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RESEARCH ARTICLE

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China's Fiscal Stimulus Package for the Current International Crisis: What does 1996–2006 Tell Us?

Abstract This paper uses Bi-Directional Reiterative Truncated Projected Least Squares (BD-RTPLS) to estimate annual $\partial GPP/\partial G$ and $\%\partial GPP/\%\partial G$ multipliers for China's 31 provinces between 1996 and 2006 (GPP = Gross Provincial Product and G = government spending in the province). In order to account for the influence of omitted variables, BD-RTPLS produces a separate $\partial GPP/\partial G$ and $\%\partial GPP/\%\partial G$ estimate for every observation in the data set. I find that $\partial GPP/\partial G$ and $\%\partial GPP/\%\partial G$ were highest in 1996 while China was drastically cutting government spending to curb inflation, were lowest in 1997 during the Asian Financial Crisis, slowly rose between 1998 and 2004, and then declined some in 2005 and 2006 when the Chinese yuan was slowly appreciating.

Keywords fiscal policy, China, crises, stimulus

JEL Classification E62, E65, N15

1 Introduction

As the worst financial crisis since the Great Depression threatens our world in the early months of 2009, governments around the globe implement the largest fiscal stimulus packages in their histories. The Chinese government has pledged to spend four trillion yuan (586 million US dollars) over the next two years (2009–2010). In contrast, during the 1997–1998 Asian Financial Crisis, the

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Chinese government spent only 0.9 trillion yuan over a six year time period. Unlike previous stimulus packages, the 2009–2010 package aims at increasing consumption, not infrastructure (Zheng, 2008). Because this stimulus package differs from previous stimulus packages in size, focus, and its global context, there is no way to perfectly predict the effects of this package. However, in depth studies of the effectiveness of past government spending in China can provide helpful insights, which can assist the government's efforts to produce the best package possible.

This paper will use "Bi-Directional, Reiterative, Truncated, Projected Least Squares" (BD-RTPLS), to estimate the effect of government spending (G) in China's 31 provinces on Gross Provincial Product (GPP) between 1996 and 2006. This paper will report a separate $\partial GPP/\partial G$ for each observation in the data. Thus the Chinese government will be able to use the results of this paper to see in which provinces and in which years government spending had the largest effect on GPP. I find that $\partial GPP/\partial G$ was the highest in 1996 while China was drastically cutting government spending to curb inflation, was the lowest in 1997 during the Asian Financial Crisis, slowly rose between 1998 and 2004, and then declined some in 2005 and 2006 when the Chinese yuan was slowly appreciating. When designing its current stimulus package, the Chinese government needs to especially consider how the Asian Financial Crisis caused government spending multipliers to plummet in China in 1997.

It should be emphasized that this paper will provide only part of the information that the Chinese government needs to develop the best stimulus package. Other issues that the Chinese government needs to consider, in addition to GPP, include inflation, income distribution, living standards, health care, security, and harmony.

The remainder of this paper is structured as follows. Section 2 surveys very recent literature that relates to the estimation of government fiscal multipliers. Section 3 explains the intuition underlying BD-RTPLS. Section 4 explains the data. Section 5 presents the empirical results. Section 6 concludes.

2 Relevant Recent Literature

Previous studies of government spending multipliers fall into three different groups: (1) studies that use structural models of the economy, (2) studies that use vector autoregressive methods, and (3) studies that use BD-RTPLS or its predecessor, RTPLS. Recent studies in each of these groups are surveyed below.

Cogan et al. (2009) dramatically demonstrates the problem with structural model approaches to estimating government fiscal multipliers. He does this by contrasting the results of Romer-Bernstein's (2009) with Taylor's (1993) model using data for the current financial crisis. He finds that the Taylor model predicts a government spending multiplier of 1.4 in the first quarter, which then steadily declines to approximately zero by the 24th quarter. In contrast the Romer-Bernstein model estimates a multiplier of approximately 1 in the first quarter which steadily rises to almost 1.6 by the 8th quarter and then stays at 1.6 until the 16th quarter. These results are dramatically different. Cogan et al. (2009) then provide a third set of results based on the Smets-Wouters (2007) model. Cogan et al. (2009) seem to imply that they believe that the Smets-Wouters model is best. However, I find that their paper provides evidence that macro economic models are often built to produce the results that the researcher wants to find. By slightly changing the model, drastically different results can be obtained. One of the great advantages of BD-RTPLS is that it is not model dependent. This great advantage entails the disadvantage of not being able to tell the mechanism through which the independent variable affects the dependent variable. However the advantages of BD-RTPLS could be combined with the advantages of structural models by choosing the structural model that best fits the BD-RTPLS results.

Cogan et al. (2009) also find that current data applied to the Smets-Wouters model produces negative government spending multipliers by the year 2013 and that these multipliers remain negative for many years beyond 2013. In the Smets-Wouters model, this negative multiplier is due to the crowding out of consumption and investment. See Coenen and Straub (2005) for a survey of the literature on crowding out.

Vector Auto regressive models also sometimes produce negative multipliers. Perotti (2002) (as cited by Giordano et al., 2009, p. 562) using data from Australia, Canada, Germany, and the UK finds that "in the pre-1980 sample, positive government spending multipliers larger than one are rare; in the post-1980 period, significantly negative multipliers are the norm." In Giordano et al. (2009), own vector auto regressive study of government spending in Italy, they find a significantly negative effect of government spending on wages after two years. Blanchard and Perotti (2002) find that government spending in the US results in an increase in consumption but a decline in private investment with an overall positive, but small, effect.

Vector autoregressive models are dependent on the variables included in the model and they theoretically require that all important variables be included.

However, they are not as structurally rigid as structural models are. As a consequence, researchers can often propose causal mechanisms that fit the vector autoregressive results, but the proposed causal mechanisms are not a necessary logical consequence of the vector autoregressive results. Thus autoregressive studies fall in between the total dependency on a structural model of traditional macroeconomic modeling and the total lack of dependency on a structural model of BD-RTPLS, or its predecessor RTPLS.

Leightner (2002) used Thai data and RTLS to show how Thai fiscal multipliers fell and became much less stable in the wake of the 1997 financial crisis. Leightner (2005b) used panel data for 23 developing countries in Asia from 1983 to 2000 and RTPLS to show that government spending multipliers varied noticeably between countries and over time (implying that the assumptions underlying both random and fixed effects models do not hold for the Asian data used). Using BD-RTPLS, Leightner and Inoue (2009) show that the negative effect of the Japanese government cutting spending in the 1990s exceeded (in absolute value terms) the positive effects of the Japanese government increasing spending during the same time period. They hypothesize that this asymmetric result is at least partially driven by expectations. In the study that best fits this current paper, Leightner (2009) using BD-RTPLS estimates government spending multipliers for the U.S. between 1930 and 2008. He finds that every time the U.S. government increased spending by an unusually large amount, the resulting government spending multiplier plummeted and then took several years to climb back to its previous level. This is the exact same pattern that this paper finds using data from China.

3 The Intuition Underlying BD-RTPLS

BD-RTPLS is designed to handle cases where the assumptions underlying more traditional techniques do not hold. Traditional techniques, like Ordinary Least Squares (OLS), assume that there are no omitted variables that can change the estimated relationship between different observations. As a result of this assumption, traditional techniques produce only one estimate for the entire data series.

There are many reasons why the assumption of no omitted variables (which is necessary for OLS) is invalid for China during the time period studied. In 1994 (just before my data series begins), China underwent massive changes in the way it collects taxes and in the way it spends tax revenues. For example, prior to 1994

most taxes were collected by the local government, after 1994 most taxes were collected by the central government (Naughton, 2007, pp 430–442). The changes due to the 1994 fiscal reform did not occur immediately; indeed they probably stretch several years into my data set. Furthermore, at the beginning and end of my data set, China was suffering from severe inflation, but in the middle of my data set China fought against two episodes of deflation. Moreover, the Chinese government's stated goal has shifted from increasing total output (*GPP*) to increasing harmony during the time period studied. In which provinces the government is spending money has also shifted—at the beginning of my data the Chinese government primarily focused on the coastal provinces of China, whereas at the end of my data, the Chinese government has begun to address the problems of the interior provinces. Furthermore, the items that the government buys with its spending have changed over time and the purchase of different items would stimulate investment and consumption to varying degrees and thus would have differing effects on gross provincial product. All of these factors affect the true relationship between government spending and gross provincial product ($\partial GPP/\partial G$). In order to correctly use traditional analytical techniques, all of these factors would have to be adequately modeled and measured. Such a task is not feasible.

