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The Pattern of Growth and Poverty Reduction in China

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Abstract

China has seen a huge reduction in the incidence of extreme poverty since the economic reforms that started in the late 1970s. Yet, the growth process has been highly uneven across sectors and regions. The paper tests whether the pattern of China´s growth mattered to poverty reduction using a new provincial panel data set constructed for this purpose. The econometric tests support the view that the primary sector (mainly agriculture) has been the main driving force in poverty reduction over the period since 1980. It was the sectoral unevenness in the growth process, rather than its geographic unevenness, that handicapped poverty reduction. Yes, China has had great success in reducing poverty through economic growth, but this happened despite the unevenness in its sectoral pattern of growth. The idea of a trade-off between these sectors in terms of overall progress against poverty in China turns out to be a moot point, given how little evidence there is of any poverty impact of non-primary sector growth, controlling for primary-sector growth. While the non-primary sectors were key drivers of aggregate growth, it was the primary sector that did the heavy lifting against poverty.

This paper—a product of the Director's Office, Development Research Group—is part of a larger effort in the department to monitor and explain progress against poverty in developing countries. Policy Research Working Papers are also posted on the Web at http://econ.worldbank.org. The author may be contacted at mravallion@worldbank.org.

The Pattern of Growth and Poverty Reduction in China

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1. Introduction

Based on cross-country comparisons, a number of papers in the literature have found that measures of absolute poverty tend to fall with economic growth.[2] However, it is also evident that there is a sizeable variance in the impacts of a given rate of growth on poverty. Some of this is measurement error, but it has also been argued that there are systematic factors influencing the elasticity of poverty measures to higher mean income.

Probably the main reason advanced in the literature and in policy discussions as to why a given rate of growth can deliver diverse outcomes for poor people is that the "pattern of growth" matters independently of the overall rate of growth. We can state this hypothesis in slightly more formal terms as follows:

> <u>Pattern of Growth Hypothesis (PGH)</u>: *The sectoral and/or geographic composition of economic activity affects the aggregate rate of poverty reduction independently of the aggregate rate of growth.*

If true, then the often-heard claim that the policies that are good for growth are necessarily also good for poverty reduction becomes questionable, given that the actions needed for growth in one sector or place need not accord with those needed elsewhere. This is particularly salient to the role of agricultural growth, which is likely to require rather different policies to other sectors (Headey, 2008).

In principle one can think of two reasons why PGH might hold. The first is that the relevant between-group component of inequality is sufficiently large that the pattern of growth across those groups systematically alters the distribution of income and (hence) the extent of poverty at any given mean income. Intuitively, if economic growth is very intense in sectors that do not benefit poor people then inequality will rise, choking off the gains to the poor from growth.

The second reason is that the composition of economic activity is one factor influencing the initial level of inequality. This holds even if the subsequent growth process is distribution-neutral (all incomes grow at the same rate). Intuitively, when the poor have a low initial share of total income they will tend to have a lower share of the gains in aggregate income during the growth process. Empirically, the initial distribution of income is known to be important for the subsequent effect of economic growth on poverty (Ravallion, 1997; Bourguignon, 2003).

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[2] A partial list of contributions includes World Bank (1990, 2000), Ravallion (1995, 2001), Ravallion and Chen (1997), Fields (2001) and Kraay (2006).

In the context of India, Ravallion and Datt (1996; 2002) and Datt and Ravallion (2002) report results indicating that the sectoral and geographic composition of growth has mattered to aggregate poverty reduction. Rural economic growth has had more impact on poverty in India than urban economic growth, and growth in the tertiary (mainly services) sector has had more impact than the primary (mainly agriculture) sector, while the secondary (mainly manufacturing) sector appears to have brought little direct gain to India's poor. Empirical support for the PGH has also come from cross-country evidence suggesting that more labor-intensive growth processes have greater impact on poverty, as found by Loayza and Raddatz (2009).

However, all this sits uneasily with the observation that the country that has undoubtedly made the most impressive progress against absolute poverty over recent decades has also had one of the most sectorally and geographically unbalanced growth processes. We refer to China. While the impressive growth performance of China since the early 1980s is well known, there has been much concern in recent times that this growth process has been "unbalanced," and in particular that growth rates in agriculture have appreciably lagged those in other sectors, notably industry and services (Kuijs and Wang, 2006; Chaudhuri and Ravallion, 2006). The primary sector's share fell from 30% in 1980 to 15% in 2001, though not montonically. Yet China´s record against absolute poverty has been impressive. Using their national poverty line, Ravallion and Chen (2007) found that the poverty rate (headcount index) fell from 53% in 1981 to 8% in 2001. Using decomposition methods, the same authors found that about three-quarters of this reduction in poverty nationally was due to poverty reduction solely within rural areas.

These observations motivate the main questions addressed by this paper: What role did the apparent "imbalances" of China´s growth process play in China's progress against poverty? Would a more balanced growth process have had a larger impact on poverty? Or could it be that the unbalanced growth actually fostered poverty reduction, by allowing a higher overall growth rate?

There is already evidence in the literature to suggest that China´s rate of poverty reduction would have been even higher if not for the pattern of growth. Using aggregate (national level) time series data for China, Ravallion and Chen (2007) find evidence that the sectoral composition of growth (how much comes from agriculture versus manufacturing versus services) matters to both poverty and inequality independently of the rate of growth. If the same rate of growth had been possible without the sectoral imbalances observed then the Ravallion and Chen results suggest that it would have taken half the time to achieve the reduction in poverty observed over 1981-2001.

This type of calculation assumes that the same overall rate of growth would have been possible without the sectoral imbalances. In principle, that is a strong assumption. However, it is not as strong as one might guess in the China context. The sectoral imbalance in China's growth process is in part the result of deliberate policies on the part of the government. A number of specific policy instruments were used for this purpose, including:[3]

- Subsidized prices for key inputs (including energy, utilities and land), weak or weakly enforced regulations (including environmental protection);
- Favoured treatment for industry in access to finance, especially for large (private and state-owned) enterprises;
- Restrictions on labor movement through the Hukou system and discriminatory regulations against migrant workers in cities; and
- Local administrative allocation of land, with the effect that out migrants from rural areas face a high likelihood that they will lose their agricultural land rights.[4]

Given that the sectoral pattern of growth was far from being a wholly market-driven process, it would clearly be hazardous to assume that the specific pattern of growth was efficient and (hence) promoted the maximum overall rate of growth. Ravallion and Chen (2007) address this issue empirically, and argue that the national-level data do not provide compelling evidence for believing that lower growth rates in the primary sector were the "price" of higher growth in the secondary and tertiary sectors.

The main contribution of the present paper is to assess the contribution to poverty reduction of the sectoral and geographic pattern of China´s growth, by extending the Ravallion-Chen analysis to the provincial level. By adding the extra variability in the geographic (inter-provincial) dimension we are able to enhance the power of the various tests of the PGH that we undertake—enhancing the scope for identification and precision of the estimates over past studies. By allowing us to introduce a latent provincial effect in the error term, our provincial panel-data analysis also addresses concerns about omitted variables. Additionally, the common origin and methodology of the primary data make this empirical

[3] For further discussion on these points see the useful overview in Kuijs and Wang (2006).

[4] The contrast with neighbouring Vietnam in land policies is notable; while China kept the non-market institutions of local administrative land allocation intact after embarking on its reform process, Vietnam introduced the essential features of a free market in land-use rights, Ravallion and van de Walle (2007) study these policies in depth and argue that Vietnam's policy was more pro-poor than China´s.

exercise more immune to the comparability problems facing cross-country studies. As is often acknowledged in this literature, international comparisons of the effect of growth on poverty and inequality are subject to a number of difficult issues of data comparability across countries, which can make it hard to detect the true relationships.

In addition to testing whether the pattern of growth has mattered to poverty reduction, we aim to assess how quantitatively important the pattern of growth has been to China's (very high) overall rate of poverty reduction. We may not reject the PGH, but find that the effect is small. Or we might find that far larger reductions in poverty could have been possible if the same growth rate was more even across sectors and areas. We investigate this issue more deeply using the sub-national data, and also see if there is any evidence of a significant trade-off between the overall growth rate and its sectoral composition.

We shall also make a number of observations comparing China with India in terms of the relevance of the pattern of growth to poverty reduction. The fact that a similar study was already conducted at the provincial level for the case of India by Ravallion and Datt (2002) allows us to compare the results of China and India.

