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The Regional Effects of Macroeconomic Shocks in China

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The Regional Effects of Macroeconomic Shocks in China

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Abstract

The extent and persistence of the inequality of regional output is an important policy issue in China and its sources have been the subject of considerable empirical research. Yet we have relatively little empirical knowledge of the effects on the regional distribution of output of shocks to national macroeconomic variables such as GDP and investment. This is an important gap in the empirical literature since much government macroeconomic policy seeks to influence GDP using instruments such as investment expenditure. It is likely that such national shocks will have differential regional impacts and so affect the regional output distribution. Policy-makers need to know the sign, size and timing of such effects before making policy decisions at the national level. We simulate the effects of aggregate shocks on individual provinces' GDP within the framework of a vector autoregressive (VAR) model restricted in a manner following Lastrapes (*Economics Letters*, 2005). We use annual data from 1953 to 2012 to estimate the model which includes 28 of China's provinces and simulate the effects on provincial outputs of shocks to aggregate output and investment. We find great diversity of effects across the provinces with discernible geographic patterns. There is evidence that output shocks benefit coastal provinces with developed industrial structure, export-exposure and less reliance on SOEs; the opposite is found for the effects of an investment shock and we conjecture that this is likely to have been the result of the strong bias in central government investment policy in favour of the interior provinces during a substantial part of our sample period.

Keywords: regional output distribution, regional disparities, economic growth, China

JEL categories: E61, R50, O53

1. Introduction

Although China has steadily climbed up the world league-table in terms of GDP per capita since opening-up and reforms began to take hold in the 1980s, there have been substantial and persistent problems with the distribution of this expanding output.¹ Of course, this tension between growth and the distribution of the fruits of growth is not new, nor is it restricted to China. A recent United Nations report (United Nations, 2013) argues that inequality is widespread, multifaceted and persistent in the process of development.

In this paper we focus on the regional distribution of GDP in China, taking the provinces as the regions. The distribution of GDP per capita has fluctuated over the period since the beginning of reforms in 1978, with the coefficient of variation falling steadily over two decades from the late 1970s until the late 1990s, when it began to rise so that by 2004 it had returned to the level of the mid-1980s, after which it declined steadily to the end of the decade.² A recent paper by Lemoine *et al.* (2014) confirms the observed recent decline in inequality and relates it to the growing convergence in manufacturing although another paper, Lyhagen and Rickne (2014), reports mixed evidence, with roughly half the possible province-pairs showing convergence and the remainder divergence.³ Whatever the precise nature of recent change in inequality, inter-regional disparities remain a serious problem with the ratio of GDP per capita in the richest province in 2012 (Jiangsu) to that of the poorest (Guizhou) was still 3.5, a very large disparity by any standards.⁴

¹ China's ranking on the basis of GNI per capita in World Bank tables rose from 130th in 1990 to 120th in 2000 and 77th in 2012. See <http://data.worldbank.org/indicator/NY.GNP.PCAP.CD> Accessed 3 November, 2014.

² This characterisation is based on the coefficient of variation for nominal provincial GDP from 1978 to 2012. The source of the data is described in the data section below.

³ The question of exactly whether, and, if so, how and when regional economies in China have been converging has been the subject of a great deal of empirical research. To survey this would take us too far afield in this introduction but see Groenewold *et al.* (2008) Chapter 2 and the interesting recent contribution by Andersson *et al.* (2013) and references there.

⁴ This comparison excludes the "city-provinces" of Tianjin, Beijing and Shanghai for which the comparable ratios are even higher at 4.7, 4.4 and 4.3, respectively.

The uneven regional distribution of output has been a perennial policy issue at the highest levels of Chinese policy-making since the inception of the People's Republic of China, with disproportionately large allocations of investment to the interior region occurring during much of Mao Zedong's rule in an attempt to redress the balance of output in favour of the poorer inland provinces. Subsequent to the beginning of reforms under Deng Xiaoping, allocation of resources swung towards the coast on the basis of the argument that investment was likely to be most productive there and that, eventually, the growing coast would drag the rest of the country with it to general prosperity and smaller disparities. By and large, the latter has not happened and since the 1990s policy-makers increasingly re-focussed on the problems of large and persistent differences in per capita GDP across the provinces.⁵

Policies to ensure a more equal distribution of output are clearly desirable on the basis of equity and have also been supported with a view to avoiding social unrest which might be caused by widening gaps between rich and poor regions. Yet, there has been a noticeable caution in the vigour with which such policies are pursued by policy makers who are reluctant to jeopardise the continuation of a high aggregate growth rate. This has been particularly true in light of the recent growth slowdown following the Global Financial Crisis and the ensuing slower growth rates in most OECD countries.

There is, in some quarters at least, a perception that directing policy to reduce regional inequality may have a cost in terms of lower national performance, a perception not restricted to policy-makers but also evident in the research literature. Thus, e.g., Kuijs and Wang (2005) argues that China can have a more balanced growth path with a sustainable reduction of income inequality if appropriate policies are implemented. Wong (2006), on the other hand, asserts that inequality is an inevitable consequence of growth policy in China and only its severity is surprising. Similarly, Knight (2008), argues that income inequality is unavoidable,

⁵ See Groenewold *et al.* (2008), Chapter 3, Xu *et al.* (2013) and Chen (2013) for more information on Chinese regional policy since the founding of the People's Republic of China.

at least in the early stages of development. Zhu and Wan (2012) also argues that there has been a trade-off between growth and equality and so that, if China is to foster a balanced and harmonious economy, there must be a shift in focus from growth to equality rather than a single-minded focus on growth.