Fortunately, Leightner (2002) introduced Reiterative Truncated Projected Least Squares (RTPLS)—a technique that produces estimates that include the influence of omitted variables without having to know, model, measure or find proxies for the omitted variables. Leightner and Inoue (2007) prove theoretically that RTPLS produces less bias than OLS when there are omitted variables that interact with the included variables. Leightner and Inoue (2007) also run 90,000 simulation tests which show that RTPLS produces (on average) less than half the error of OLS when there are omitted variables that interact with the included variables. They show that this result is robust — the results were confirmed when the omitted variable makes a 1000%, 100% or 10% difference to the real slope, to when 10%, 1%, or 0% measurement and rounding error is included, and to when sample sizes of 500 or 100 observations were used. Leightner (2005a, 2005b) are published applications of RTPLS. Leightner (2007) proposed improvements in RTPLS to produce BD-RTPLS (bi-directional RTPLS). Four published applications of BD-RTPLS are in Leightner (2008) and Leightner and Inoue (2008a, 2008b, 2009).

The key to understanding BD-RTPLS is Fig. 1. To construct Fig. 1, I randomly generated two series of numbers, X and q, which ranged from 0 to 100. I then defined $Y = 200 + 10X + 0.4Xq$. I plotted (in X, Y space) the resulting points in Fig. 1 and identified each point with its value for q. Notice that the upper left

hand edge of the data corresponds to when q is at its largest values — 99, 97, and 96. Also notice that the lower right hand edge of the data corresponds to the lowest values for q –4 and 5. This makes sense, Y is actually generated in a three dimensional plane. When that plane is projected down to a two dimensional surface in just X and Y dimensions, the upper edge of the data will correspond to when q was at its most favorable level, and the lower edge will be the opposite. Viewed a slightly different way, the true value for $\partial Y/\partial X = 10 + 0.4q$. Thus when q is large, the slope will be big. When q is small, the slope will be small. Furthermore, since q ranges from 0 to 100, the true slope will range from 10 (when $q = 0$) to 50 (when $q = 100$). Thus, in this case, q makes a 500% difference in the true slope.

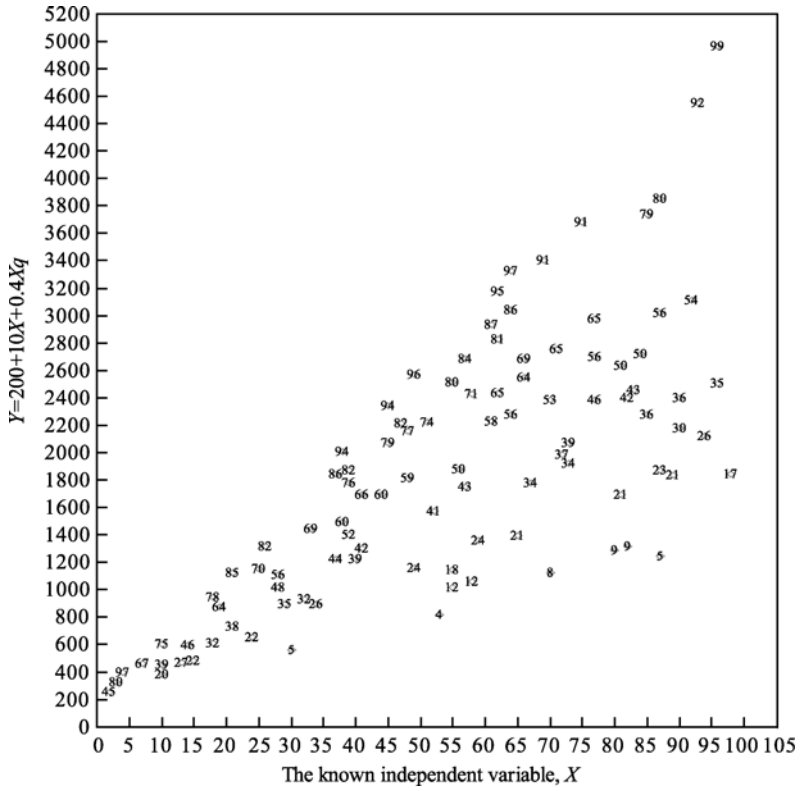

Fig. 1 The Intuition Behind BD-RTPLS

Note: Data points are identified by the value of q.

Now imagine that we do not know what q is, and we have to omit it from our analysis. In this case, traditional regression techniques (like OLS) produce an estimate for $\partial Y/\partial X$ of 10 + 0.4 $E(q)$, where $E(q)$ is the expected (*mean*) value for

q. Notice that this OLS estimate is a single number (it does not vary) and that the true slope does vary from observation to observation. Thus OLS is hopelessly biased. BD-RTPLS is based upon the insight that, even though we may not know *q*, we do know that the relative vertical position of different observations in Fig. 1 contains information about *q*. Specifically, we know that the upper edge of the data corresponds to when q is at its most favorable level and that the lower edge is when *q* is at its least favorable level. Branson and Lovell (2000) were the first to realize this intuition. BD-RTPLS exploits this intuition by peeling the data down from the top and then, starting over, peeling the data up from the bottom.

The first iteration when peeling the data downward shows the relationship between the dependent and independent variable when the omitted variables are at their most favorable levels (the observations at the top of the data); the second iteration shows the same relationship when the omitted variables are at the second most favorable levels, etc. Thus, the peeling down and up process captures how omitted variables affect the relationship between the dependent and independent variable without having to model the omitted variables or find proxies for them. The most important steps of the BD-RTPLS process can be summarized as follows. The process for peeling the data down from the top is given in the primary text, the process for peeling the data up from the bottom is given in brackets.

(1) Two Stage Least Squares is applied to the data where the first stage is replaced by an output-oriented [input-oriented], variable-returns-to-scale DEA problem. These DEA problems are explained in more detail below. The output used for the DEA problem is the dependent [independent] variable and the input used for the DEA problem is the independent [dependent] variable. After solving the DEA problem, the data is projected to the frontier by multiplying the dependent variable by the efficiency scores (Φ, see below). OLS is applied to the projected data to generate a slope estimate for that iteration. It is important to realize that these DEA problems are used solely for eliminating the effects of omitted variables. All estimations in this process are done using OLS and, thus, they produce estimates of the "marginal" effects.

(2) Delete the efficient observations (observations that had Φ =1) from the previous step and reiterate the previous step. Continue to do steps 1 and 2 until the sample size is too small. Specifically, an additional iteration was not conducted if that iteration's second stage regression would use fewer than ten observations.

(3) Enter the slope estimate from each iteration into the data for the observations that were efficient in that iteration.

(4) Start over with the original data and re-do steps 1–3, but this time start at the bottom of the data and peel the data up. This is accomplished by redoing steps 1–3 while substituting the words in brackets for the words immediately

proceeding them.

(5) Combine the results from peeling the data down from the top with the results from peeling the data up from the bottom (by stacking one of them on top of the other). Using this combined data, conduct a final regression that makes the slope estimates from each iteration a function of a constant, the inverse of the independent variable, and the ratio of the dependent to independent variable.

(6) Plug the original data back into this final regression to obtain a slope estimate for each observation.

The above process captures the influence of omitted variables in two separate, but complimentary ways. Firstly, peeling the data down and then up produces slope estimates that include the effects of omitted variables. Secondly, the fifth step further refines these slope estimates by using the intuition that the dependent variable is co-determined by the known independent variable and the omitted variables. Thus the dependent variable — independent variable combination contains information about the influence of the omitted variable which this final regression estimates. The regressors used in this final regression are based on the following derivation. Consider Eq. (1) where the part usually omitted ($\alpha_2 X_1^n q^m$) could be of many different functional forms (n and m could be any real number, positive or negative).

$$Y = \alpha_0 + \alpha_1 X_1 + \alpha_2 X_1^n q^m \tag{1}$$

$$dY/dX_1 = \alpha_1 + n\alpha_2 X_1^{n-1} q^m \quad \text{(Derivative of Eq. 1)} \tag{2}$$

$$Y/X_1 = \alpha_0/X_1 + \alpha_1 + \alpha_2 X_1^{n-1} q^m \quad \text{(Dividing Eq. 1 by } X_1\text{)} \tag{3}$$

$$\alpha_1 + \alpha_2 X_1^{n-1} q^m = Y/X_1 - \alpha_0/X_1 \quad \text{(Rearranging Eq. 3)} \tag{4}$$

$$dY/dX_1 = \text{fn}\,(Y/X_1,\ 1/X_1) \quad \text{(From equations 2 and 4)} \tag{5}$$

When Eq. 5 is estimated, a constant is used to capture the α_1 part of dY/dX_1, and Y/X_1 and $1/X_1$ are used to capture the $n\alpha_2 X_1^{n-1} q^m$ part of dY/dX_1. In other words, Y/X_1 and $1/X_1$ are used as a proxy for the omitted, unknown, or un-measurable q.