The following section describes the trends in poverty reduction across China´s provinces that we find in the data. Section 3 examines the role played by the sectoral composition of growth, and section 4 extends this analysis to allow for differing parameters across provinces. Section 5 uses counterfactual analysis to quantify the importance of the pattern of growth to poverty reduction. Section 6 concludes.

2. Poverty trends in China at provincial level

While the reduction of poverty in China has been dramatic during the last twenty-five years, it has also been quite uneven in both the temporal and the spatial dimensions (Ravallion and Chen, 2007). Table 1 shows the trend rates of poverty reduction, measured using the headcount index of poverty (H), by province[5] during the study period.[6] H is defined as the percentage of the relevant population living in households with income per capita below the poverty line. Here we use the higher of the two poverty lines used by Ravallion and Chen (2007). In all other respects the methods used in constructing the data set follow

[5] Among the provinces we include also the municipalities: Beijing, Tianjin and Shanghai. The recent creation of a new municipality, Chongquing, preclude us from including it in our empirical analysis. Tibet is not included because data to construct the poverty measures are not availability.

[6] In general it covers the 1983-2001 period for rural areas, and the 1986-2001 period for urban areas but there are some special cases as the reader can notice in Table 1. This is the longest time period with complete data that was feasible at the time of writing.

those described in Ravallion and Chen (2007, Section 2 and Annex). We have combined these estimates of poverty measures by province and over time with official data on the sources of provincial GDP from various issues of China's statistical yearbooks. The trends reported in Table 1 are OLS estimates of the β_i's in the regressions: $\ln H_{it} = \alpha_i + \beta_i t + \varepsilon_{it}$ for provinces i=1,..,n and dates t=1,..,T. (When we quote the trend as % per annum we mean $-100\beta_i$.)

The rates of rural poverty reduction differ markedly across provinces. In particular, while there is a noticeable negative trend in poverty in most of the provinces, the municipalities (Beijing, Tianjin and Shanghai) show no tendency towards rural poverty reduction. This is not surprising since in the initial year the level of rural poverty was already very small in these provinces; the initial headcount index was 0.35% in Beijing, 0.77% in Shanghai and 3.44% in Tianjin while the average headcount index was 28.7% in 1983. Figure 1 presents the evolution of poverty in the province with the highest negative trend in rural poverty, Guangdong, and one of the municipalities (Shanghai). The figure makes clear how different is the evolution of poverty in these two provinces. In Guangdong the rate of rural poverty reduction is an astonishing 28.5% per annum. In the municipalities, including Shanghai, there was no significant reduction in poverty. All the rest of the provinces fit inside the cone generated by Guangdong and the municipalities but closer to the top than to the bottom.

The last two columns of Table 1 refer to the headcount index in the urban areas of each province. The average trend for poverty reduction in urban areas ($\hat{\beta} = 0.131$) is higher than for rural areas ($\hat{\beta} = 0.089$). It is again Guangdong that shows the fastest trend in urban poverty reduction: 33% per annum. However, in the case of urban poverty, the municipalities show a significant reduction. The rates for Beijing, Tianjin and Shanghai are 10%, 11.7% and 8.4% respectively.

The temporal evolution of rural poverty is quite different to that found in urban areas. Figure 2 gives an example of the typical trends of poverty reduction for provinces between Guangdong and the municipalities in terms of their trend of poverty reduction. Giangxi and Anhui start and end at similar levels. However, Giangxi shows a monotonic decrease in the headcount index, similar to Guangdong, while Anhui is a prototype of a different temporal evolution, which implies an increase in rural poverty when aggregate economic growth slows down.[7] We find large differences across provinces in the variance of the poverty measures over time.

Figure 3 gives some examples of the evolution of rural poverty. In general most of the series belong to one of two groups: no reduction in urban poverty or monotonic reduction.

Comparing these results to India, it is evident that the rates of poverty reduction in the provinces of China between 1983 and 2001 has tended to be greater than in the states of India during the longer period of 1970-1994 (Ravallion and Datt 2002). However, and more importantly in this context, the variability across provinces of the trend in the reduction of poverty is larger in the Chinese case (standard deviation of the trend in rural, or urban, poverty is 0.07) than in India (0.05).

3. The role played by the sectoral pattern of growth

We now examine to what extent the diverse trends in China's progress against poverty revealed by the results of the previous section are explicable in terms of the sectoral pattern of economic growth. We use the standard classification of the origins of GDP, namely "primary" (mainly agriculture), "secondary" (manufacturing and construction) and "tertiary" (services and trade). We let these three sectors "compete" in explaining the variance in poverty measures over time and across provinces. There are, of course, various sources of interdependence amongst these sectors, including externalities. If sector A's influence on poverty occurs via sector B's output then we will attribute it to sector B. So we only identify what can be termed the proximate impacts of the sectoral pattern of growth. We return to this point in discussing our results.

We do not have information for all the years of the 80's in all the provinces.[8] In addition, since urban poverty is very small even at the beginning of the period, and almost all the poverty reduction was for rural areas, we consider rural poverty separately to overall poverty (urban plus rural areas). Finally, we consider two subsamples: one time series difference (all the years versus years after 1989) and one cross section (all the provinces versus all the provinces except municipalities and Guangdong).

Our starting point in testing whether the pattern of growth matters to poverty reduction is the following specification for the log of the headcount index of poverty, H_{jt}, for province *i* at time *t*:

7 In fact there are other provinces that show an increase in rural poverty at the end of the 90's. Another example of this case is Ningxia.

8 Small sample problems impede using the aggregate data of some provinces in several years.

$$\ln H_{it} = \pi_{0i} + \sum_{j=1}^{3} \pi_j \ln S_{ijt} + \delta \ln Y_{it} + \gamma INF_{it} + \alpha t + \varepsilon_{it} \tag{1}$$

where $S_{ijt} = Y_{ijt} / Y_{it}$ is the share of output produced by sector *j* (*j*=1,2,3 for primary, secondary and tertiary) in province *i* at time *t* and Y_{ijt} is the output per capita in each sector for province *i* at date *t* with aggregate output (GDP) per capita for province *i* given by Y_{it}. We also control for the rate of inflation, *INF* (the time difference in log of the Consumer Price Index),[9] and we allow for an economy-wide trend. To assess whether the pattern of growth matters we test $H_0 : \pi_j = 0$ for all *j*. If we reject this null hypothesis then a further test of interest is whether $\sum_{j=1}^{3} \pi_j = \delta$, in which case (1) collapses to:

$$\ln H_{it} = \pi_{0i} + \sum_{j=1}^{3} \pi_j \ln Y_{ijt} + \gamma INF_{it} + \alpha t + \varepsilon_{it}\,, \tag{2}$$

which is a specification used by Ravallion and Datt (2002) for India.

Table 2 gives our estimates of equation (1) on various samples and with and without province-specific trends. We can clearly reject the null hypothesis that the composition of growth does not matter. We see a significant poverty-reducing effect of a higher agricultural share of GDP in rural areas. We can also reject the null that the parameters for the sector shares are equal to each other. In column (1) the specification cannot reject that the sum of the parameters for the shares is equal to the parameter for total GDP per capita. However, in (2) and (3) this null hypothesis is rejected. Column 4 presents the results for the total headcount index, which combines the rural and the urban areas, for the set of provinces included in column 3. As in the previous columns, the agricultural share in GDP reduces poverty at a rate similar to the one found for rural areas alone. Total GDP per capita is also statistically relevant in the reduction in overall provincial poverty. Coinciding with columns (2) and (3), all the tests of equality of the coefficients are clearly rejected as well as the test for equality of the sum of the coefficients of the shares to the coefficient on aggregate GDP.

The results are slightly different if we include a province-specific trend (Table 2, columns 5 to 8). The equality of the parameters of the shares is still rejected. The equality of all the parameters to zero is also rejected. But, in these cases (columns 5 to 8), there is no rejection of the null hypothesis that the sum of the coefficient on the shares is equal to the

[9] Previous studies, including Ravallion and Datt (2002), have found that the rate of inflation is an important determinant of poverty.

coefficient on aggregate GDP. There is also a rejection of the null in the case of the overall (rural and urban) headcount index. We proceed to impose the restriction that $\sum_{j=1}^{3} \pi_j = \delta$.