Those familiar with the literature on economic development and on regional development in particular, will realise that the consideration of such a trade-off is not new. Indeed, it dates back at least to the work on the inverted-U curve between economic development and inequality; see particularly Williamson (1965) and earlier work by Kuznets (1955), Myrdal (1957) and Hirschman (1958). The idea captured by the inverted-U curve is that in the early stages of development regional (and other) inequality rises but eventually falls as development (usually measured in terms of income or output per capita) proceeds. There is thus a systematic relationship between inequality and development which has an inverted-U shape. Not only does the issue of growth *versus* equality have a long history, but it is an area of active current research as evidenced by a recent special issue of *Spatial Economic Analysis* (see the introductory essay by Lopez-Bazo *et al.*, 2014) and a survey paper by Cunha Neves and Tavares Silva (2014). Both papers reflect the thrust of earlier literature that the issue is far from settled and the relationship between growth and inequality depends not only on the precise measures used and the sample periods examined, but also the drivers of growth.

By comparison to the international literature, published empirical research on inequality and development in China is sparse. Wan *et al.* (2006) explicitly tests the growth-inequality nexus in China, focusing on rural-urban income inequality and regional growth using a provincial-level panel data set. They find that an increase in inequality has negative effects on growth, irrespective of time horizons so that reductions in inequality will be growth-enhancing. Qiao *et al.* (2008) finds the opposite: fiscal decentralisation has resulted

in more rapid economic growth accompanied by greater regional inequality. Related papers by Huang and Chen (2012) and Song (2013) show that the effect of fiscal decentralisation depends importantly on the categories of revenues and expenditures being decentralised.

However, with the exception of the paper by Wan *et al.* (2006), these papers are only indirectly related to the growth-inequality question. A more direct approach has been taken in Chen (2010) which reports tests of the relationship between growth in per capita GDP and the Gini coefficient as a measure of inter-regional inequality in a multivariate time-series model. It was found that a reduction in inequality comes at the cost of growth in the short run but not in the long run. A similar analysis is reported in Risso and Sanchez Carrera (2012) and an extension to three variables (with saving being the additional variable) is reported in Gu and Tam (2013). In general it appears from this research that inequality and growth are positively related so that a better inequality outcome can be had only at the cost of lower growth. Finally, on the basis of a mixture of theoretical and empirical analysis, Zheng and Kuroda (2013) argues that whether there is a trade-off between growth and regional equality depends on the driver of growth – if growth is driven by transportation infrastructure expenditure, it comes at the cost of increased inequality while the opposite is true if growth is generated by investment in knowledge infrastructure.

To sum up, there is a substantial literature, both theoretical and empirical, in the broadly-defined area of inequality and development but no consensus on the sign of the relationship between them. Moreover, while there is a number of papers which throw indirect light on the issue for China, there are relatively few which deal directly and explicitly with the trade-off between the two variables in China and the findings of such work as there is are not unanimous.

In the work reported in this paper we contribute to the empirical literature on China in several ways. First, we focus on the provincial distribution of output (rather than a single

inequality measure) and for this we use a novel empirical approach which allows us to analyse how a change in national growth is distributed across the provinces. Secondly, we go on to investigate whether the source of the growth matters by explicitly adding aggregate investment to the model. Third, we explore the factors which explain regional differences in responses to aggregate shock, using both maps and cross-section regressions.

The method we use is based on a restricted VAR model developed by Lastrapes (2005). It has been applied to the analysis of the relationship between changes in the aggregate inflation rate and the dispersion of individual prices in Lastrapes (2006) and the regional effects of monetary policy shocks by Beckworth (2010) for the US and by Fraser *et al.* (2014) for Australia. Applying this procedure to regional issues is, therefore, not new although it is rare and our application in the regional growth context allows us to trace through the effects of a change in an aggregate variable such as the growth rate on the per capita GDP of all provinces rather than on a single summary measure of the distribution such as the coefficient of variation or the Gini coefficient, which has been a characteristic of most existing empirical work.

We find that aggregate multipliers for both output and investment shocks are plausible, with the effect of a boost to investment being larger than that of a general output shock. At the provincial level, we find great diversity in the geographical distribution of the effects of aggregate shocks – in most cases the vast majority of the provinces have short-run responses significantly different to the national average. For the main sample period (1980-2012), we find that the above-average responses to an output shock are concentrated in the coastal provinces with a more advanced industrial structure, less reliance on SOEs and greater export-exposure. The effects of an investment shock are the opposite, with weaker effects for the coastal provinces. We conjecture that this is likely to be the effect of central government policies which favoured investment in the interior in much of our sample period.

The remainder of the paper is structured as follows. In section 2 we set out the empirical model based on the work of Lastrapes. The data to be used are described in section 3. The results for the base model are discussed in section 4, with extensions and robustness tests reported in section 5. Conclusions are drawn in the final section.

2. The empirical model

As observed in the previous section, existing empirical literature which examines the effect of growth shocks on regional output distributions typically uses a summary measure of the distribution such as the Gini coefficient or the coefficient of variation calculated from the cross-section of regional GDP per capita values. This makes the analysis tractable but loses much of the information about the distribution across regions as well as information on the response of individual regions to aggregate shocks. An alternative approach is to estimate and simulate a model which includes the aggregate variables such as the national growth rate as well as all the regional per capita GDP variables. This is possible if there are relatively few regions so that there are sufficient degrees of freedom given the size of the data sample. Where this is not the case, the estimation of such a model becomes intractable unless restrictions are imposed to reduce the number of parameters which must be estimated.

There are various ways in which the system can be restricted to achieve tractability. One is to reduce the number of regions into a few large ones, on the assumption that the components of the larger region are homogeneous – see, e.g., Carlino and DeFina (1998). A variation of this approach is to estimate a separate model for each region which includes a limited number of measures of activity of the aggregate of regions in a manner similar to that of the GVAR model of Pesaran *et al* (2004). The disadvantage of the use of a few large regions is that detail on regional disaggregation is lost while the second set of alternatives

generally suffers from the drawback that the aggregate shocks are not constrained to be the same across the regions since each regional VAR model is used to identify its own aggregate shocks.