The DEA problems used in the above process are: Denote the outputs of an observation by y_{im}, $i = 1, \cdots, \text{I}$, $m = 1, \cdots, \text{M}$ and the inputs of an observation by x_{in}, $i = 1, \cdots, \text{I}$, $n = 1, \cdots, \text{N}$. Consider the following variable returns to scale, output oriented DEA problem, which is used when peeling the data downward:

$$\begin{aligned} &\max\ \Phi \\ &\text{subject to} \quad \Sigma_i \lambda_i x_{ni} \leqslant x_n^0,\ n = 1, \cdots, \text{N} \\ &\Phi y_m^0 \leqslant \Sigma_i \lambda_i y_{mi}, \quad m = 1, \cdots, \text{M} \\ &\Sigma_i \lambda_i = 1;\ \ \lambda_i \geqslant 0, \quad i = 1, \cdots, \text{I} \end{aligned} \tag{6}$$

The ratio of maximally expanded output production to actual output production (Φ) provides a measure of the influence of unfavorable omitted

variables on each observation. This problem is solved I times, once for each observation in the sample. For observation 0 under evaluation, the problem seeks the maximum radial expansion in all outputs y_m^0 consistent with best practice observed in the sample, i.e., subject to the constraints in the problem.

The variable returns to scale, input oriented DEA problem used when peeling the data upwards is:

$$\begin{aligned} &\min \ \Phi \\ &\text{subject to} \qquad \Sigma_k \lambda_k y_k \geqslant y_i \\ &\Phi x_{ji} \geqslant \Sigma_k \lambda_k x_{jk} \qquad j = 1, \cdots, \mathrm{J} \\ &\Sigma_i \lambda_i = 1; \ \ \lambda_k \geqslant 0, \quad k = 1, \cdots, \mathrm{I} \end{aligned} \tag{7}$$

For the output-oriented DEA problem used to peel the data down from the top, the data was projected to the frontier by multiplying the output (or dependent variable when peeling from the top) by Φ, the omitted variables score. For the input oriented DEA problem used to peel the data up from the bottom, the data is projected to the frontier by multiplying the input (or dependent variable when peeling from the bottom) by Φ, the omitted variables score. Note: Φ will be $\geqslant 0$ for the output case and $\leqslant 0$ for the input case. By multiplying the dependent variable by a $\Phi \geqslant 0$ when peeling from the top, the influence of the omitted variables is projected to its most favorable level (i.e., where the greatest amount of *GPP* is found for a given level of government spending). By multiplying the dependent variable by a $\Phi \leqslant 0$ when peeling from the bottom, the influence of the omitted variables is projected to its least favorable level.

BD-RTPLS estimates are reduced form estimates that capture all the ways that *Y* and *X* are correlated. Thus complicated systems of equations do not have to be created, justified, and solved to use BD-RTPLS. In other words, I do not have to build and justify an entire macroeconomic model in order to use BD-RTPLS to estimate $\partial GDP/\partial G$. However, the resulting $\partial GPP/\partial G$ estimates would capture all the ways that *GPP* and *G* are correlated. Thus if, when faced with high inflation, governments cut spending and reduce the money supply and they do the opposite when fighting unemployment, then BD-RTPLS estimates of $\partial GPP/\partial G$ would include the combined effects of the coordinated fiscal and monetary policies.

This contrasts with more traditional regression approaches that attempt to include all significant variables in the estimation so that the resulting slope estimate for dy/dx is for the effects of just *x*—holding all other included variables constant. Therefore BD-RTPLS estimates are not substitutes for more traditional regression analysis. Instead BD-RTPLS estimates are compliments which capture information that traditional regression techniques do not capture. One disadvantage of BD-RTPLS estimates is that they do not tell us by which mechanism *G* affects *GPP*. On the other hand, BD-RTPLS does not have to model and find data for all the forces that can affect *GPP* in order to estimate $\partial GPP/\partial G$. This is a tremendous advantage for BD-RTPLS. Often traditional

regression analysis assumes that it has included all important variables when any reasonable, intelligent person would know that they did not. For example, I know of no traditional studies of $\partial GPP/\partial G$ which include weather; however, weather would greatly affect both *GPP* and *G* in agriculturally based provinces. When weather is bad and crops fail, *GPP* falls and *G* often rises as the government provides for its citizens. It is quite possible that one reason that some of my BD-RTPLS estimates for $\partial GPP/\partial G$ are low for more agricultural interior provinces is due to the influence of this negative correlation between *GPP* and *G* when weather is bad. Finally it is important to realize that both traditional regression techniques and BD-RTPLS find "correlations." It is impossible for either one of them to prove "causation."

Additional information on exactly how BD-RTPLS uses the relative vertical position of observations to capture the effects of omitted variables can be found in Leightner and Inoue (2007) and in Leightner (2007). Peer reviewed journal publications that contain applications of RTPLS or BD-RTPLS include Leightner (2005a, 2005b, 2007, and 2008) and Leightner and Inoue (2007, 2008a, 2008b, 2009).

4 The Data

This paper's analysis used annual data on gross provincial product (*GPP*) and government spending in each province from 1995 to 2006 for all 31 of China's provinces. This data was acquired from *China Statistical Yearbook.* All data was normalized by adding one to the percentage change in that data. For example, Beijing's gross provincial product (*GPP*) was 108.40 billion yuan in 1995 and 161.67 billion yuan in 1996. The percentage change in Beijing's *GPP* from 1996 to 1995 was [161.67–108.40]/108.40 or 0.49. Thus the normalized value for Beijing's *GPP* in 1996 was 1+0.49 =1.49 (see the top left corner of Table 1). This normalized value means that Beijing's *GPP* in 1996 was 149% of its 1995 *GPP*. Normalized values for government spending in each province and in each year were calculated in the same fashion. By normalizing the data, I make sure that my BD-RTPLS estimates capture the effects of just *this year's* spending on *this year's GPP*. If I did not normalize the data and if last year's spending was correlated with this year's spending, then the reduced form estimates produced by BD-RTPLS would capture the influence on *GPP* of (1) this year's spending and (2) of last year's spending multiplied by a factor showing how last year's spending was correlated with this year's spending. By normalizing the data, I prevent this problem.

The slope estimates produced when using normalized data are equal to elasticities of the original data [$\partial(\%y)/\partial(\%x)$] because the normalized *y* and *x* are the $\%y$ and $\%x$ of the original data. Finding an elasticity of 0.34, for example, implies that a change in *x* of one percent is correlated with a 0.34 percent change

in *y*. In this paper, I first estimate $\partial[\%GPP]/\partial[\%G]$ using the normalized data. I then change these elasticities into yuan slope estimates by multiplying them by GPP/G. $\partial[\%GPP]/\partial[\%G] = [\partial GPP/GPP]/[\partial G/G]$. Thus $[\partial GPP/GPP]/[\partial G/G]* GPP/G$ causes the *G* and *GPP* to cancel producing $\partial GPP/\partial G$, which is a yuan fiscal multiplier. A yuan fiscal multiplier of 3.05 means that a one yuan increase in government spending would cause *GPP* to increase by 3.05 yuan.

