \beta_2 \square RLPR_{it}+ \varepsilon_i$

Impact after program finished

$Log(inc)_{it}=\beta_0+\beta_1 Treat_{it}+\sum\delta year_t+\beta_2 RLPR_{it}+Treat_{it}*year2007+ Treat_{it}*year2008+\alpha i+u_{it}$

Sub-group test

$Log(inc)_{it}=\beta_0+\beta_1 Treat_{it}+\sum\delta year_t+\beta_2 RLPR_{it}+Treat_{it}*Treat2001+\alpha_i+u_{it}$

D: Models

	Model1	Model2	Model3	Model4
VARIABLES	loginc	loginc	loginc	loginc
treat	0.112***	0.120***	0.120***	0.120***
	(0.016)	(0.017)	(0.028)	(0.021)
RLPR		0.126***	0.126*	0.126***
		（0.048）	(0.067)	（0.061）
Constant	7.186***	7.130***	7.130***	7.130***
	（0.012）	（0.027）	(0.035)	（0.021）
Observations	1967	1865	1865	1865
R-squared	0.814	0.81	0.810	
Number of id	159	158	158	158
Rmse	0.148	0.148	0.142	
Standard errors in parentheses				
***** p<0.01, ** p<0.05, * p<0.1**				

Note:

Model1: Two-way fixed effects with only treat and year dummies as independent variables

Model2: Add rural labor participation as control variable

Model3: Robust—one level data (county level)

Mode4: Newey-West standard errors

E: Probit Model

Determinant of the Treatment Project Targeting

	(1)	(2)
VARIABLES	treatever	treatever
(mean) loginc	-0.539***	-0.534***
	(0.085)	(0.087)
(mean) loggrain	0.150***	0.155***
	(0.056)	(0.058)
(mean) revolutionary	0.088	
	(0.079)	
Observations	154	154
rmse	.	.
Standard errors in parentheses		
***** p<0.01, ** p<0.05, * p<0.1**		

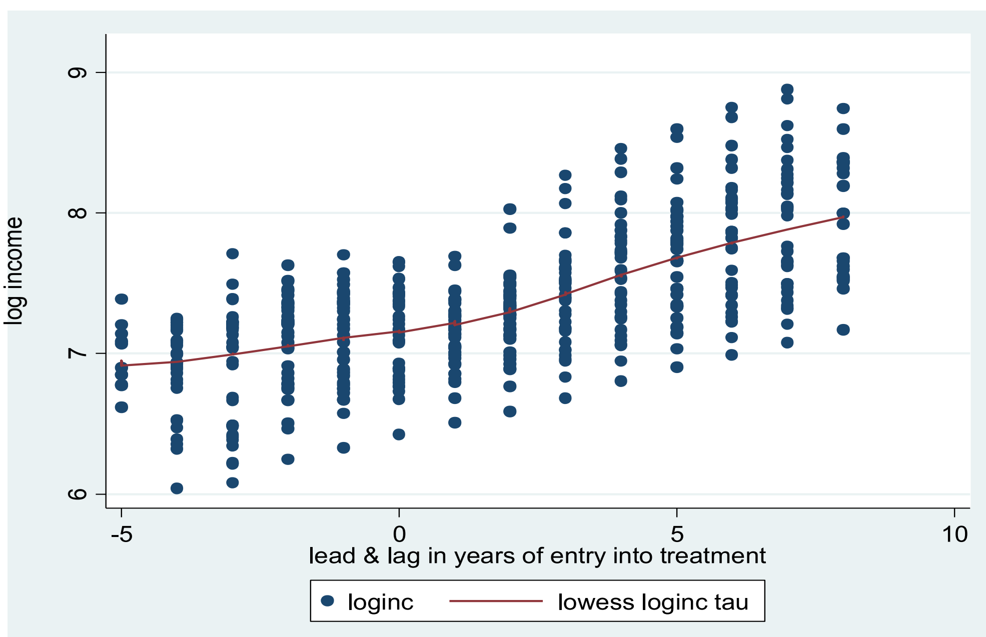
F. Test the Difference of Log (rural income) between Treat Group and non-Treated Group

	(1)
VARIABLES	loginc
treatever	-0.401***
	(0.039)
RLPR	0.606***
	(0.144)
Constant	7.185***
	(0.070)
Observations	530
R-squared	0.199
rmse	0.388
Standard errors in parentheses	
***** p<0.01, ** p<0.05, * p<0.1**	

G: Test Changes in Pre-Treat Period

	(1)	(2)
VARIABLES	loginc_df	loginc_df
Treat2000	0.004	
	(0.015)	
Treat2001		-0.027
		(0.021)
RLPR_df	0.027	-0.007
	(0.044)	(0.050)
Constant	0.077***	0.074***
	(0.007)	(0.006)
Observations	226	499
R-squared	0.002	0.003
rmse	0.0890	0.125
Standard errors in parentheses		
***** p<0.01, ** p<0.05, * p<0.1**		

H: Lowess Log (income) with "Tau"-Leads and Lags of the Reform



I: Autocorrelation Check

VARIABLES	Ehat
ehatlag1	0.894***
	(0.025)
ehatlag2	0.083**
	(0.033)
ehatlag3	0.017
	(0.025)
Constant	-0.000
	(0.003)
Observations	1376
R-squared	0.937
rmse	0.113
Standard errors in parentheses	
*** p<0.01, ** p<0.05, * p<0.1	

J: Autocorrelation correction using Bi-annual data

	(1)
VARIABLES	Loginc
treat	0.121***
	(0.024)
RLPR	0.150**
	(0.068)
Constant	7.106***
	(0.034)
Observations	1114
Number of id	157
R-squared	0.839
rmse	0.152
Standard errors in parentheses	
*** p<0.01, ** p<0.05, * p<0.1	

K:Impact After Program Finished

	(1)
VARIABLES	Loginc
treat	0.111***
	(0.018)
RLPR	0.127***
	(0.048)
Treat*year07	0.035
	(0.030)
Treat*year08	0.055*
	(0.030)
Constant	7.130***
	(0.027)
Observations	1865
Number of id	158
R-squared	0.810
rmse	0.148
Standard errors in parentheses	
***** p<0.01, ** p<0.05, * p<0.1**	

L:Sub-group Test

VARIABLES	**loginc**
treat	0.103***
	(0.020)
RLPR	0.127***
	(0.048)
treat2001*treat	0.054*
	(0.032)
Constant	7.130***
	(0.027)
Observations	1865
Number of id	158
R-squared	0.810
rmse	0.148
Standard errors in parentheses	
***** p<0.01, ** p<0.05, * p<0.1**	