Lastrapes (2005) proposes a set of restrictions which overcomes both of these disadvantages. Essentially, he restricted the interaction both between the aggregate variables and the disaggregated variables as well as amongst the disaggregated variables themselves. Lastrapes (2006) applies the approach to an analysis of the effects of inflation shocks on individual prices and both Beckworth (2010) and Fraser *et al* (2014), apply the approach to the regional effects of monetary policy in the US and Australia respectively.

We wish to analyse the effects of aggregate macroeconomic shocks on individual provincial GDPs in China. With 31 provinces and annual GDP data for (at most) 60 years, estimation of a VAR with both macroeconomic variables and regional outputs would run into degrees-of-freedom problems very quickly so that the Lastrapes procedure seems ideally suited to this application.

The Lastrapes approach can be developed as follows. Consider a vector of variables, \mathbf{z}_t which includes both national and regional variables. Partition \mathbf{z}_t into two parts,

$$(1) \quad \mathbf{z}_t = (\mathbf{z}_{1t}, \mathbf{z}_{2t})'$$

where the first component consists of the regional variables (regional per capita GDPs in our case) and the second consists of the national variables. It is expected that there are many regional variables and few national variables. Assume that the elements of \mathbf{z}_t are related by a linear structural dynamic model of the form:

$$(2) \quad \mathbf{A}_0 \mathbf{z}_t = \mathbf{A}_1 \mathbf{z}_{t-1} + \dots + \mathbf{A}_p \mathbf{z}_{t-p} + \mathbf{u}_t = \mathbf{A}(\mathbf{L}) \mathbf{z}_t + \mathbf{u}_t$$

where $\mathbf{A}(\mathbf{L})$ is a polynomial in the lag operator, L , $\mathbf{A}(\mathbf{L}) = \mathbf{A}_1 L + \dots + \mathbf{A}_p L^p$ and the error process satisfies $E(\mathbf{u}_t) = \mathbf{0}$ and $E(\mathbf{u}_t \mathbf{u}_t') = \mathbf{I}$, the identity matrix. Thus the errors in the structural model

(the structural errors) are assumed mutually uncorrelated and the equations of the model are normalised so as to ensure a unit variance for each error.

There are two difficulties in using the model as it stands. The first is that it is not identified – all the equations in (2) have the same variables. This is a standard problem with structural models of this type and requires additional restrictions to be placed on the model, the most common of which are short-run Bernanke-Sims restrictions (including those based on the Cholesky decomposition of the covariance matrix of the errors) and the long-run Blanchard-Quah restrictions.⁶ In either case the model is first transformed into a reduced-form one by pre-multiplying by the inverse of the matrix A_0 to obtain:

$$(3) \quad z_t = A_0^{-1}A(L)z_t + A_0^{-1}u_t \equiv B(L)z_t + \varepsilon_t$$

where $B(L) \equiv A_0^{-1}A(L)$ and $\varepsilon_t \equiv A_0^{-1}u_t$. The reduced-form model can be estimated by OLS and the restrictions can be used to identify the elements of the A_0 matrix which can then be used to retrieve the structural parameters and errors from their reduced-form counterparts. The retrieval of the structural errors is important since the reduced-form errors will be correlated with each other (each is a linear combination of all the same structural errors), making it illegitimate to shock them independently. The structural errors are, by assumption, uncorrelated and can, therefore, legitimately be shocked independently.

The second difficulty likely to be faced in the estimation of model (2) is a degrees-of-freedom problem that arises if there are many regional variables relative to the number of observations in the sample period. Lastrapes (2005) develops a method for overcoming this problem in a model in which there was a small number of aggregate variables (national variables in our case) and a large number of disaggregated variables (regional variables in our application). He proposed two assumptions: (i) the aggregate variables are block exogenous, and (ii) the disaggregated variables are mutually independent once they have been

⁶ See Enders (2010) for a textbook treatment of these issues.

conditioned on the aggregate variables. The first of these assumptions implies that the disaggregated variables do not jointly (Granger-) cause any of the aggregate variables and the second implies that the disaggregated variables are mutually correlated only insofar as they are related to common aggregate variables. Under these assumptions, Lastrapes shows that the model could be written as two components, one a standard VAR in the aggregate variables and the other a series of individual equations for the disaggregated variables. In particular:

$$(4a) \quad z_{1t} = \sum_{i=1}^p \mathbf{B}_{11}^i z_{1t-i} + \sum_{i=0}^p \mathbf{G}_i z_{2t-i} + \mathbf{v}_t$$

$$(4b) \quad z_{2t} = \sum_{i=1}^p \mathbf{B}_{22}^i z_{2t-i} + \boldsymbol{\varepsilon}_{2t}$$

The equations in (4b) are simply a standard VAR in the aggregate variables and can legitimately be estimated by OLS. Since we are interested in shocking the errors in the equations only for the aggregate variables, identification of the structural errors is necessary only for the VAR in (4b) and can be based on commonly used restrictions for VARs mentioned earlier. Lastrapes shows that the matrix \mathbf{B}_{11}^i in equation (4a) is diagonal so that each of the equations for the disaggregated variables has only lags of the dependent variable and current and lagged values of the aggregate variables as regressors. The assumption of the block exogeneity of the aggregate variables ensures that there is no contemporaneous correlation between the regressors and the errors terms in the equations. In addition Lastrapes shows that the covariance matrix of the errors in (4a) is diagonal so that there is no gain to be had from estimating the equations simultaneously by the Seemingly Unrelated Regressors Estimator rather than by OLS. Hence, the equations in (4a) can also legitimately be estimated (one-by-one) by OLS.

In our application, the aggregate variables will be national GDP and investment and the disaggregated variables will be provincial GDPs. We will use the Cholesky scheme for identifying the structural errors in the VAR part of the model. We assess the robustness of our results by including a wider range of aggregate variables as well as by experimenting with alternative Bernanke-Sims identification schemes for the aggregate VAR component of the model.