Table 1 The Normalized Gross Provincial Product Data

Province	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	*mean*
Beijing	1.49	1.12	1.11	1.08	1.14	1.15	1.13	1.14	1.17	1.61	1.14	1.21
Tianjin	1.52	1.13	1.08	1.09	1.13	1.12	1.11	1.19	1.20	1.26	1.18	1.18
Hebei	1.58	1.15	1.08	1.07	1.11	1.10	1.10	1.16	1.24	1.15	1.15	1.17
Liaoning	1.28	1.11	1.11	1.07	1.12	1.08	1.08	1.10	1.14	1.17	1.16	1.13
Jilin	1.43	1.08	1.08	1.07	1.09	1.12	1.11	1.12	1.17	1.22	1.18	1.15
Heilongjiang	1.48	1.13	1.05	1.02	1.12	1.09	1.09	1.14	1.20	1.04	1.12	1.14
Shanghai	1.47	1.16	1.10	1.09	1.13	1.09	1.09	1.16	1.19	1.23	1.13	1.17
Jiangsu	1.48	1.11	1.08	1.07	1.11	1.11	1.12	1.17	1.24	1.19	1.18	1.17
Zhejiang	1.55	1.12	1.08	1.08	1.13	1.12	1.16	1.21	1.20	1.20	1.17	1.18
Anhui	1.57	1.14	1.05	1.04	1.04	1.08	1.08	1.11	1.21	1.12	1.14	1.15
Fujian	1.55	1.15	1.11	1.07	1.10	1.09	1.10	1.12	1.16	1.09	1.16	1.15
Jiangxi	1.60	1.13	1.08	1.06	1.02	1.09	1.13	1.16	1.24	1.16	1.15	1.16
Shandong	1.54	1.12	1.08	1.07	1.11	1.10	1.12	1.18	1.25	1.20	1.19	1.18
Henan	1.66	1.11	1.07	1.05	1.12	1.10	1.09	1.14	1.25	1.20	1.18	1.18
Hubei	1.58	1.16	1.07	1.04	1.11	1.09	1.07	1.09	1.17	1.03	1.16	1.14
Hunan	1.56	1.13	1.07	1.04	1.11	1.08	1.09	1.07	1.21	1.16	1.16	1.15
Guangdong	1.54	1.12	1.08	1.07	1.14	1.10	1.11	1.16	1.18	1.39	1.17	1.19
Guangxi	1.51	1.08	0.94	1.03	1.05	1.09	1.10	1.11	1.21	1.23	1.18	1.14
Hainan	1.18	1.05	1.07	1.07	1.10	1.05	1.11	1.11	1.15	1.16	1.18	1.11
Shanxi	1.53	1.13	1.08	0.94	1.09	1.08	1.13	1.22	1.24	1.37	1.14	1.18
Inner Mongolia	1.44	1.11	1.09	1.06	1.10	1.10	1.12	1.24	1.26	1.44	1.23	1.20
Sichuan			1.06	1.04	1.07	1.10	1.13	1.14	1.18	1.15	1.14	1.11
Chongqing			1.08	1.04	1.08	1.10	1.10	1.12	1.20	1.13	1.17	1.11
Guizhou	1.38	1.10	1.06	1.08	1.09	1.09	1.09	1.14	1.17	1.24	1.15	1.15
Yunnan	1.53	1.10	1.09	1.03	1.05	1.06	1.08	1.10	1.20	1.17	1.15	1.14
Tibet	1.41	1.19	1.18	1.16	1.11	1.18	1.16	1.14	1.15	1.19	1.16	1.19
Shaanxi	1.44	1.13	1.04	1.08	1.12	1.11	1.10	1.18	1.20	1.27	1.23	1.17
Gansu	1.58	1.09	1.11	1.07	1.06	1.09	1.08	1.12	1.19	1.24	1.18	1.17
Qinghai	1.33	1.10	1.09	1.08	1.11	1.14	1.13	1.14	1.19	1.17	1.18	1.15
Ningxia	1.45	1.09	1.08	1.06	1.10	1.12	1.10	1.17	1.19	1.32	1.17	1.17
Xinjiang	1.35	1.15	1.06	1.05	1.17	1.09	1.08	1.17	1.17	1.18	1.17	1.15
mean	1.48	1.12	1.08	1.06	1.10	1.10	1.11	1.15	1.20	1.22	1.17	

Finally, there are three small gaps in the data used. The first two gaps are due to a new province, Chongqing, being separated from Sichuan province in March of 1997. This split caused Sichuan's *GPP* and *G* data to fall in 1997 relative to what it would have been if there had not been a split. In order to avoid this artificially caused decline, data for both Chongqing and Sichuan was not used for 1996 and 1997. The third gap is due to a major anomaly in the data for Tibet. As Row 26, columns 1 and 2, of Table 2 shows, reported government spending in Tibet fell to only 7% of its previous value in 1996 and then rose by 1 566% in

Table 2 The normalized government spending data

Province	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	*mean*
Beijing	0.98	1.57	1.19	1.27	1.25	1.26	1.11	1.19	1.22	1.18	1.23	1.22
Tianjin	0.85	1.55	1.12	1.14	1.19	1.25	1.13	1.18	1.20	1.18	1.23	1.18
Hebei	0.79	1.78	1.11	1.16	1.18	1.24	1.12	1.12	1.21	1.25	1.21	1.20
Liaoning	0.77	1.61	1.15	1.17	1.13	1.23	1.09	1.14	1.19	1.29	1.18	1.18
Jilin	0.63	2.20	1.13	1.23	1.11	1.25	1.11	1.13	1.24	1.24	1.14	1.22
Heilongjiang	0.73	1.74	1.18	1.31	1.13	1.25	1.11	1.06	1.23	1.13	1.23	1.19
Shanghai	1.08	1.46	1.15	1.14	1.14	1.16	1.22	1.26	1.27	1.19	1.09	1.20
Jiangsu	0.88	1.63	1.17	1.14	1.22	1.23	1.18	1.22	1.25	1.28	1.20	1.22
Zhejiang	0.77	1.72	1.19	1.20	1.25	1.38	1.26	1.20	1.19	1.19	1.16	1.23
Anhui	0.84	1.81	1.17	1.19	1.12	1.25	1.13	1.11	1.19	1.19	1.32	1.21
Fujian	0.83	1.58	1.14	1.10	1.16	1.15	1.07	1.14	1.14	1.15	1.23	1.15
Jiangxi	0.70	1.95	1.17	1.19	1.08	1.27	1.20	1.12	1.19	1.24	1.23	1.21
Shandong	0.88	1.69	1.20	1.13	1.11	1.23	1.14	1.17	1.18	1.23	1.25	1.20
Henan	0.78	1.75	1.14	1.19	1.16	1.14	1.24	1.14	1.23	1.27	1.29	1.21
Hubei	0.77	1.80	1.25	1.20	1.10	1.31	1.06	1.06	1.20	1.20	1.34	1.21
Hunan	0.75	1.77	1.19	1.14	1.11	1.24	1.23	1.08	1.25	1.21	1.22	1.20
Guangdong	0.91	1.42	1.21	1.17	1.12	1.22	1.15	1.11	1.09	1.24	1.12	1.16
Guangxi	0.64	1.89	1.16	1.13	1.15	1.36	1.19	1.06	1.14	1.20	1.19	1.19
Hainan	0.72	1.56	1.15	1.03	1.13	1.23	1.17	1.14	1.21	1.19	1.15	1.15
Shanxi	0.75	1.71	1.15	1.13	1.21	1.29	1.15	1.24	1.25	1.29	1.37	1.23
Inner Mongolia	0.56	2.50	1.19	1.17	1.24	1.29	1.23	1.14	1.26	1.21	1.19	1.27
Sichuan			1.25	1.19	1.25	1.27	1.29	1.12	1.16	1.23	1.22	1.22
Chongqing			1.17	1.13	1.24	1.31	1.18	1.04	1.22	1.21	1.25	1.20
Guizhou	0.58	2.26	1.19	1.28	1.18	1.37	1.15	1.05	1.26	1.24	1.17	1.25
Yunnan	0.55	2.41	1.05	1.15	1.10	1.20	1.06	1.11	1.13	1.15	1.17	1.19
Tibet	0.07	15.66	1.19	1.18	1.13	1.74	1.32	1.06	0.92	1.39	1.08	2.43
Shaanxi	0.66	2.04	1.21	1.24	1.32	1.29	1.16	1.03	1.23	1.24	1.29	1.25
Gansu	0.53	2.40	1.20	1.18	1.27	1.25	1.16	1.09	1.19	1.20	1.23	1.25
Qinghai	0.33	3.81	1.21	1.26	1.23	1.48	1.17	1.03	1.13	1.24	1.26	1.38
Ningxia	0.55	2.65	1.34	1.10	1.23	1.54	1.22	0.92	1.16	1.30	1.21	1.29
Xinjiang	0.50	2.55	1.18	1.14	1.15	1.38	1.37	1.02	1.14	1.23	1.31	1.27
mean	0.70	2.43	1.18	1.17	1.17	1.29	1.17	1.11	1.19	1.23	1.22	

1997. Because I suspect that these numbers may not be accurate, I deleted the data for Tibet in 1996 and 1997 before conducting the analysis. A total of 335 observations were used in the analysis.