Table 3 contains our estimates of equation (2). Given the small number of regressors, the explanatory power is quite good, being marginally better in the second period than the first. The elasticity of poverty with respect to GDP per capita in the primary and secondary sectors is significantly different from zero. The estimation shows that—in marked contrast to Ravallion and Datt's (2002) findings for India—the elasticity of poverty with respect to the output per capita in the services sector is not significantly different from zero. The coefficients for the sectoral elasticities in Table 3 are similar in the full sample and the estimation with the sample excluding the municipalities. The most important difference between the two samples is for the coefficient on the time trend, which is (as expected) larger in the case of the sample that excludes the municipalities. Finally, as was found by Ravallion and Datt (2002) for India, inflation has a positive and significant effect on poverty.

A sufficient condition for the fixed effects estimation in Table 3 to be consistent is the strict exogeneity of the explanatory variables conditional on the unobservable provincial effects. The efficiency of such an estimation method rests on the assumption of a diagonal variance-covariance matrix of the perturbations conditional on the explanatory variables and the unobserved effects. Another popular strategy to deal with the unobserved effects is to use a first differences transformation. The condition for consistency of this estimator is weaker than the needed in the case of the fixed effects estimator. In we assume strict exogeneity, as before, but add the assumption that the first difference of the errors is not correlated, then the following first differences estimator is the most efficient of all the estimators:

$$\Delta \ln H_{it} = \alpha_i + \sum_{j=1}^{3} \pi_j \Delta \ln Y_{ijt} + \gamma \Delta INF_{it} + \xi_{it} \tag{3}$$

where Y_{ijt} is the output per capita in each sector (j=1,2,3) for province i at date t. Notice that equation (3) includes province-specific trends.[10]

Table 4 presents our estimates of the first differences specification in equation (3). As before, we distinguish between the full rural areas and the rural areas without the municipalities, as well as the province aggregates as a whole (urban plus rural). Under each panel, the first column presents the elasticity of changes in the headcount index with respect to aggregate output per capita. The following columns present the estimation with the sectoral

[10] The estimation without province specific intercepts delivers similar results but the R^2 is much smaller.

disaggregation of output. In the complete sample, the elasticity of changes in poverty with respect changes in output per capita is not significantly different from zero. When output per capita is separated by sector the coefficient on the change in output per capita of the primary sector is significant if the change in the inflation rate is not included. If we include the change in inflation, column 3, none of the elasticities is statistically significant with the exception of the coefficient on changes in inflation.

The results for the rural sample without the municipalities are quite different. In this case the elasticity of the change in poverty with respect to changes in aggregate output per capita is significant. When we included the output per capita by sectors, only the coefficient associated with the primary sector is significantly different from zero. This result is not affected by the inclusion of the change in inflation as an additional explanatory variable.

The results for the provinces as a whole show that the elasticity of the change in poverty with respect to changes in output per capita is not significant, as was the case for the rural areas including all the provinces. The results are similar to those obtained in the columns for the rural area without municipalities if we eliminate the municipalities from the overall headcount index (including the urban and rural areas). As shown already in Table 3, the results for the sample of rural and urban areas without the municipalities are very similar to the ones for rural areas without municipalities. Therefore, the relevant difference is the inclusion, or not, of the municipalities and not the use of rural poverty versus overall poverty.

From the previous analysis it seems that only the growth in the primary sector has a significant effect on poverty in rural China, without considering the rural areas of the municipalities. This result is compatible with Ravallion and Chen (2007) who find, using nation-wide data for China, that the primary sector has far higher impact on poverty that either the secondary or the tertiary sectors. However, Ravallion and Chen found significant effects of non-primary growth, which we do not confirm using this sub-national data set.

In Table 5 we present analogous results in which the growth rates for the output of each sector are weighted by the proportion of each sector on total output. This transformation is of interest because if the coefficients with respect to all the (weighted) sectoral outputs are the same across sectors then the estimation collapses in a simple regression of the rate of poverty reduction on the rate of growth of output. Thus we have a straightforward statistical test of the PGH. In order to make the comparison as close as possible to the national results reported by Ravallion and Chen (2007), we eliminate the trends and the inflation rate and work only with the growth rate of the three sectors (j=1,2,3). In this case there are fewer observations because there are gaps between surveys. Assuming a common slope for each change in output per capita we obtain the following regression:

$$\Delta \ln H_{it} = \alpha_i + \sum_{j=1}^{n} \pi_j S_{ijt} \Delta \ln Y_{ijt} + \zeta_{it} \tag{4}$$

Again we see from Table 5 that only the growth in the primary sector reduced rural poverty. In fact the order of magnitude of the coefficient on the primary sector component (-10.83) is quite similar to the corresponding parameter estimated by Ravallion and Chen (2007) using national data (-8.06). This result is not affected by the exclusion of the municipalities from the sample. Additionally, the parameter for the primary sector is significantly different from that for industry or services. However, we cannot reject the null hypothesis that the parameters on the secondary and tertiary sectors are equal, consistently with Ravallion and Chen (2007). However, as shown in column 3, when we impose the hypothesis that both parameters are the same we find that the common parameter is not significantly different from zero. All the results carry over the sample that excludes municipalities and to the regressions that use the overall (rural plus urban) headcount index. Therefore, this estimator shows again that only the growth rate of agricultural output matters for poverty reduction in rural areas.

We cannot rule out the possibility that secondary or tertiary sector growth is having an indirect effect via primary sector growth. However, we would also note that the development literature has tended to emphasize the spillover effects <u>from</u> agriculture to other sectors, not the reverse.[11] In the case of China there is evidence of quite strong externalities in the rural economic growth process, whereby agricultural growth has second-round effects in stimulating growth in other sectors (Ravallion, 2005, using micro panel data for southwest China in the 1980s).

Given that we find so little evidence that secondary or tertiary sector growth has helped directly reduce poverty in China, the issue of a trade-off between a more balanced pattern of growth across sectors and a higher overall growth rate does not arise. As we noted in the introduction, the non-market processes influencing the pattern of growth in China warn against assuming that higher agricultural growth would have come at the expense of growth in the other sectors. However, even if that was the case, there is no sign here of a trade-off from the point of view of poverty reduction.

[11] For a recent overview of this literature see Bezemer and Headey (2008).

Comparing these findings to past research on the pattern of growth in India, it is notable that the primary sector is clearly more important to poverty reduction in China than India (comparing our results for China with those of Ravallion and Datt, 1996, for India). Differences in the sectoral priorities of the two governments undoubtedly played a role. While China put high priority on agriculture in the early stages of its reform period, starting in the late 1970s, India's commitment to this sector has varied over time, with greater emphasis on non-farm sectors in some periods, including the recent reform period in which trade and industrial policies have taken center stage, while agriculture has received less attention.[12] The heavy protection of India's secondary sector in the "pre-reform" period probably also dulled labor absorption and (hence) the impact of that sector's growth on poverty.

However, there is also an important historical-institutional difference. The relatively greater importance of agricultural growth to poverty reduction in China than India probably reflects, at least in part, the difference in the distribution of agricultural land. While India has a large landless population in rural areas, such landlessness is rare in China. At the time of de-collectivization—starting in the late 1970s—agricultural land appears to have been distributed to households within the communes in a relatively equitable way (though without mobility, inequalities naturally emerged between communes).[13] We hypothesize that starting with a less unequal distribution of agricultural land meant that China's agricultural output growth had a larger proportionate impact on the poverty rate. This assumes that a larger share of agricultural land held by the poor in a rural economy allows them to capture a larger share of the gains from agricultural growth. We emphasize that this is an assumption, as there are potential mitigating factors, notably the likely effect of agricultural growth on the wages received by India's rural landless, many of whom work in agriculture.[14] However, we would conjecture that this effect is unlikely to be strong enough in this context to outweigh the

[12] India's policy reforms in other areas (lower industrial protection and exchange rate depreciation) have brought indirect benefits to agriculture, notably through improved terms of trade, and some growth in agricultural exports. However, at the same time, the reform period saw a decline in public investment in key areas for agriculture, notably rural infrastructure.

[13] The forces for an against this outcome were clearly similar to Vietnam, as studied by Ravallion and van de Walle (2008), who find that the process there resulted in a relatively equitable allocation of land. Unlike China, Vietnam also took the further step of creating a market in land-use rights; the results of Ravallion and van de Walle (2008) suggest that this increased the inequality of landholdings over time, but was nonetheless a poverty-reducing policy reform. In the case of China, agricultural land has remained subject to non-market (administrative) re-allocation.

[14] In principle, the possibility that agricultural growth came with rising land inequality would also attenuate the advantage of starting with low inequality.

adverse direct effect of India's higher land inequality on the elasticity of poverty to agricultural output.