3. The data

We require data for two types of variables: national and regional. With one exception, all data are annual from 1953 to 2012.⁷ The regional variables are real provincial GDP which we use in log per capita terms. The data are taken from Wu (2004) and *China Statistical Yearbook* (National Statistical Bureau, various issues) and are in terms of yuan per capita in 1953 prices. We use data for 28 of China's 31 provinces (including the "city-provinces" of Beijing, Shanghai and Tianjin) with Chongqing included in Sichuan, Hainan included in Guangdong and Tibet excluded, all for reasons of missing data.

Two national variables were used in the main analysis: real GDP and real investment in fixed assets. Additional variables used in the robustness tests are consumption expenditure, government expenditure, merchandise exports and imports and world GDP. All are in real per capita terms and, except for the world GDP, all variables are in yuan at 1953 prices and taken from *New China 60 Years Statistics Compilation* (National Statistical Bureau, 2009) and *China Statistical Yearbook* (National Statistical Bureau, various issues). Population data used to compute per capita magnitudes come from the same sources. World GDP data come from the World Bank data set in the dXTime data base.

⁷ World GDP are available only from 1980 onwards. They are in terms of US dollars in 2000 prices.

Before proceeding with the estimation and simulation of the model, we test the data for stationarity using an augmented Dickey-Fuller test. The results for the (logs of) provincial real GDP per capita are in Table 1 and for the set of aggregate variables (also in log real per capita form) in Table 2.

[Tables 1 and 2 about here]

While there are some exceptions, most of the series appear to be $I(1)$.⁸ Since the Lastrapes procedure assumes a stationary VAR, we proceed as Lastrapes (2006) and Beckworth (2010) do and work with variables in first differences.

4. Results: base models

4.1 A model with one aggregate variable: GDP

We begin with the simplest case of a single aggregate variable, real GDP.

Preliminary tests for lag length (in the VAR part of the model) showed that two lags were required to remove autocorrelation in the residuals as well as being the choice of standard lag-length criteria. The model was therefore estimated using two lags.

With only a single aggregate variable, the VAR part of the model (corresponding to equation (4b)) is a single equation and the issue of identification of the structural errors does not arise since there is only a single aggregate error which is both structural and reduced-form. The block-exogeneity assumption ensures that the VAR error is independent of the errors of the regional equations so that the VAR can be estimated separately by OLS. The model is estimated in first-difference form and the impulse response functions (IRFs) are accumulated so that they may be interpreted as (log) levels. The sample used is 1953-2012.

⁸ While a few of the provincial GDP series appear to be non-stationary even after differencing, their impulse response functions reported later in the paper show no evidence of divergence.

The IRF for aggregate GDP following a unit GDP shock, together with confidence bounds, is illustrated in Figure 1. The effect on GDP of the shock is permanent and positive, rising from a value of 1 to peak of almost 1.5 in the second year before subsiding to a level of approximately 1.3 in the long run, which is reached after about 5 years. The effect is clearly significant by conventional standards.

[Figure 1 about here]

The next step is to generate similar IRFs for the provincial GDP variables. We do this by feeding the IRF for national GDP into the estimated provincial equations, taking account of the dynamics both in the aggregate VAR and in the provincial equations. The provincial IRFs are reported in the Appendix, Figure A1 and their magnitudes relative to the aggregate effects are summarised in Table 3. The regional IRFs can be compared to their national counterpart at various forecast horizons; in Table 3 we choose to compare at two – after one period (the “short run”) and after four periods (the “long run”).⁹ We use A, B and C to denote a regional IRF which is above, below, coincident with the national IRF, respectively, with C defined such that the distance between the regional and national IRFs is less than 10% of the distance between the aggregate IRF and its confidence bound; we use an asterisk to denote a provincial IRF which lies outside the aggregate confidence bounds and call this a significant difference from the aggregate.

[Table 3 about here]

The first striking feature of the provincial IRFs is their diversity; there is clear evidence that a shock to national GDP is very unevenly distributed across the provinces; a total of 18 of the 28 provinces have a response which is significantly different to that of the nation as a whole

⁹ These refer to horizons of 2 and 5 in the IFR diagrams in which the horizon of 1 is the point at which the shock is imposed so that 2 is one period after the shock. The short run therefore captures both the initial impact and the first-period dynamics.

in the short run. The number of significant differences is substantially reduced in the long run owing to the wider confidence bounds.

While the significance of the difference between the national and provincial IRFs falls with the forecast horizon, the broad categorisation is consistent over time with only three provinces (Shandong, Anhui and Hunan) switching between (A*, A) and (B*, B); none of these switches involves a significant difference in either period. This implies that the long-run effects on a province relative to the nation as a whole are determined almost completely by the short-run effects. Moreover, a similar allocation of categorisation of provincial IRFs based on the initial effect (at horizon zero) is almost identical to the short-run column in Table 3 and the categorisation at horizons of 10 or 20 are very similar to that at five. Thus if the immediate impact of a national shock on a province exceeds that on the nation as a whole, it is likely to continue to do so over time and *vice versa*.

At a more general level, more than half of the regional IRFs lie outside the confidence bounds for the national IRF for at least a substantial part of the forecast horizon which shows greater diversity than that found by Beckworth (2010), for example, which finds that approximately 18 of the 48 (37.5%) US states in the sample have a significantly different response to national monetary policy to that of the nation as a whole which is interpreted as “wide variation among the states”. Finally, not surprisingly, about half the regional IRFs are above the national IRF and about half below in the short run.

Before looking at the pattern of the regional results in more detail, we assess their sensitivity to choice of sample. The results reported in Figures 1 and A1 and summarised in the relevant column in Table 3 are based on the full sample of 1953-2012. This covers a period of Chinese economic history during which there have been enormous changes and it is reasonable to ask whether a single model with constant coefficients is credible for this period. While we do not have sufficient degrees of freedom to estimate the whole model as the basis

for a formal test for breaks in the coefficients, we can assess this informally by comparing the results for separate sub-samples. We choose two sub-samples: 1953-1979 and 1980-2012, with the break corresponding to the beginning of reforms and opening-up of the Chinese economy in the late 1970s.¹⁰

For both sub-samples we impose a unit shock on national GDP. The effects on national GDP itself are pictured in Figures 2 and 3.