This paper's division between coastal and interior provinces follows other researchers (like Wei and Ma, 1996) who begin with the regionalization scheme of China's seventh five year plan (1986–1990) which divides China into western, central, and eastern regions. However, to reduce the number of figures and to simplify the analysis in this paper, provinces in the central region were split between the coast and interior in the way that produces the straightest possible north to south boundary line between the coast and interior.

The normalized data is presented in Tables 1 and 2 and depicted in Fig. 2. The data points in Fig. 2 are identified by the year. Notice that most of the 1996 data points are in the upper left hand corner of Fig. 2 and that most of the 1997 data points are in the lower right hand corner of Fig. 2. By just looking at Fig. 2,

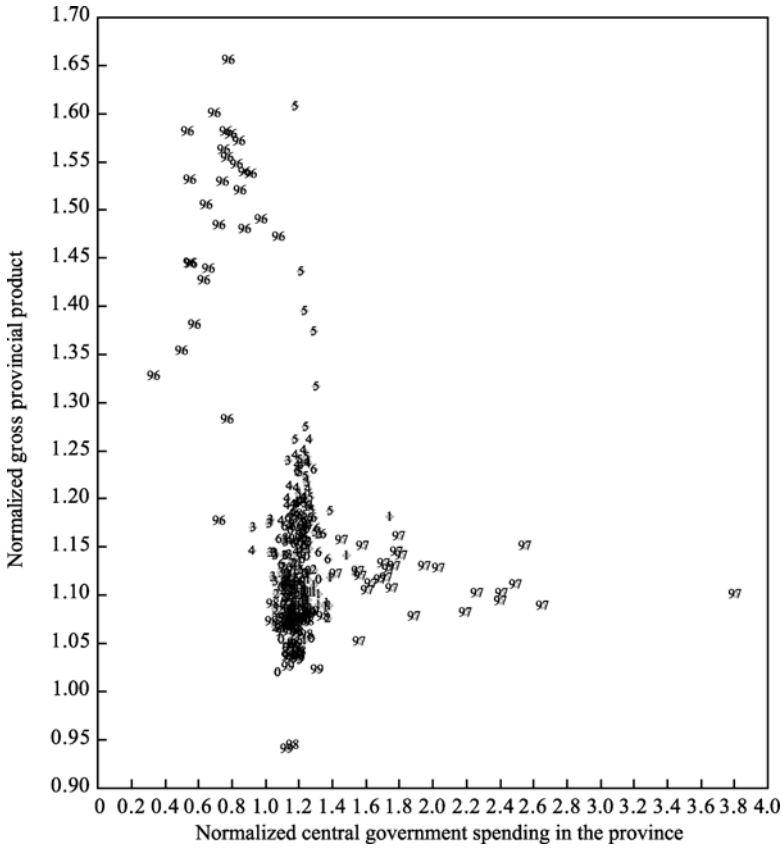

Fig. 2 The Normalized Data

Note: Data points are identified by year, where "96"=1996; "6"=2006, etc.

I expect that the true relationship between government spending and *GPP* to be at its highest in 1996, to fall to its lowest in 1997 and then to hit a medium between these two extremes for the rest of the data set.

5 Empirical Results

The empirical results are given in tables 3 and 4 and graphically depicted in Fig. 3 through 6. The mean elasticity was 0.34 (see the lower right hand corner of Table 3 where the "Mean" column meets the "Mean" row). This elasticity implies that a one percent increase in government spending would cause *GPP* to increase by 0.34 percent on average in the average province in the average year. When each elasticity in Table 3 was multiplied by its corresponding *GPP/G* ratio, it was changed into a fiscal multiplier ($\partial GPP/\partial G$). These multipliers are given in Table 4. The mean multiplier of 3.05 (Table 4 where the "mean" column and "mean" row meet) implies that a one yuan increase in government spending would cause *GPP* to increase by 3.05 yuan on average for the average province in the average year.

This multiplier effect is a direct consequence of government spending causing an increase in income, and the recipient of that income spends part of that income which, in turn, becomes someone else's income who spends part of that income, and the process continues. The total increase in *GPP* would be the government spending plus all the subsequent increases in consumption (minus any increases in imports, plus any increases in investment and exports). In a simple macroeconomic model, the multiplier is equal to $1/(1-MPC-MPI+MPM)$ where *MPC* is the marginal propensity to consume, *MPI* is the marginal propensity to invest, and *MPM* is the marginal propensity to import. Since we are examining gross provincial product, imports would include goods purchased from other provinces. For example, if $MPC=0.70$, $MPI=0.20$ and $MPM=0.228$, then the fiscal multiplier in this simplistic model should be 3.05.

Eq. 8 (which is based on the central limit theorem) can be applied to the BD-RTPLS estimates given in Panel B of Table 3 to produce a 99% confidence interval for the average elasticity.

$$\text{Confidence interval} = mean \pm (s\sqrt{n})\, t_{n-1,\,\alpha/2} \tag{8}$$

In this case the "*mean*" = 0.34, $s = 0.2074$ (which is the standard deviation), $n = 335$ (which is the number of observations), and $t_{n-1,\,\alpha/2} = 2.576$ from off of the standard T table. The resulting 99% confidence interval is 0.31 to 0.37. Since this confidence interval does not contain zero, the average elasticity is significantly different from zero at a 99% confidence level. A 99% confidence interval for the average fiscal multiplier is 2.61 to 3.49.

The third to the last column of Table 3, Panel B shows the mean value for

Table 3 Percentage Change in *GPP*/Percentage Change in Government Spending

	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	*mean*	99% interval	
A: Region														
Coastal mean	0.70	0.10	0.23	0.21	0.32	0.23	0.32	0.40	0.50	0.50	0.41	0.36	0.32	0.39
Interior mean	0.24	–0.09	0.24	0.19	0.25	0.20	0.29	0.48	0.51	0.59	0.43	0.31	0.27	0.36
B: Province														
Beijing	0.96	0.14	0.30	0.18	0.34	0.35	0.40	0.37	0.42	1.42	0.35	0.47	0.14	0.81
Tianjin	0.79	0.16	0.28	0.28	0.35	0.29	0.35	0.49	0.50	0.64	0.44	0.42	0.25	0.58
Hebei	0.68	0.17	0.29	0.24	0.31	0.23	0.32	0.45	0.58	0.37	0.39	0.37	0.23	0.50
Liaoning	0.69	0.07	0.33	0.23	0.36	0.20	0.33	0.32	0.38	0.38	0.41	0.34	0.20	0.47
Jilin	0.43	–0.19	0.27	0.18	0.32	0.27	0.35	0.37	0.42	0.55	0.48	0.31	0.14	0.49
Heilongjiang	0.56	0.11	0.16	–0.01	0.37	0.22	0.32	0.45	0.48	0.20	0.30	0.29	0.13	0.44
Shanghai	1.03	0.30	0.30	0.30	0.37	0.27	0.24	0.37	0.46	0.57	0.41	0.42	0.22	0.62
Jiangsu	0.82	0.09	0.24	0.25	0.29	0.27	0.32	0.43	0.58	0.45	0.46	0.38	0.20	0.56
Zhejiang	0.64	0.08	0.22	0.21	0.30	0.21	0.37	0.51	0.50	0.49	0.45	0.36	0.21	0.51
Anhui	0.80	0.15	0.18	0.13	0.22	0.19	0.29	0.36	0.53	0.32	0.31	0.32	0.14	0.49
Fujian	0.76	0.24	0.34	0.28	0.31	0.27	0.38	0.35	0.43	0.28	0.39	0.37	0.24	0.49
Jiangxi	0.38	0.07	0.25	0.19	0.22	0.19	0.33	0.44	0.58	0.39	0.37	0.31	0.18	0.44
Shandong	0.85	0.08	0.22	0.26	0.36	0.26	0.35	0.46	0.61	0.48	0.47	0.40	0.21	0.59
Henan	0.64	0.03	0.25	0.16	0.35	0.31	0.23	0.40	0.62	0.48	0.42	0.35	0.19	0.52
Hubei	0.61	0.23	0.17	0.13	0.36	0.17	0.33	0.36	0.43	0.11	0.35	0.29	0.16	0.43
Hunan	0.57	0.11	0.22	0.17	0.35	0.19	0.22	0.31	0.51	0.40	0.40	0.31	0.18	0.45
Guangdong	0.92	0.20	0.22	0.22	0.41	0.26	0.32	0.45	0.50	0.97	0.47	0.45	0.21	0.69
Guangxi	0.33	–0.13	–0.04	0.17	0.20	0.14	0.27	0.41	0.55	0.56	0.47	0.27	0.06	0.47
Hainan	0.77	–0.09	0.24	0.36	0.32	0.13	0.31	0.33	0.37	0.42	0.47	0.33	0.14	0.52
Shanxi	0.57	0.14	0.27	0.00	0.24	0.17	0.37	0.53	0.58	0.93	0.27	0.37	0.14	0.61
Inner Mongolia	0.22	–0.11	0.25	0.21	0.25	0.22	0.30	0.60	0.64	1.06	0.57	0.38	0.10	0.66
Chongqing			0.13	0.12	0.17	0.20	0.28	0.41	0.48	0.37	0.34	0.28	0.15	0.41
Sichuan			0.24	0.19	0.19	0.23	0.29	0.43	0.50	0.32	0.41	0.31	0.20	0.42
Guizhou	0.44	–0.12	0.19	0.17	0.26	0.14	0.29	0.46	0.42	0.59	0.41	0.29	0.12	0.47
Yunnan	–0.07	–0.14	0.38	0.16	0.26	0.18	0.34	0.34	0.53	0.46	0.41	0.26	0.07	0.45
Tibet			0.47	0.42	0.35	0.31	0.37	0.45	0.57	0.41	0.47	0.42	0.35	0.50
Shaanxi	0.46	0.04	0.13	0.18	0.24	0.24	0.31	0.53	0.50	0.67	0.56	0.35	0.17	0.53
Gansu	–0.33	–0.18	0.30	0.22	0.10	0.21	0.26	0.39	0.49	0.59	0.44	0.23	–0.02	0.48
Qinghai	0.25	–0.30	0.24	0.18	0.26	0.24	0.36	0.48	0.51	0.41	0.43	0.28	0.08	0.48
Ningxia	0.19	–0.24	0.12	0.27	0.25	0.16	0.26	0.59	0.50	0.78	0.43	0.30	0.06	0.54
Xinjiang	0.40	0.07	0.20	0.20	0.45	0.13	0.09	0.53	0.46	0.45	0.39	0.31	0.15	0.46
mean	0.55	0.04	0.24	0.20	0.29	0.22	0.31	0.43	0.50	0.53	0.42	0.34		
99%	0.43	–0.02	0.20	0.17	0.27	0.20	0.29	0.40	0.48	0.44	0.40		0.31	
interval	0.67	0.10	0.27	0.23	0.32	0.24	0.33	0.46	0.53	0.63	0.44			0.37