4. Allowing for different parameters across provinces

The various tests on provincial data reported in the last section confirm the finding of Ravallion and Chen (2007) on national-level data that it is the primary sector that has been the main driving force of China's poverty reduction, rather than the secondary or tertiary sectors. However, in the previous section we only considered regressions with constant elasticities across provinces for each sector. As we argued before, and was shown by Ravallion and Datt (2002) for the case of the states of India, the composition of output and the geographical distribution of growth are potentially important for the analysis of the elasticity of poverty reduction to economic growth. As a starting point for investigating this issue, we use a similar specification to that of Ravallion and Datt (2002) for India, in which all parameters are now allowed to differ across provinces:

$$\ln H_{it} = \pi_{0i} + \sum_{j=1}^{3} \pi_{ijt} \ln Y_{ijt} + \gamma_i INF_i + \alpha_i t + \varepsilon_{it} \qquad (5)$$

Note that this specification includes a state-specific time trend and a state fixed effect.

Equation (5) can be interpreted as postulating a separate regression for each province. We use this regression to test for the poolability of the coefficients on the various explanatory variables. We exclude from the sample the municipalities since we learned in the previous section that the rural areas of the municipalities are special and have an important effect on the estimation. We should also notice that the definition of the rural part of a municipality is subject to geographical changes over time, which recommends their exclusion from the sample in any serious analysis of rural poverty in China.

Table 6 contains the test results. It shows that the coefficients on inflation and GDP per capita in the primary sector can be pooled across provinces while the rest of the explanatory variables (specially the trend) should not be pooled. Notice that this result is not very surprising since we are dealing with rural poverty and we showed before that, when the coefficient are forced to take a common value across provinces, only the growth rate of GDP in the primary sector has an effect on changes in poverty. The same results are found if we use the overall headcount index (rural plus urban areas) instead of the headcount index for the rural areas alone.

Table 7 presents the estimates of the restricted model with common coefficients for GDP in the primary sector and inflation. The elasticity of poverty with respect to GDP per capita in the primary sector is -2.23 while the coefficient on inflation is 0.02. For the estimation using the rural and urban areas the elasticity is -1.98 while the coefficient on inflation is also 0.02. Both estimates are similar to the ones obtained by assuming constant elasticities for all the variables. Inflation increases poverty and, in most of the provinces, there is a significant positive time trend in poverty. These two results are identical to the findings in Ravallion and Datt (2002). However, the magnitude of the effect is quite different: the positive effect of the time trend is much more important in the provinces of China than in the states of India. The coefficient on inflation is practically identical in the estimation using the provinces of China or the states of India (elasticity around 0.02).

Another similarity with the results of Ravallion and Datt (2002) for India is the pooling of the coefficients for the primary sector but not for the industrial or the services sector. The test for the equality of industrial and services output elasticities across all provinces rejects the null hypothesis. Figures 4, 5 and 6 contain the elasticities for each of the provinces.

It is again striking how weak the evidence is of significant poverty-reducing effects of non-primary sector growth. For the secondary sector, we find a significant negative elasticity in only one province, Hebei. For the tertiary sector, we only find a significant negative coefficient in two provinces, Anhui and Qinghai. Taken as a whole, our results re-affirm the importance of primary sector growth, and reveal very little sign that growth in other sectors was poverty reducing.

5. Counterfactual analysis

We now consider the evolution of rural poverty in China under alternative counterfactual scenarios, which are designed to quantify the contribution of the pattern of growth to overall poverty reduction. We focus on rural poverty and we continue using the sub-sample of the provinces where the municipalities (Beijing, Tianjin, Shanghai, Chongqing) and Tibet have been dropped. The reason why we dropped the municipalities is the problematic, and changing, definition of rural areas in those provinces (and therefore the poverty of rural areas) as well as the already very low level of poverty in those provinces. The elimination of Tibet is due to the scarcity of data for this province. The estimation takes 1988 as the starting point since there are many missing years before 1988 (basically before that year there is only information for 1983).

The first exercise considers the effect of assuming that all the provinces and sectors had grown at the national growth rate of GDP per capita. The counterfactual change in the headcount index is calculated as if all the provinces and sectors had the national average growth rate. Notice that since this exercise is a reduced-form simulation we do not consider the effect that the growth of all the provinces and sector at the same rate may have had on the overall growth of GDP of China, which we take as given. Based on equation (2), the counterfactual vector of rates of poverty reduction across time under counterfactual (1) is formed from:

$$\Delta \ln \hat{H}_{it}^{(1)} = (\hat{\pi}_1 + \hat{\pi}_{2i} + \hat{\pi}_{3i})\Delta \ln Y_t + \hat{\alpha}_i + \hat{\gamma}_i \Delta INF_{it} \quad (t=1,..,T) \tag{6}$$

In the second exercise the counterfactual change in the headcount index is calculated as if all the sectors in each province had the average growth rate of GDP per capita of each province, giving:

$$\Delta \ln \hat{H}_{it}^{(2)} = (\hat{\pi}_1 + \hat{\pi}_{2i} + \hat{\pi}_{3i})\Delta \ln Y_{it} + \hat{\alpha}_i + \hat{\gamma}_i \Delta INF_{it} \tag{7}$$

Finally, in the third exercise we construct a counterfactual that assumes that all the provinces have the average growth of each sector, giving:

$$\Delta \ln \hat{H}_{it}^{(3)} = \hat{\pi}_1 \Delta \ln Y_{1t} + \hat{\pi}_{2i} \Delta \ln Y_{2t} + \hat{\pi}_{3i} \Delta \ln Y_{3t} + \hat{\alpha}_i + \hat{\gamma}_i \Delta INF_{it} \tag{8}$$

Once the adjusted changes have been calculated the headcount index for each year is obtained using the following equation (starting in 1988):[15]

$$\hat{H}_{it}^{(k)} = \hat{H}_{it-1}^{(k)}(1 + \Delta \ln \hat{H}_{it}^{(k)}) \quad (k=1,2,3) \tag{9}$$

The aggregation procedure across provinces is calculated using the following formula:

$$H_t^{(k)} = \sum_{i=1}^{N} w_i H_{it}^{(k)} \tag{10}$$

where i is the index of the provinces and w_i is the rural population share of province i.

Figure 7 presents the evolution of rural poverty in China and the evolution under the first counterfactual (all provinces and sectors grow at the same rate as the national growth rate). This allows us to assess the contribution of the pattern of growth to aggregate poverty reduction in rural China. Under this scenario the reduction in the headcount index would have been faster than that observed (solid line).

Figure 8 considers the effect of the second counterfactual: the assumption that all the sectors would grow at the average growth rate of each province. In this case the

[15] Obviously, depending on the growth rate of the province/sectors and the parameter estimates it is possible that this loops generating headcount indices over 100 or below 0. In the unlikely event that for one province the index goes over 100 or below 0 the headcount for that province is set equal to the value in the previous period. Using an alternative convention (setting the index to 100 or 0 and keeping it at that level) does not alter significantly any of the following results since there are very few provinces where this problem is present.

counterfactual reduction in poverty is again larger than the actually observed although the difference is less than we found for counterfactual (1) (comparing Figures 7 and 8).

Finally, Figure 9 shows the comparison of the actual and the counterfactual poverty rate under the third scenario of common sectoral growth across all the provinces. In this case, and opposite to the finding of the previous scenarios, actual and counterfactual poverty are quite close over the sample period.

Thus it is clear from Figures 7-9 that it is the sectoral unevenness in the growth process, rather than its geographic unevenness, that led to lower poverty reduction. Without the sectoral unevenness in growth rates (but maintaining the geographic structure) the poverty rate would have been less than half its actual value by the end of the period.

We checked the effect of producing the counterfactuals using the fixed effects estimator instead of the first differences estimator. The process is the same as described above, but the estimated parameters correspond to this alternative estimation method. Notice that the estimation does not have to deliver the same results since the estimators are different and the sample is smaller than before (the calculation of first differences eliminates many observations for the need to find consecutive non missing data). The results in Figures 7-9 were very similar using this estimation method.

6. Conclusions

A long-standing development policy debate has concerned the priority to be given to agriculture versus industrialization or an expanding services sector as the routes out of poverty. We have studied the experience of the country that has almost certainly had the greatest success in reducing poverty in modern times, China. A newly constructed sub-national panel data set offers a powerful lens on the role played by the geographic and sectoral pattern of growth in China's progress against poverty.