[Figures 2 and 3 about here]

The effect for 1953-1979 is similar to but slightly smaller than the effect for the full sample: it is permanent, positive and significant, rising from a value of 1 to peak of about 1.4 in the second year before subsiding to a level of approximately 1.2 in the long run, which is reached after about 5 years. For the second sub-period the effect is larger than that for the full sample: it rises to a peak of about 2 after three periods and settles down to a level of approximately 1.6 after 10 periods, with most of the movement to the long run being achieved by period 6.

This similarity of the full-sample results to those of the earlier sub-sample and the dissimilarity to the second sub-sample carry over to the regional effects which are pictured in Figures A2 and A3 and summarised in the relevant columns of Table 3. Focussing first on the summary of the results in Table 3, we find that in both sub-samples there is considerable diversity of regional effects – for the first sub-sample there are 16 of the 28 provinces with significantly different IRFs in the short run and in the second sub-sample this rises somewhat to 18. In both sub-samples there are far fewer significant differences in the long run. The overall pattern in the first sub-sample is similar to that for the whole sample; in the long run only one province switches between (A*,A) and (B*, B), viz. Anhui while there are greater difference between the second sub-sample and the full sample – six provinces switch between (A*, A) and (B*, B). The obvious difference between the two sub-samples suggests that it

¹⁰ We also experimented with earlier break-dates of 1979 and 1978 but they made little difference to the overall thrust of the results.

makes little sense to analyse the full-sample results. Moreover, the data for the first sub-sample are likely to be of poorer quality than the more recent data – the 1953-79 data were mostly compiled well after the event and, besides, the period included such major upheavals as the Great Famine, the Great Leap Forward and the Cultural Revolution. We, therefore, restrict our sample period to 1980-2012 for the remainder of the paper.

Consider then the provincial results for the second sub-sample in more detail. We focus on the long-run effects which are pictured in the map in Figure 4.

[Figure 4 about here]

While it is difficult to discern any regional pattern from the summary in Table 3, the map shows considerable contiguity in the provinces for which the IRFs are above- and below-average. With some notable exceptions, the below-average effects are concentrated in the geographical extremities of the country – the north and north-west and the south, while the above-average effects are mainly in the central and coastal provinces, stretching from Jilin in the north-east to Sichuan in the south-west and including Gansu province in the north-west.

It seems plausible to explain the below-average response of northern provinces such as Heilongjiang, Inner Mongolia, Xinjiang and Qinghai and southern provinces such as Guangxi and Guizhou in terms of their distance, both physical and economic, from the centre.

Similarly, the above-average responses for the coastal and central provinces such as Jiangsu, Fujian, Anhui, Jiangxi, Hubei and Shaanxi might be attributed to their proximity to the centre.

However, there are some important exceptions to these patterns. In particular, both Beijing and Shanghai show significantly below-average responses while they are surely close to the centre, however that is interpreted. This may reflect the fact that Beijing and Shanghai are so different in many dimensions (their geographic extent, their industrial structure and so on) that it is perhaps not surprising that they are outliers in this analysis. Similarly, Gansu and

Sichuan are not likely to be considered close to the national action and yet perform above average.

Thus, all in all, there is considerable diversity in the way in which the provinces reacted to a change in national GDP and there is evidence of contiguity of provinces which experience above- and below-average effects of a national shocks, although there are important exceptions to this apparent pattern. Moreover, the basis for the observed pattern in the map is not obvious. We consider possible determinants of the pattern more formally later using cross-section regressions but first we extend the aggregate VAR component of the model to include two variables, GDP and investment.

4.2 A model with two aggregate variables: GDP and investment

There are at least two reasons for extending the model to include a second aggregate variable: first, to assess whether the effects of a GDP shock are affected by the inclusion of the extra variable and, second, to assess the effects of a shock to the second variable itself. The second aim dictates that we use an additional aggregate variable which is likely to substantially affect aggregate GDP and in this application we choose investment, which has been an important driver of GDP growth in China and, moreover, has been widely used as an instrument by the central government in influencing the regional distribution of output in China (see, e.g., Groenewold *et al.*, 2010). Other possibilities are international trade, consumption and government expenditure, all of which have been channels through which the national government in China has attempted to boost output. The results of the use of a more extensive model including all these variables will be briefly described in the next section on robustness-testing.

Before simulating the effects on the regional outputs of a macroeconomic shock, we need to choose the order of the two variables in the aggregate VAR part of the model. Recall

that we use the Cholesky approach so that a shock to the first-ordered variable has a contemporaneous effect on both variables while a shock to the second affects only itself within the period. We therefore choose to order the variables as (investment, GDP) since investment, being a component of GDP must necessarily have a contemporaneous effect on GDP (except in the highly unlikely event that it is exactly offset by changes in the other components) but the reverse is not true – it is quite likely that it will take time for a change in GDP to affect investment.¹¹ As indicated in the previous sub-section, we restrict the sample to 1980-2012 and use a model with two lags.

Consider a shock to GDP first. The effect on aggregate GDP itself is reported in Figure 5 and the effect on regional GDPs is pictured in Figure A4 and summarised in the relevant columns of Table 3, with a map provided in Figure 6.

[Figures 5 and 6 near here]

A comparison of Figure 5 with Figure 3 above shows that the effect of the shock on aggregate output itself is very little altered by the inclusion of a second aggregate variable although both short- and long-run multipliers are a little smaller and the confidence bounds wider than in the single-variable model. There is a peak of about 1.5 at period 2 and the long-run effect is approximately 1.3, compared to 2 and 1.6 respectively for the one-variable model.