Table 4 Change in *GPP*/ change in government spending

	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	*mean*	99% interval	
A: Region														
coastal mean	12.9	1.27	2.66	2.19	3.21	2.06	2.69	3.44	4.31	4.06	3.33	3.83	3.20	4.46
interior mean	4.02	–0.50	1.60	1.10	1.40	0.93	1.26	2.24	2.43	2.87	1.92	1.75	1.35	2.15
B: Province														
Beijing	10.3	1.08	2.17	1.08	1.88	1.78	2.06	1.83	2.00	9.24	2.15	3.23	0.33	6.14
Tianjin	11.0	1.64	2.71	2.58	3.03	2.26	2.71	3.87	3.87	5.39	3.54	3.87	1.58	6.17
Hebei	15.6	2.44	4.03	3.09	3.80	2.53	3.42	4.89	6.48	3.77	3.89	4.90	1.59	8.21
Liaoning	10.3	0.75	3.32	2.11	3.23	1.56	2.58	2.41	2.80	2.54	2.64	3.11	0.88	5.35
Jilin	7.53	–1.65	2.21	1.25	2.22	1.70	2.14	2.27	2.45	3.14	2.87	2.38	0.47	4.28
Heilongjiang	10.6	1.37	1.79	–0.08	3.14	1.64	2.30	3.51	3.67	1.38	1.94	2.84	0.36	5.32
Shanghai	10.7	2.48	2.35	2.30	2.77	1.87	1.49	2.12	2.47	3.17	2.38	3.10	0.82	5.39
Jiangsu	22.1	1.66	4.13	3.93	4.21	3.46	3.99	5.09	6.76	4.90	4.93	5.93	1.01	10.80
Zhejiang	18.9	1.63	3.75	3.31	4.14	2.36	3.86	5.38	5.27	5.23	4.82	5.33	1.16	9.50
Anhui	16.4	1.88	2.12	1.30	2.03	1.57	2.25	2.83	4.25	2.39	2.05	3.55	–0.31	7.41
Fujian	14.0	3.23	4.39	3.61	3.69	3.10	4.42	4.05	5.03	3.05	4.10	4.79	2.01	7.56
Jiangxi	7.54	0.81	2.61	1.77	2.00	1.43	2.35	3.25	4.50	2.80	2.48	2.87	1.24	4.50
Shandong	21.0	1.36	3.20	3.63	5.04	3.26	4.27	5.68	7.95	6.05	5.61	6.10	1.40	10.80
Henan	14.6	0.45	3.33	1.95	4.00	3.40	2.23	3.95	6.16	4.58	3.66	4.39	1.09	7.69
Hubei	14.6	3.50	2.21	1.51	4.22	1.63	3.18	3.57	4.18	0.91	2.57	3.82	0.49	7.15
Hunan	11.6	1.49	2.55	1.85	3.76	1.74	1.79	2.49	3.97	2.99	2.88	3.37	0.84	5.90
Guangdong	12.4	2.19	2.11	1.94	3.68	2.07	2.44	3.59	4.28	9.45	4.86	4.46	1.40	7.51
Guangxi	6.72	–1.48	–0.40	1.44	1.58	0.86	1.60	2.50	3.59	3.76	3.10	2.11	0.14	4.09
Hainan	9.71	–0.74	1.96	2.99	2.60	0.91	2.00	2.12	2.26	2.48	2.81	2.65	0.35	4.94
Shanxi	8.92	1.49	2.63	0.00	1.73	1.02	2.25	3.14	3.41	5.83	1.41	2.89	0.65	5.14
Inner Mongolia	3.79	–0.87	1.75	1.31	1.44	1.06	1.32	2.91	3.07	6.03	3.38	2.29	0.67	3.91
Chongqing			1.53	1.21	1.48	1.46	1.81	2.72	3.24	2.35	2.02	1.98	1.32	2.64
Sichuan			2.73	1.92	1.65	1.72	2.00	3.17	3.64	2.21	2.64	2.41	1.74	3.08
Guizhou	6.35	–0.84	1.19	0.91	1.27	0.57	1.08	1.89	1.58	2.26	1.52	1.62	0.04	3.19
Yunnan	–0.78	–0.75	2.05	0.80	1.23	0.75	1.42	1.43	2.34	2.08	1.84	1.13	0.18	2.08
Tibet			0.94	0.82	0.68	0.41	0.43	0.57	0.90	0.56	0.68	0.67	0.48	0.86
Shaanxi	8.06	0.41	1.05	1.31	1.46	1.26	1.55	3.02	2.77	3.87	3.05	2.53	0.64	4.42
Gansu	–5.47	–1.34	2.07	1.38	0.54	0.96	1.09	1.71	2.15	2.68	1.88	0.69	–1.37	2.75
Qinghai	4.86	–1.68	1.19	0.78	1.02	0.72	1.04	1.52	1.74	1.30	1.29	1.25	–0.09	2.59
Ningxia	2.91	–1.52	0.60	1.33	1.08	0.52	0.75	2.14	1.88	2.97	1.60	1.30	0.17	2.42
Xinjiang	7.56	0.58	1.51	1.42	3.21	0.71	0.41	2.70	2.41	2.26	1.74	2.23	0.46	4.00
mean	10.1	0.70	2.25	1.77	2.51	1.62	2.14	2.98	3.58	3.60	2.78	3.05		
99%	7.75	0.12	1.86	1.40	2.06	1.31	1.76	2.55	2.99	2.84	2.35		2.61	
interval	12.4	1.28	2.64	2.13	2.96	1.93	2.52	3.42	4.18	4.37	3.22			3.49