We find that the primary sector was the real driving force in China's remarkable success against absolute poverty, rather than the secondary (manufacturing) or tertiary (services) sectors, and that the unevenness of the growth process across sectors greatly attenuated the overall pace of poverty reduction. Yes, China has had great success in reducing poverty through economic growth, but this happened despite the unevenness in its sectoral pattern of growth. The idea of a trade-off between these sectors in terms of overall progress against poverty in China turns out to be a moot point, given how little evidence we find of any poverty impact of non-primary sector growth, controlling for primary-sector growth. We do not doubt that the non-primary sectors were at least the proximate drivers of aggregate growth, but it was the primary sector that did the heavy lifting against poverty.[16]

The revealed importance of agricultural growth to China's success against poverty stands in marked contrast to India, where the services sector has been the more powerful force. Policy choices in the reform periods have clearly played a role. So too have differences in the initial distribution of assets, with access to agricultural land being more equitably distributed in China than India. China's advantage in this respect reflected the historical opportunity created by the de-collectivization of agriculture and introduction of the "household responsibility system."

[16] We say "proximate" since it can also be argued that the primary sector is a driving force behind growth in other sectors; for this argument and evidence to support it see Tiffin and Irz (2006).

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Table 1. Trends in the headcount index by provinces and areas

	Rural		Urban	
	Initial year	Trend	Initial year	Trend
Beijing	1988	0.034	1986	-0.100
Tianjin	1983	0.009	1986	-0.117
Hebei	1983	-0.141	1986	-0.092
Shanxi	1983	-0.082	1986	-0.066
Inner Mongolia	1983	-0.080	1986	-0.173
Liaoning	1988	-0.072	1986	-0.047
Jilin	1983	-0.053	1986	-0.148
Heilongjiang	1988	-0.067	1986	-0.229
Shanghai	1983	0.022	1986	-0.084
Jiangsu	1983	-0.200	1986	-0.067
Zhejiang	1983	-0.116	1986	-0.103
Anhui	1983	-0.143	1986	-0.245
Fujian	1988	-0.220	1986	-0.162
Jiangxi	1983	-0.122	1986	-0.251
Shangdong	1983	-0.127	1986	-0.093
Henan	1983	-0.161	1986	-0.175
Hubei	1983	-0.133	1986	-0.099
Hunan	1983	-0.069	1986	-0.151
Guangdong	1988	-0.285	1986	-0.330
Guangxi	1983	-0.115	1986	-0.184
Hainan	1990	-0.100	1988	-0.190
Sichuan	1983	-0.110	1986	-0.083
Guizhou	1988	-0.064	1986	-0.180
Yunnan	1983	-0.006	1986	-0.110
Shaanxi	1983	-0.034	1986	-0.078
Gansu	1983	-0.066	1986	-0.064
Qinghai	1988	-0.047	1986	-0.071
Ningxia	1983	-0.029	1986	0.020
Xinjiang	1988	0.003	1986	-0.118

Note: The reported trends are the regression coefficients of the log headcount index on time.

Table 2: Tests of the pattern of growth hypothesis based on equation (1) for various samples

	Rural			Urban+rural	Rural			Urban+rural
	All provinces	Without municipalities and Tibet	Without municipalities, Tibet and Guangdong	Without municipalities, Tibet and Guangdong	All provinces	Without municipalities and Tibet	Without municipalities, Tibet and Guangdong	Without municipalities, Tibet and Guangdong
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Without province-specific trends				With province-specific trends			
LnS_1	-1.01	-0.36	-0.84	-0.92	-2.83	-2.03	-2.15	-1.61
	(-3.43)	(-1.26)	(-2.86)	(-2.83)	(-4.90)	(-3.86)	(-4.03)	(-2.52)
LnS_2	-1.48	0.29	0.05	0.58	-1.34	-0.25	-0.45	0.21
	(-2.95)	(0.62)	(0.12)	(1.02)	(-1.24)	(-0.30)	(-0.54)	(0.20)
LnS_3	0.62	1.00	0.48	0.21	0.62	0.80	0.65	1.51
	(1.40)	(2.87)	(1.37)	(0.44)	(1.06)	(1.78)	(1.43)	(1.11)
LnY	-2.54	-2.88	-3.17	-3.61	-2.39	-3.30	-3.49	-3.36
	(-7.04)	(-9.78)	(10.99)	(-11.05)	(-4.88)	(-8.74)	(-9.10)	(-7.40)
INF	0.02	0.002	0.02	0.02	0.01	0.01	0.01	0.01
	(5.03)	(6.32)	(6.23)	(5.68)	(2.89)	(5.17)	(5.28)	(4.96)
Trend	0.11	0.14	0.15	0.17	n.a.	n.a.	n.a.	n.a.
	(4.00)	(6.25)	(7.01)	(7.01)				
R^2	0.88	0.87	0.85	0.87	0.92	0.91	0.90	0.91
N	328	296	285	271	328	296	285	271
Intercept specific	yes	yes	yes	yes	Yes	yes	yes	Yes
Trend specific	No	no	no	no	Yes	yes	yes	Yes
H_0: $\pi_1=\pi_2=\pi_3=0$	10.97	4.12	4.52	3.92	11.90	10.56	10.53	7.69
p-value	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
H_0: $\pi_1=\pi_2=\pi_3$	11.12	6.02	5.82	4.07	14.99	15.59	15.32	11.16
p-value	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00
H_0: $\Sigma\pi_j=\delta$	0.56	21.76	12.49	11.83	0.40	1.54	1.08	2.71
p-value	0.45	0.00	0.00	0.00	0.52	0.21	0.30	0.10

Table 3. Fixed effects estimation of equation (2)

	1983-2001				1990-2001			
	Rural, all provinces	Without muni-cipalities	Urban+ rural	Urban+rural without muni-cipalities	Rural, all provinces	Without muni-cipalities	Urban+ rural	Urban+rural without muni-cipalities
LnY_1	-1.05	-0.85	-0.35	-0.87	-1.10	-1.04	-0.24	-0.89
	(-3.61)	(-3.02)	(-1.02)	(-2.80)	(-3.00)	(-3.12)	(-0.62)	(.2.52)
LnY_2	-1.82	-1.77	-1.99	-1.70	-2.58	-1.98	-2.15	-1.83
	(-8.47)	(-9.92)	(-6.98)	(-7.23)	(-8.02)	(-7.50)	(-6.11)	(-6.50)
LnY_3	0.39	-0.15	0.21	-0.46	1.43	0.18	0.53	-0.23
	(1.23)	(-0.85)	(0.51)	(-12.9)	(3.07)	(0.46)	(1.05)	(-0.55)
INF	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02
	(5.49)	(8.14)	(5.70)	(7.04)	(5.67)	(7.04)	(5.36)	(6.69)
Trend	0.11	0.15	0.12	0.16	0.10	0.14	0.10	0.15
	(4.04)	(6.74)	(3.57)	(6.40)	(2.86)	(5.00)	(2.44)	(5.04)
R2	0.88	0.85	0.90	0.86	0.89	0.86	0.90	0.86
N	328	296	313	282	287	259	280	257

Note: t-ratios in parentheses.

Table 4: First differences estimation of the effect of sectoral composition 1983-2001

	Rural, all provinces			Rural, without municipalities			Urban+rural		
ΔLnY	-0.68			-2.18			0.50		
	(-0.81)			(-3.49)			(0.45)		
ΔLnY_1		-2.03	-1.04		-2.92	-2.02		-1.31	-0.39
		(-3.19)	(-1.57)		(-5.92)	(-4.01)		(-1.53)	(-0.43)
ΔLnY_2		0.14	-0.00		-0.60	-0.65		-0.28	-0.40
		(0.15)	(-0.00)		(-0.80)	(-0.92)		(-0.21)	(-0.31)
ΔlnY_3		0.75	0.23		1.07	0.39		1.87	1.41
		(0.74)	(0.24)		(1.38)	(0.53)		(1.38)	(1.05)
Δ*INF*			0.02			0.02			0.02
			(3.85)			(4.52)			(2.61)
R^2	0.09	0.14	0.21	0.10	0.25	0.34	0.03	0.06	0.10
N	198	198	198	180	180	180	199	199	199

Note: t-ratios in parentheses.