Turning now to the summary of the provincial responses in Table 3 and the corresponding map in Figure 6, it appears that not a great deal has changed as a result of adding the second variable to the VAR part of the model. From the table it is clear that, in the long run, there are six switches between (A*, A) and (B*, B). This is also evident from the map; a comparison of Figures 6 and 4 shows that the grouping of the blue (below-national)

¹¹ Technically, there are two shocks, the first of which affects both output and investment contemporaneously; we call this the investment shock. The second affects only output contemporaneously and we call this the output shock and think of it as capturing shocks to all components of output excluding investment.

regions in the north of the country are little changed while the blue region in the south-east has shrunk somewhat; the red (above-national) areas has shifted to the coast from the centre.

To explore the patterns more formally, we report the results of some cross-section regressions in Table 4 in which we regress the gap between the regional and national IRFs at a horizon of five on a number of province-specific variables. The first three columns of figures are relevant to the GDP shock being considered now. We begin by asking whether there was a specific policy by the central government which allocated output changes in a way that favoured provinces which were poor at the beginning of the sample by using provincial GDP in 1980 as a regressor. Results are reported in Table 4 in the row for PROVGD. It is clear that provinces with a lower starting GDP actually did worse in terms of their ability to benefit from national GDP shocks, although the result is not significant. Thus, there seems to be no basis for this “bias-to-the-poor” hypothesis.

Next we consider a common variable in the explanation of cross-provincial growth models in China, *viz.*, a regional dummy variable. In the second row of the table, COAST has a value of 1 when the province is a coastal one and zero otherwise.¹² Clearly this variable is significant and its sign indicates that coastal provinces were generally able to benefit more from national shocks than others. Over 20% of the cross-section variation is explained by this dummy variable.

Was the coastal effect simply a matter of distance from the national capital, Beijing? We address this in the next row by using DISTANCE, the distance from Beijing, as a regressor.¹³ The sign is as expected – the further from Beijing, the weaker the effect – but it is not significant.

An alternative explanation is that a province did better if it had a more developed industrial structure at the beginning of the sample period and we test this by using

¹² Coastal provinces are Liaoning, Beijing, Tianjin, Hebei, Shandong, Jiangsu, Shanghai, Zhejiang, Fujian, Guangdong and Guangxi.

¹³ Distance from Beijing was measured as the direct distance from Beijing to the relevant provincial capital.

INDUSTRY, the proportion of non-agricultural employment in 1980, as a regressor. Again, it has the expected sign (more industry, bigger effects) but is insignificant.

An alternative measure of industrial development often used in cross-regional regressions is the extent of export activity and we experimented next with EXPORTS, a measure of the ratio of exports to GDP in 1980, which clearly has the expected sign and is significant at 6% – the more important are exports in GDP, the more likely is a province to benefit from national output shocks.

Finally we used another variable which is also frequently used in the provincial growth context – the importance of SOEs; in our case, we used the SOE share of total employment in 1980 and found it to be significant and of the expected sign – the more important SOEs are in the province’s industrial structure, the less likely are they to benefit from national growth.¹⁴

We also experimented with various combinations of these variables but invariably, all variables were insignificant in such combinations, suggesting strong multicollinearity. An inspection of the correlation matrix for these regressors showed correlation coefficient always in excess of 0.55 and often in the range of 0.9 to 1.0, confirming the presence of strong multicollinearity. This is hardly surprising – in practice, the coastal provinces are also the provinces which are least dependent on agriculture, which are most export-oriented and which are less dependent on SOE employment. The multicollinearity problem simply reflects the fact that the limited data are not sufficiently informative to disentangle the separate effects of these variables so that we have to be satisfied with a more general conclusion that the coastal provinces benefit more because of their industrial composition – the relative importance of industry rather than agriculture, their stronger export-orientation and their lesser dependence on SOEs.

¹⁴ All the data for the cross-section regressors come from *China Statistical Yearbook* (National Statistical Bureau, various issues) and *New China 60 Years Statistics Compilation* (National Statistical Bureau, 2009).

The regional divide above used the common two-region scheme (coast and interior). Many alternatives have been proposed and we experimented with one of these based on the distinction in Lemoine *et al.*(2014) between four regions: coast, centre, north-east and periphery.¹⁵ The results of this, using the periphery as the omitted category, are in the next three rows of the table. They show that the effects in both the coast and the centre differ from the periphery but those in the north-east do not. Not surprisingly, perhaps, the effects on all these three regions are stronger than they are in the periphery supporting our earlier results but making them somewhat more nuanced. To test the significance of the difference between the coast and the centre on the one hand and the north-east on the other, we also used the north-east as the omitted category. Results are in the last three rows: the coast preforms better than the north-east but the centre and the periphery do not but only the difference between the periphery and the north-east is significant.

Consider now a shock to investment in the same model. For the purposes of comparability, the shock is set so that there is a unit first-period effect on aggregate output. The effects on national GDP are reported in Figure 7 and the provincial effects in Figure A5, with the summary in Table 3 and Figure 8.

[Figures 7, 8 about here]

A comparison of the aggregate IRF for investment to that for GDP (Figures 7 and 5), shows that investment has a considerably greater multiplier effect – in the short run it rises to about 3.5, subsiding after 10 years to a value of approximately 3, compared to values of 1.5 and 1.3 for an output shock which has the same initial effect.

¹⁵ In coast we include Beijing, Tianjin, Hebei, Shandong, Jiangsu, Shanghai, Zhejiang, Fujian, Guangdong; in centre: Anhui, Guizhou, Henan, Hubei, Hunan, Jiangxi, Shanxi, Shaanxi and Sichuan; in north-east; Heilongjiang, Jilin, Liaoning and in the periphery: Inner Mongolia, Ningxia, Gansu, Qinghai, Xinjiang, Yunnan and Guangxi. This differs slightly from the allocation in Lemoine *et al.* (2014) who include Gansu, Qinghai and Yunnan in the centre.