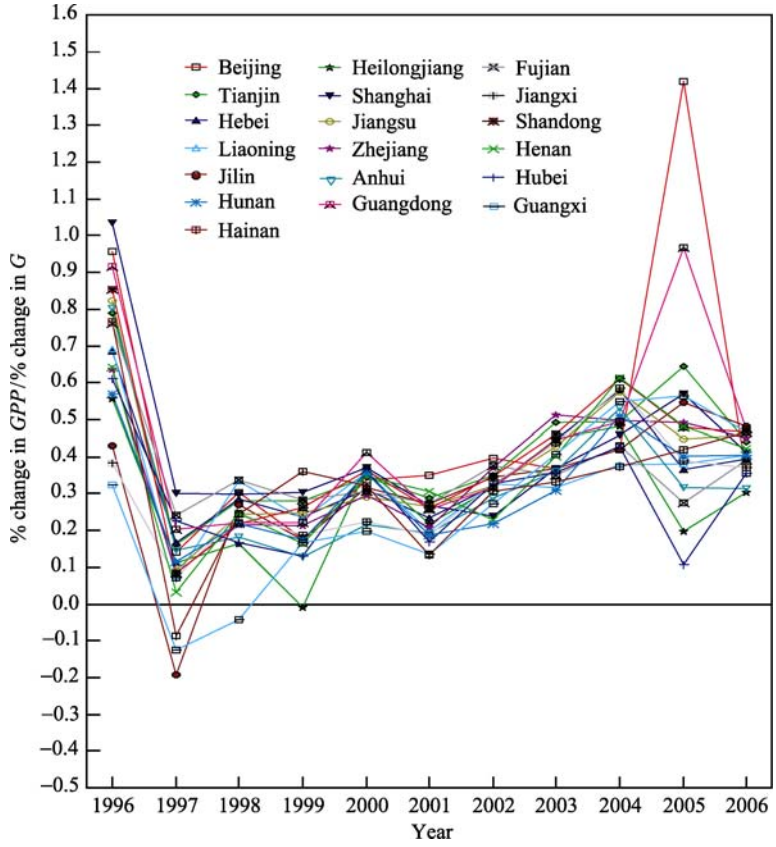

Fig. 3 % Change in *GPP*/% Change in Government Spending

Note: Coastal provinces.

$\partial(\%GPP)/\partial(\%G)$ for each province. Again, Eq. 8 (where this time $n = 11$ and $t_{n-1,\,\alpha/2} = 3.106$) can be used to find a 99% confidence interval for the average value of $\partial(\%GPP)/\partial(\%G)$ for each province. It is important to realize that this confidence interval is for the "*mean*" relationship for a given province over time. The minimum of this 99% confidence interval is given in the penultimate column and the maximum is given in the last column of Table 3. All of these province specific confidence intervals overlap—they all contain 0.35 to 0.41. In contrast to the province results, confidence intervals calculated for each year (see last two lines of Table 3) do not all over lap—1997's confidence interval of –0.024 to 0.096 is very different from 2005's confidence interval of 0.437 to 0.630. In a similar fashion, the confidence intervals for the fiscal multipliers (Table 4) overlap between 2.01 and 2.08, if Tibet is ignored, but the annual confidence intervals are extremely different from each other. This means that omitted variables that affect the estimated elasticities and fiscal multipliers over time are

much more important than the omitted variables that affect different provinces.

It should also be noted that all provinces had statistically significant (at a 99% confidence level) elasticities (Table 3) except for Gansu province and that all years had statistically significant elasticities except for 1997—the year the Asian financial crisis began. Fiscal multipliers (Table 4) were statistically significant (at a 99% confidence level) for all years, but were not statistically significant for Anhui, Gansu, and Qinghai provinces.

Panel A of Table 3 shows that the mean elasticity for coastal provinces exceeded the mean elasticity for interior provinces for 1996, 1997, 1999, 2000, 2001, and 2002 (Coastal provinces are listed in the legend of figures 3 and 5 and interior provinces are listed in the legend of figures 4 and 6.) However, the opposite was true for 2003, 2004, 2005, and 2006; for these more recent years the mean elasticity for interior provinces exceeded the mean elasticity for coastal provinces. This implies that for 2003 to 2006 a one percent increase in

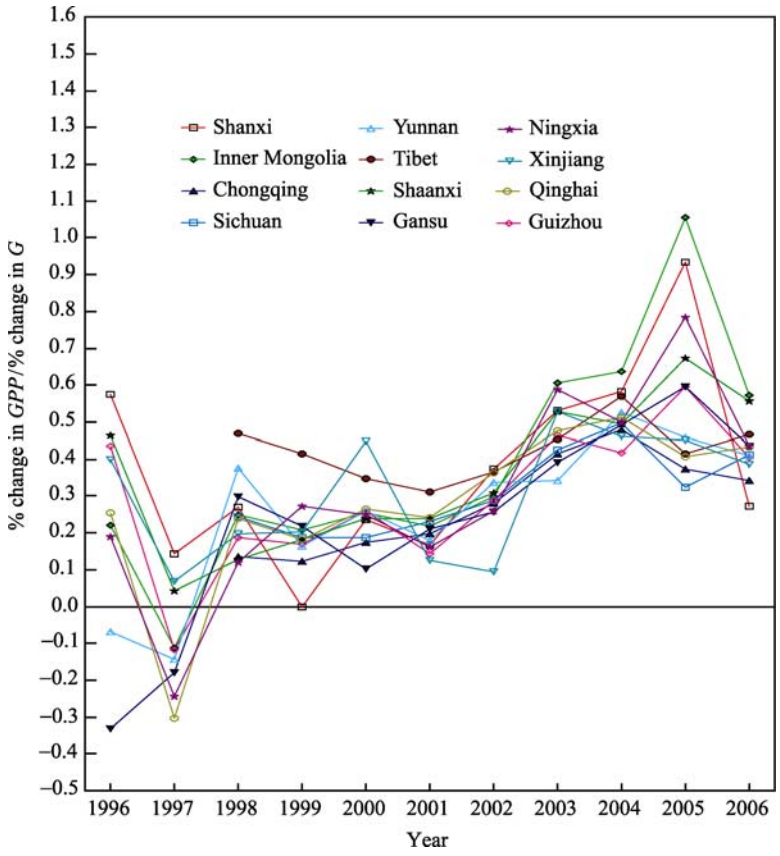

Fig. 4 % Change in *GPP*/% Change in Government Spending

Note: Interior provinces.

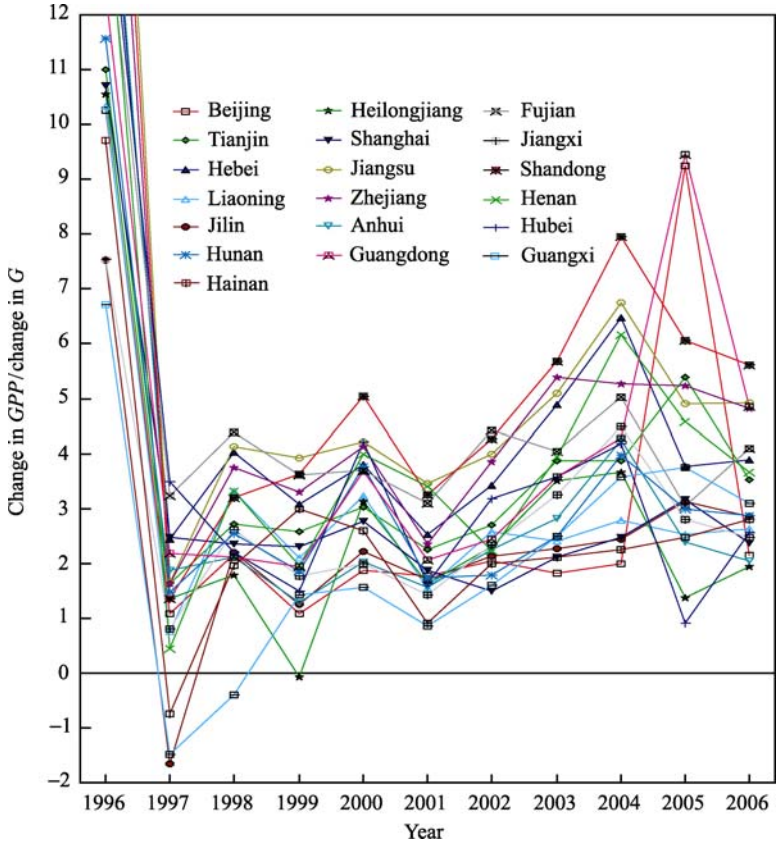

Fig. 5 Change in *GPP*/Change in Government Spending

Note: Coastal provinces.