Table 5: Sectoral composition effects in first differences;share-weighted; 1983-2001

$$(1)\Delta \ln H_{it} = \alpha + \sum_{j=1}^{3} \pi_j s_{ijt}^{Y} \Delta \ln Y_{ijt} + \xi_{it}$$

$$(2)\Delta \ln H_{it} = \alpha_i + \sum_{j=1}^{3} \pi_j s_{ijt}^{Y} \Delta \ln Y_{ijt} + \xi_{it}$$

$$(3)\Delta \ln H_{it} = \alpha_i + \sum_{j=1}^{2} \pi_j s_{ijt}^{Y} \Delta \ln Y_{ijt} + \xi_{it}$$

	Rural, all provinces			Rural, without municipalities			Urban+rural		
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
$\Delta \mathrm{Ln} Y_1$	-10.83	-13.56	-13.43	-10.03	-12.15	-12.35	-9.86	-12.86	-13.08
	(-3.92)	(-4.33)	(-4.32)	(-4.68)	(-4.93)	(-5.06)	(-2.72)	(-3.02)	(-3.09)
$\Delta \ln Y_2$	-0.62	1.80		-2.36	-1.15		-0.36	1.60	
	(-0.54)	(1.14)		(-2.51)	(-0.83)		(-0.24)	(0.75)	
$\Delta \ln Y_3$	1.31	0.42		1.92	1.49		4.03	3.86	
	(0.71)	(0.19)		(1.30)	(0.83)		(1.66)	(1.29)	
$\Delta \mathrm{Ln}(Y_2+Y_3)$			1.27			0.15			2.51
			(1.40)			(0.23)			(1.05)
$\pi_1=\pi_2$	10.82	16.31		9.96	13.09		5.43	7.81	
	p=0.00	P=0.00		p=0.00	p=0.00		P=0.00	P=0.00	
$\pi_2=\pi_3$	0.60	0.18		4.65	0.91		1.80	0.25	
	p=0.43	P=0.67		p=0.03	p=0.34		P=0.18	P=0.61	
R^2	0.07	0.18	0.18	0.15	0.20	0.20	0.05	0.10	0.10
N	198	198	198	180	180	180	199	199	199

Table 6: Poolability tests; provinces not including municipalities,1983-2001

	Rural only	Urban+rural
Primary	F(25,140)=0.81	F(25,126)=1.06
	Prob.=0.71	Prob.=0.39
Secondary	F(25,140)=1.71	F(25,126)=1.99
	Prob.=0.02	Prob.=0.00
Tertiary	F(25,140)=1.87	F(25,126)=2.15
	Prob.=0.01	Prob.=0.00
Inflation	F(25,140)=1.05	F(25,126)=1.21
	Prob.=0.41	Prob.=0.24
Trend	F(25,140)=2.30	F(25,126)=1.80
	Prob.=0.00	Prob.=0.01

Note: N=296

Table 7. Estimate of equation (5) under non-rejected pooling restictions

		Rural only		Urban+rural	
Variable	Province	Coeff.	t-stat.	Coeff.	t-stat.
LnY_1		-2.23	-5.49	-1.98	-4.00
LnY_2	Hebei	-2.89	-2.20	-3.07	-2.18
	Shanxi	1.04	0.58	1.62	0.79
	Inner Mongolia	-5.17	-1.51	-5.30	-1.45
	Liaoning	4.07	1.99	4.20	1.93
	Jilin	0.16	0.09	-2.63	-0.91
	Heilongjiang	0.02	0.00	-1.93	-0.25
	Shanghai	-0.84	-0.50	-2.56	-1.16
	Jiangsu	1.69	0.91	1.91	0.97
	Zhejiang	1.99	1.24	2.22	1.30
	Anhui	8.04	3.64	8.10	3.43
	Fujian	-0.77	-0.45	-0.47	-0.26
	Jiangxi	2.24	1.14	1.86	0.77
	Shangdong	0.81	0.54	1.01	0.62
	Henan	1.40	0.92	1.33	0.78
	Hubei	1.46	0.94	-1.20	-0.33
	Hunan	-1.96	-0.89	-1.71	-0.73
	Guangdong	1.49	0.98	1.50	0.91
	Guangxi	3.00	1.86	3.17	1.84
	Sicuani	0.09	0.05	0.23	0.12
	Guizhou	-1.17	-0.45	-0.92	-0.33
	Yunnan	2.82	1.12	2.08	0.29
	Shaanxi	2.35	1.17	2.03	0.79
	Gansu	-0.38	-0.14	0.82	0.25
	Qinghai	8.34	3.54	8.24	3.28
	Ningxia	-0.92	-0.24	2.46	0.51
	Xinjiang	3.56	1.32	3.41	1.19
LnY_3	Hebei	-1.27	-0.66	-1.04	-0.51
	Shanxi	-0.75	-0.31	1.82	0.45
	Inner Mongolia	10.12	2.21	10.24	2.09
	Liaoning	-7.51	-1.91	-7.41	-1.76
	Jilin	1.81	0.82	7.00	1.50
	Heilongjiang	6.78	1.25	6.10	0.79
	Shanghai	4.22	1.84	8.48	2.56
	Jiangsu	0.77	0.29	0.50	0.17
	Zhejiang	-0.89	-0.34	-1.42	-0.51
	Anhui	-17.80	-3.55	-17.89	-3.34
	Fujian	7.53	1.68	6.87	1.44
	Jiangxi	-0.82	-0.34	-0.49	-0.16
	Shangdong	1.11	0.38	0.87	0.27
	Henan	5.52	1.53	5.82	1.30
	Hubei	1.78	0.70	6.30	1.03
	Hunan	10.02	2.62	9.53	2.32
	Guangdong	5.64	2.17	6.31	1.97
	Guangxi	1.21	0.57	0.98	0.43
	Sichuan	8.52	1.96	8.45	1.82

	Guizhou	2.11	0.62	1.99	0.55
	Yunnan	0.93	0.32	2.59	0.21
	Shaanxi	0.80	0.39	1.36	0.44
	Gansu	1.01	0.46	-0.96	-0.27
	Qinghai	-11.27	-2.39	-11.30	-2.25
	Ningxia	2.86	0.95	-2.31	-0.44
	Xinjiang	3.09	1.04	2.72	0.85
Trend	Hebei	0.45	2.70	0.43	2.40
	Shanxi	-0.16	-0.64	-0.36	-1.15
	Inner Mongolia	-0.41	-1.68	-0.41	-1.59
	Liaoning	0.29	1.01	0.27	0.87
	Jilin	-0.20	-1.03	-0.45	-1.64
	Heilongjiang	-0.61	-2.68	-0.43	-1.54
	Shanghai	-0.49	-2.29	-0.88	-3.48
	Jiangsu	-0.24	-1.24	-0.24	-1.14
	Zhejiang	-0.16	-0.74	-0.13	-0.57
	Anhui	0.88	2.72	0.89	2.56
	Fujian	-0.65	-1.73	-0.61	-1.54
	Jiangxi	-0.15	-0.73	-0.14	-0.64
	Shangdong	-0.25	-0.76	-0.25	-0.71
	Henan	-0.80	-2.16	-0.82	-1.89
	Hubei	-0.32	-1.36	-0.45	-1.52
	Hunan	-0.79	-4.06	-0.77	-3.71
	Guangdong	-0.61	-3.21	-0.67	-2.89
	Guangxi	-0.39	-2.26	-0.39	-2.13
	Sichuan	-0.81	-2.47	-0.81	-2.32
	Guizhou	-0.17	-0.74	-0.18	-0.71
	Yunnan	-0.34	-1.50	-0.43	-0.74
	Shaanxi	-0.30	-1.46	-0.30	-1.36
	Gansu	-0.14	-0.53	-0.05	-0.16
	Qinghai	0.11	0.40	0.13	0.46
	Ningxia	-0.25	-1.06	-0.13	-0.45
	Xinjiang	-0.56	-2.61	-0.52	-2.27
INF		0.02	6.27	0.02	5.21
R^2		0.95		0.95	
N		296		282	
F(same coeff. Ln IND)		2.33	p=0.00	2.08	P=0.00
F(same coeff. Ln SERV)		2.96	p=0.00	2.58	P=0.00
F(same coeff. Trend)		3.46	p=0.00	3.07	P=0.00