While the regional effects of the investment shock are only slightly less diverse than those of an output shock (16 of the 28 provinces are significant in the short run), the distributional effects are very different from those of a GDP shock. This is clear from the map as well as from the summary in Table 3 which shows that in the short run 10 of the 28 provinces switched between (A*, A) and (B, B*) when moving from the GDP shock to the investment shock. The long run shifts are more dramatic (12 switches) despite wider confidence bounds. The above-national provinces have shifted from the south-east coast and some in the centre to predominantly in the north-east and centre of the country. Only Shaanxi province retains its significant above-national status.

The contrast to the effects of an output shock is also evident in the cross-section regression results reported in the second set of columns in Table 4. Except for the SOE and distance variables (neither of which is significant), all signs are reversed compared to the output-shock case. Thus, the evidence is consistent with the view that the allocation of the investment shock was biased to the provinces which were relatively poor in the beginning of the sample and this is supported by the results that the COAST, INDUSTRY and EXPORTS variables all have negative coefficients although EXPORTS is not significant. On average, therefore, there seems to have been a reversal of results: the coastal provinces with more developed industry and greater export exposure seem to have fared worse following an investment shock which can be explained by the “bias-to-the-poor” hypothesis suggested by the significantly negative coefficient on PROVGDP. This is likely to reflect the specific policies implemented during the ninth and tenth five-year plans (1996-2000 and 2001-2005) which sought to redress the balance towards the interior provinces with such schemes as “The Great Western Experiment” and the “Resurgence of the Old Northeast Industrial Base”.¹⁶

¹⁶ See Groenewold *et al.* (2008), Chapter 3 for more details of these policies.

Combinations of regressors were again experimented with but were invariably insignificant, not surprisingly since it is the same set of regressor as used in the explanation of the effects of the output shock and the cross-correlations are the same. Finally, the use of a four-region scheme was also used here with the results showing that the coast fared worst in comparison to all three other regions.

The results for the base models analysed in this section may be summarised as follows. Firstly, for both variants of the model, the provincial responses to an aggregate shock show great diversity. We found that very few provinces responded similarly to the country as a whole; indeed, based on the confidence bounds for the national response, we found that in the short run between 16 and 19 of the 28 provinces show a response which is significantly different to that at the aggregate level. Thus, analysing the response to an aggregate shock only at the aggregate level hides a considerable diversity of underlying regional detail.

Secondly, in distinguishing between short-run and long-run effects, we found the significance of the long-run effects to be generally weaker due to broader confidence intervals but the long-run distributional pattern across the provinces on the whole follows the short-run pattern which, in turn, is similar to that of the initial impact. Thus, from a policy perspective, the initial distribution is important, even if policy goals are long run.

Thirdly, whether the aggregate output shock is analysed in a model with one or two aggregate variables matters relatively little for the aggregate effect – the addition of investment to the aggregate VAR part of the model has little effect on the response to an output shock. In both models the above-average responses tend to be concentrated in the central and coastal regions of the country while the below-average responses tend to be found in the geographical extremities (the north-west and the south) although there are important exceptions to this pattern.

Fourthly, an investment shock has a markedly different effect to that of an output shock. This is true both at the national and provincial levels. The aggregate effect of an investment shock is considerably larger in both the short and long runs than an output shock of equivalent initial magnitude. Further, at the provincial level, the above average effects of an investment shock are more concentrated in the centre and less in the coast.

Finally, cross-section regressions showed that the beneficial effects of output shocks tended to be concentrated in the coastal provinces which had a strong industrial structure and export orientation, with low reliance on SOEs at the beginning of the sample period. The reverse was generally true of the effects of an investment shock; in this case the coastal, industrial, export-oriented provinces fared worse. We conjecture that this is consistent with explicit policy choices during the 1990s and 2000s favouring the inland provinces.

5. Results: Extensions and robustness

In this section we briefly report on a range alternative simulations which we undertook to assess the robustness of the results reported in the previous section.

We began our extensions by introducing more aggregate variables into the VAR part of the model. In particular, we considered a simple open-economy ISLM model as the basis for variable choice and included a foreign demand variable, domestic output, national investment, national government expenditure and national consumption, making for five aggregate variables including the two used in the analysis reported in the previous section (GDP and investment). The detailed results are not reported but in summary we found that:

- (a) the presence of the additional variables in the aggregate VAR model did not markedly affect the aggregate IRFs for shocks to output and investment;

- (b) alternative definitions of the world output, government expenditure, and consumption variables did not greatly affect the earlier conclusions;¹⁷
- (c) plausible alternative variable orderings in the VAR did not affect earlier conclusions;
- (d) experimentation with alternative Bernanke-Sims identification schemes in the aggregate VAR model showed no sensitivity of the aggregate results;
- (e) excluding the three cities of Beijing, Tianjin and Shanghai from the sample made little difference to the overall conclusions.

Further experimentation with models with between two and five variables provided additional support for this conclusion – again, the aggregate effects of shocks to output and investment themselves were robust to the inclusion of other variables in the model.

All this suggests that most of the important aggregate effects are adequately captured by GDP and investment. Additional support for this comes from correlation analysis. Recall that one of the underlying assumptions of the Lastrapes procedure is that the regional variables are independent once they have been conditioned on the aggregate variables. While it is impossible to test this formally (since it would require the estimation of the whole model simultaneously with and without the restriction imposed), we can assess an implication of the model less formally – that the correlations of the regional variables are zero once they have been regressed on the aggregate variables. The unconditioned regional variables were strongly correlated – the average absolute correlation coefficient was 0.4559 compared to a 5% two-tailed critical value of 0.3443. Conditioning on output and investment reduced the average absolute correlation coefficient to 0.2643 which is sufficiently below the 5% critical value to suggest that these two variables are sufficient to absorb the cross-correlations of the regional GDPs. Adding further variables (consumption, government expenditure and world

¹⁷ In the initial model we used world GDP as the world demand variable; alternatives tried were exports and trade (the sum of exports and imports); alternatives for government expenditure, consumption and investment involved the use of national-accounting-based data.

demand) had little effect on the average correlation and were not necessary to reduce the average correlation to insignificance.