government spending in interior provinces would cause a larger percentage increase in *GPP* than it would in coastal provinces on average. However, when these elasticities are changed into yuan fiscal multipliers (by multiplying the elasticities by *GPP/G*), coastal yuan fiscal multipliers noticeably exceed interior yuan fiscal multipliers for all years (compare figures 5 and 6). However the gap between coastal and interior yuan fiscal multipliers appears to have decreased over time (see Panel A of Table 4). These patterns are probably partially due to the Chinese government's shift in focus from concern for only the coastal areas to a more balanced concern for both the interior and coastal areas. In the context of the current financial crisis and the Chinese fiscal stimulus package, these results imply that the Chinese government could probably create a bigger percent increase in *GPP* by spending stimulus yuan in the interior provinces, but that it could get a larger yuan increase in *GPP* by spending that money in the coastal areas. As mentioned earlier, when deciding where to spend this stimulus money,

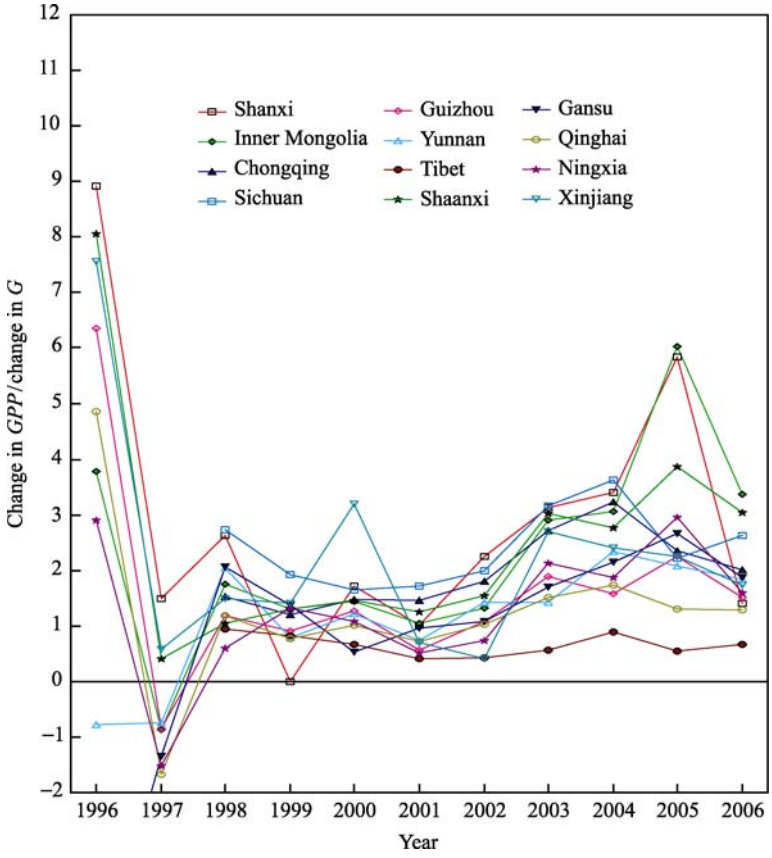

Fig. 6 Change in *GPP*/Change in Government Spending

Note: Interior provinces.

the Chinese government should consider more than just *GPP* — it also should consider income distribution, equality, and harmony issues.

For all coastal provinces and for more than half of the interior provinces, the yuan fiscal multipliers for 1996 are the highest for all the years in the data set. See Table 4, column 1 and figures 5 and 6 (notice that some of these multipliers even extend beyond the page in Fig. 5). Immediately after the high yuan fiscal multipliers of 1996, these yuan fiscal multipliers plummet in 1997 to their lowest level for over half of the provinces in the data set. These results fit with Fig. 2 — the graph of the normalized data. In order to provide an explanation for what figures 2 through 6 consistently show, it is important to realize that my data has not been adjusted for inflation.

China suffered from inflation rates of greater than twenty percent in 1989 and 1995 — the highest inflation had been in China since 1949. Even in 1996, the

inflation rate was still approximately ten percent (Naughton, 2007). This inflation partially explains why the *GPP* numbers in the first column of Table 1 are so high. In response to this inflation, government spending was cut in 1996 in every province except for Shanghai (see the first column of Table 2). Indeed in the average province government spending in 1996 was only 70% (73% if Tibet is excluded) of what it had been in 1995. From the point of view of the whole country, total government spending in 1995 and 1996 were 455 and 354 billion yuan respectively (not including Chongqing and Sichuan province which split); thus total government spending fell by 22.2 percent between 1995 and 1996.

The high mean yuan fiscal multiplier for 1996 (Table 4, the third to the last row) of 10.06 means that for every yuan cut in government spending in 1996, nominal *GPP* fell by 10.06 yuan in the average province, causing inflation to decline. Cutting government spending in China during the high inflation of 1996 was effective. Furthermore, recall that BD-RTPLS produces *reduced form* estimates that show all the ways that *GPP* and *G* are correlated. In 1996, the Chinese government not only cut government spending, it also instructed China's banks to not lend to specific "overheated" sectors of the economy. To the extent that cuts in government spending were correlated with simultaneous decreases in credit, BD-RTPLS estimates would capture the effects of both on *GPP*.

Column 2 of Table 2 shows that in 1997, with inflation back under control, government spending increased by 243% (196% if Tibet is excluded) in the average province. The second column of Table 4 shows that these increases in government spending caused much smaller increases in *GPP* than the cuts in government spending in 1996 caused declines. Indeed the estimated yuan fiscal multiplier was even negative in 1997 for ten provinces. However, the mean estimated elasticity was not significantly different from zero in 1997. These results are reasonable in the context of world events. The Asian financial crisis began in Thailand in July of 1997 and quickly spread throughout Asia. Investor and consumer confidence plummeted and China lost exports as the currencies of several of its neighbors fell to half of their previous values while China's currency firmly stayed fixed. Thus, as government spending increased in China's provinces by an average 196%, excluding Tibet (column 2, Table 2), *GPP* increased by a measly 12% on average (column 2 of Table 1). These BD-RTPLS estimates seemed to have correctly captured the influence of omitted variables, like the Asian financial crises, causing the correlation between changes in government spending and changes in *GPP* to fall in 1997. It is very likely that the current world financial crisis is also causing the yuan fiscal multipliers to decline in China today. This paper's results for 1996 to 1997 provide the Chinese government with some empirical evidence on how far these multipliers can fall during crises.

An examination of the elasticities and yuan fiscal multipliers for specific provinces over time shows that these estimates fluctuate some between 1998 and 2006. However, figures 3 through 6 show that there was an overall upward trend in these estimates between 1998 and 2004. Tables 3 and 4 and figures 3 through 6 also show that these estimates fell for most provinces in 2005 and/or 2006. One possible explanation for the 2005 and 2006 declining multipliers is based on the Chinese government allowing the yuan to start appreciating in June 2005. An appreciating yuan causes exports to fall, relative to what they would have been. If government spending increased as the yuan was slowly appreciating, then the reduced form estimates of $\partial GPP/\partial G$ should fall due to the contemporaneous decline in exports. Recall that BD-RTPLS produces reduced form estimates that capture all the ways that the dependent (*GPP*) and independent (*G*) variables are correlated. A very important decision for the Chinese government in the midst of the current financial crisis is whether or not to allow the yuan to further appreciate against the US dollar.

6 Conclusion

As the government of China decides exactly how to spend the four trillion yuan stimulus package it has promised to spend in China between 2009 and 2010, it needs to consider the following. Firstly, the mean government spending multiplier fell from 10.06 to 0.70 between 1996 and 1997 as the Asian financial crisis began in 1997. It is extremely likely that the current crisis also will cause the government spending multiplier to plummet. This is not good news; however, by knowing what is likely to happen, the Chinese government is more likely to design policies that can offset such negative effects. The Chinese government is already taking steps that may help. For example, the Chinese government has promised to cut taxes.

Secondly, if the Chinese government chooses to spend the fiscal stimulus money in interior provinces, it will produce a bigger percent increase in the corresponding gross provincial products; however, if it chooses to spend that money in coastal provinces, it will produce a bigger yuan increase in the corresponding gross provincial products.

Thirdly, allowing the yuan to further appreciate against the US dollar is likely to be correlated to an additional decline in the government spending multiplier. These are the most important lessons we can draw from examining the relationship between gross provincial product and government spending in China's 31 provinces between 1996 and 2006. Hopefully the leaders of China and of other countries will be able to design economic policies that can stop this crisis soon.

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