Figure 1: Evolution of the headcount index: Guangdong versus Shanghai

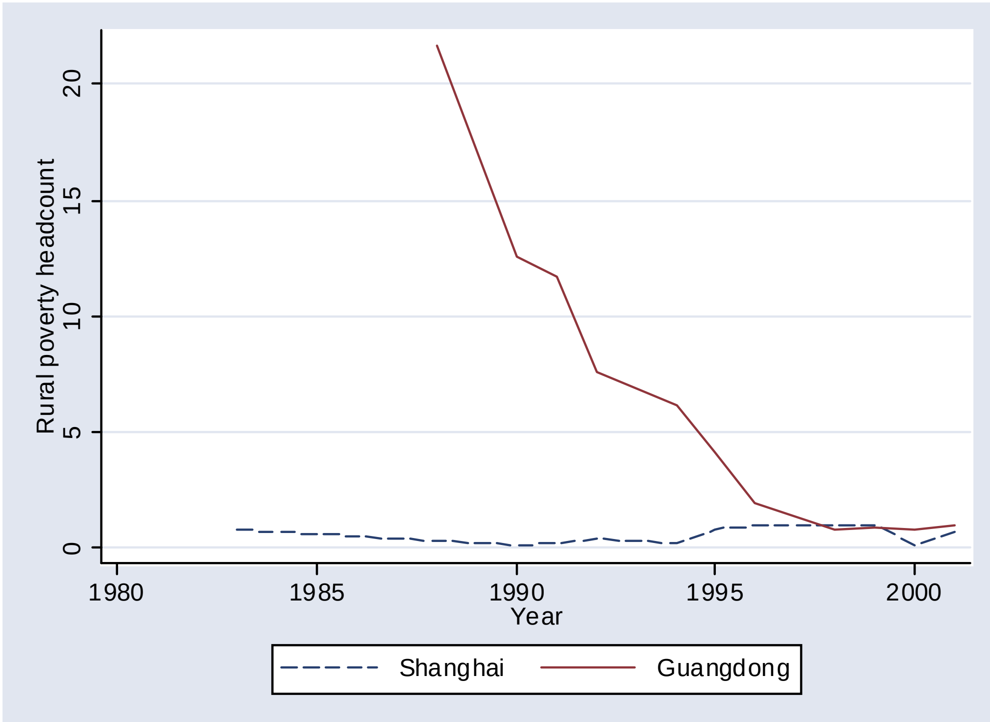

Figure 2: Evolution of the headcount index: Jiangxi versus Anhui

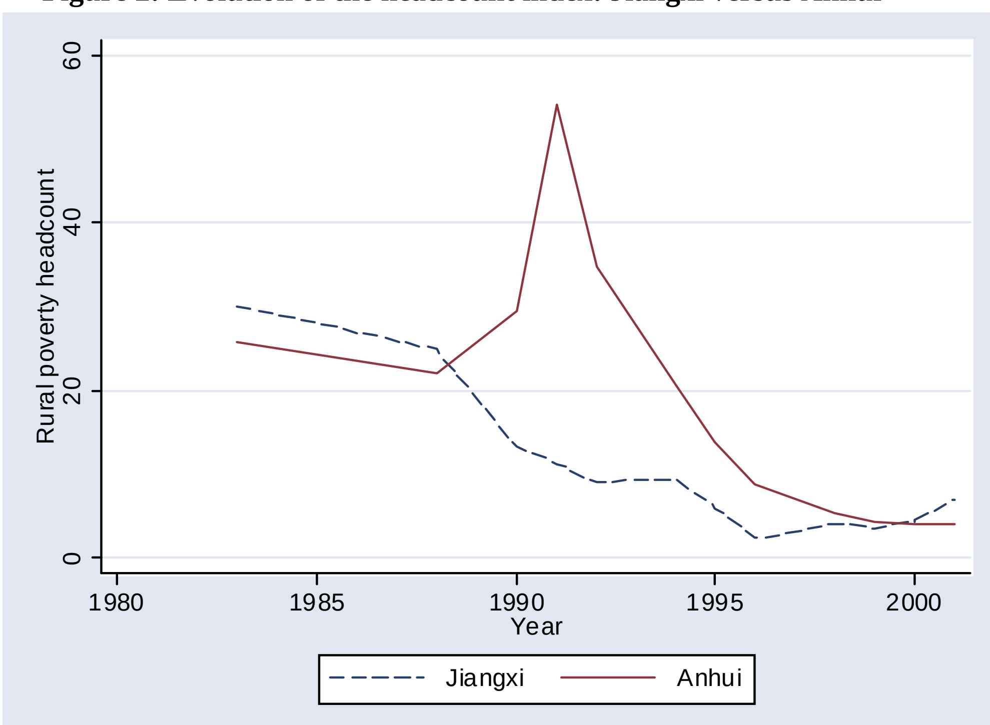

Figure 3: The evolution of urban poverty in three provinces: Beijing, Jilin and Henan

Figure 4: Provincial elasticities of poverty to GDP in the industrial sector

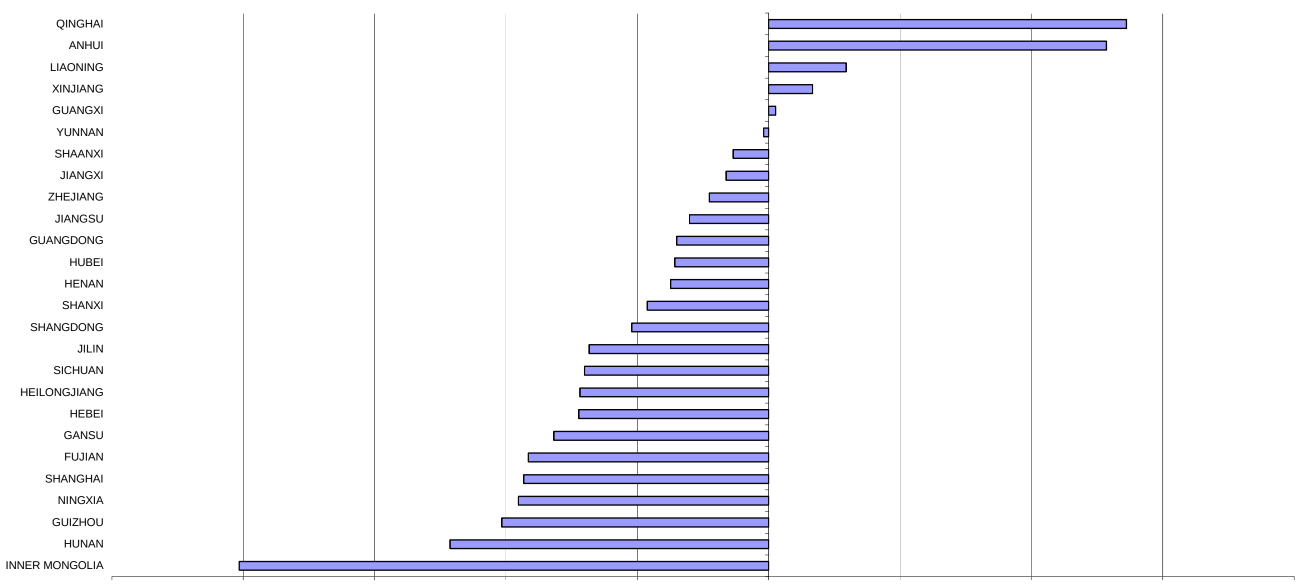

Figure 5: Provincial elasticities of poverty to GDP in the services sector

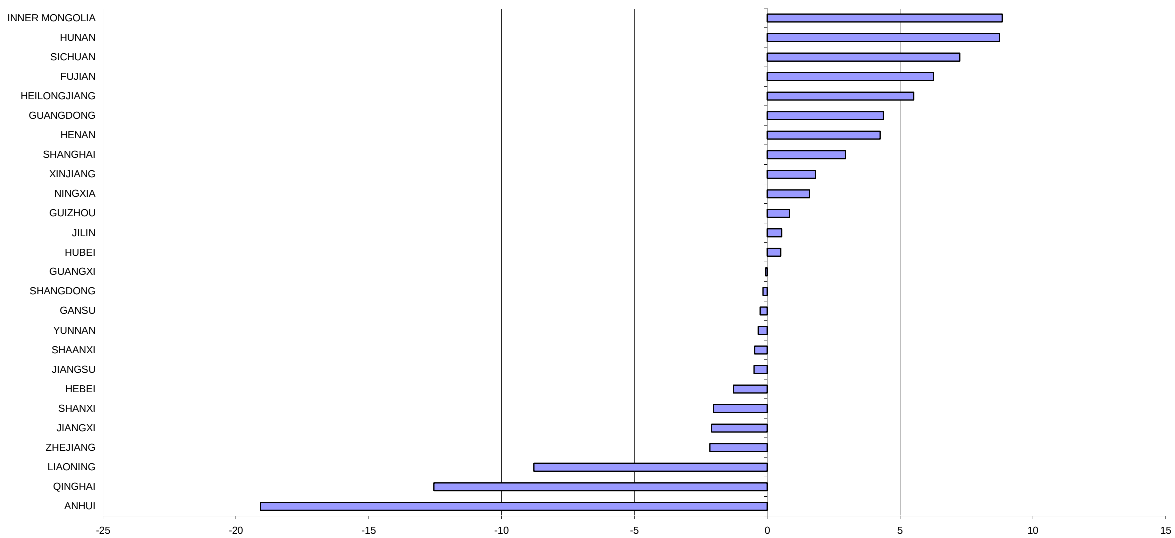

Figure 6: Coefficient on the trend by provinces

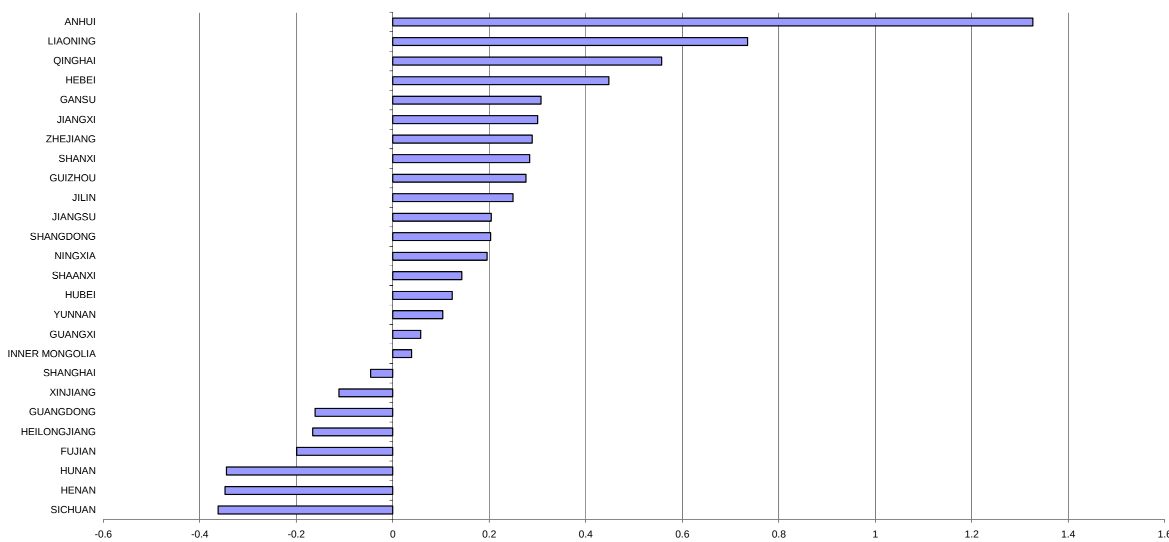

Figure 7: Actual and counterfactual poverty measures under a sectorally and geographically even growth process at the same overall rate

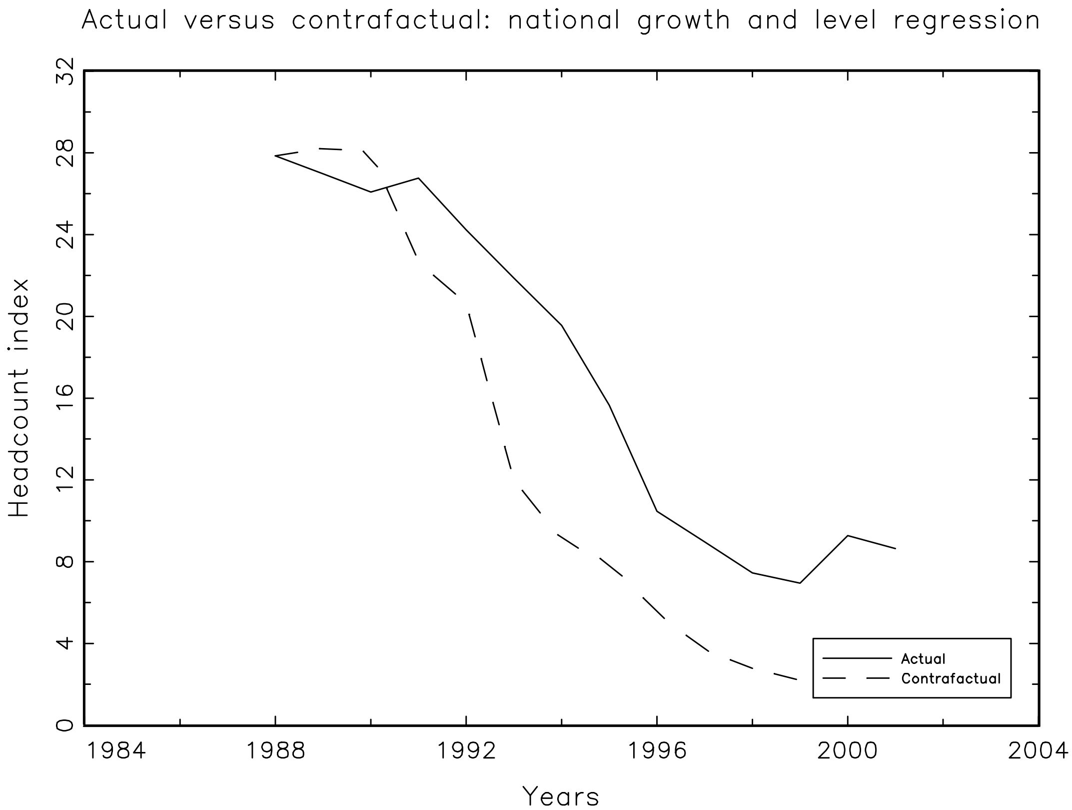

Figure 8: Actual and counterfactual poverty measures under a sectorally even growth process at the same overall rate for each province

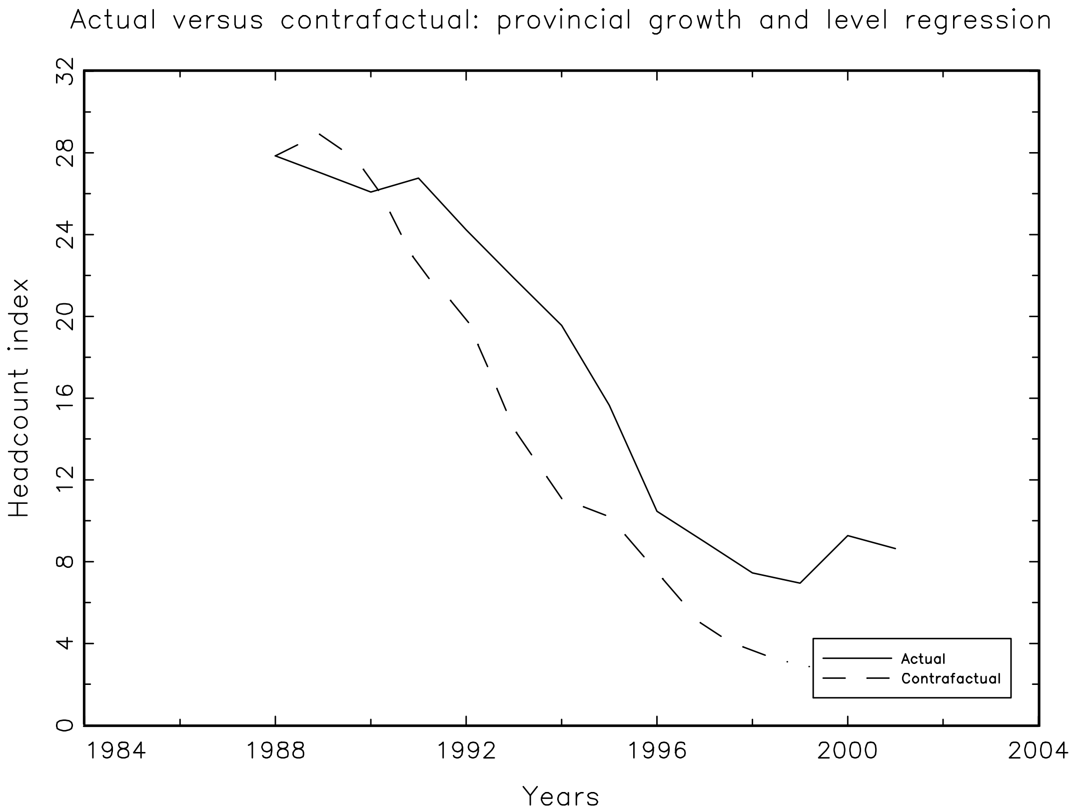

Figure 9: Actual and counterfactual poverty measures under a geographically even growth process at the same overall rate for each sector