We conclude that the results reported in the previous section are quite robust to alternative specifications of the model and definitions of the data.

6. Conclusions

In this paper we have investigated the effects on the provincial outputs in China of shocks to a variety of aggregate variables. Models to address this sort of issue quickly run into problems of insufficient degrees of freedom if there is a large number of regionally disaggregated variables (provincial outputs in our case) relative to the number of observations and we used a procedure due to Lastrapes (2005) which resolves this difficulty by imposing some restrictions on a VAR model which make estimation and simulation feasible.

Our main results were derived from two models – one with a single aggregate variable (GDP) and one with two such variables (GDP and investment). We found that shocks to both variables had significant effects on aggregate output itself and that multipliers were of a plausible magnitude. The effects of the shocks on regional GDPs were characterised by great diversity – the vast majority of the provincial GDPs showed a short-run response which was significantly different to the aggregate response. Thus a great deal of interesting regional diversity is lost by restricting analysis to the national level.

We found that the responses at both the national and provincial levels to a national output shock was not greatly dependent on whether a one- or two-variable aggregate model was used. The provinces' responses to an investment shock were very different, however, to their responses to the output shock. Thus the source of the shock matters.

Maps of the regional effects and subsequent cross-section regression analysis showed that output shocks tend to benefit the coastal provinces with a more developed industrial

structure, less reliance on SOEs and a greater export exposure while the opposite tends to be the case for the regional distribution of investment shocks. We provided the tentative explanation that during much of the sample period there was a growing bias in investment to the poorer provinces with policies such as “The Great Western Experiment” and the “Resurgence of the Old Northeast Industrial Base” in the 1990s and 2000s designed to help compensate for the natural advantages of the coastal provinces in their ability to benefit from national shocks.

The final section of our paper reported a number of extensions of the model and other evidence to assess the robustness of our results. In general, the overall flavour of the results for the base models showed little sensitivity to model specification and variable definitions and so supported our original conclusions.

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Table 1: Stationarity tests for log provincial real GDP per capita

Province	Level		First difference	
	Intercept	Intercept and trend	No intercept	Intercept
Beijing	0.8008	0.1740	0.4284	0.0002
Tianjin	0.9972	0.5870	0.3002	0.0209
Hebei	0.9963	0.0253	0.3372	0.0034
Guangdong	0.3946	0.9594	0.0875	0.0007
Shandong	0.9923	0.2204	0.7299	0.0163
Fujian	0.9043	0.3755	0.5452	0.0039
Zhejiang	0.7471	0.1465	0.1984	0.0321
Jiangsu	0.9759	0.0060	0.2095	0.0058
Shanghai	0.7820	0.9412	0.3844	0.0002
Liaoning	1.0000	0.7130	0.2697	0.0198
Guangxi	0.9979	0.8070	0.3167	0.0380
Sichuan	0.9999	0.9684	0.7294	0.7100
Guizhou	0.9996	0.9999	0.7386	0.0284
Yunnan	0.9985	0.9872	0.7751	0.0004
Shaanxi	1.0000	0.9963	0.6158	0.0108
Gansu	0.9999	0.8018	0.4392	0.0009
Qinghai	0.9999	0.9998	0.8213	0.3367
Ningxia	1.0000	0.9990	0.8189	0.0039
Xinjiang	0.8376	0.1222	0.7840	0.4754
Shanxi	0.9991	0.4884	0.6000	0.0094
Inner Mongolia	0.9999	0.9344	0.3107	0.0841
Jilin	0.9996	0.8623	0.2003	0.0043
Heilongjiang	1.0000	0.9994	0.8252	0.5396
Anhui	0.9901	0.4113	0.1933	0.0250
Jiangxi	1.0000	0.3282	0.2116	0.0100
Henan	0.9987	0.9344	0.3999	0.0005
Hubei	1.0000	0.8026	0.1835	0.0117
Hunan	0.9997	0.8264	0.4500	0.1474

Notes: Values in the cells are marginal probability levels for the ADF test for a unit root. Tests are based on lags chosen using the SIC criterion with a maximum number of lags of 8 using data for 1980-2012.

Table 2: Stationarity tests for aggregate data

Variable	Level		First difference	
	Intercept	Intercept and trend	No intercept	Intercept
C	0.8913	0.2229	0.2124	0.0030
G	1.0000	0.9562	0.1154	0.1638
M	0.5347	0.2766	0.0033	0.0017
N	0.9611	0.1733	0.0510	0.0071
X	0.3776	0.6703	0.1613	0.0000
Y	0.9861	0.0178	0.3919	0.0023
Y*	0.9692	0.0174	0.0049	0.0006

Notes: The symbols C, G, M, N, X, Y, Y* denote real log per capita values of consumption, government expenditure, imports, investment, exports, GDP and world GDP respectively. Values in the cells are marginal probability levels for the ADF test for a unit root. Tests are based on lags chosen using the SIC criterion with a maximum number of lags of 8 using data for 1980-2012.

Table 3: Regional effects of aggregate shocks

Province	One-variable aggregate VAR						Two-variable aggregate VAR			
	1953-2012		1953-1979		1980-2012		GDP-shock		Invest-shock	
	SR	LR	SR	LR	SR	LR	SR	LR	SR	LR
Beijing	A*	C	A*	A	B*	B	B	B	B*	B
Tianjin	A*	A	A*	A	B	A	A*	A*	B*	B
Hebei	A*	A	A*	A	A	C	A	A	A	C
Guangdong	B*	B	B*	B	A	B	A*	A*	A	B
Shandong	B	A	B	C	A*	C	A	B	A*	A
Fujian	A	A	B	C	B	A	A*	A*	B	B
Zhejiang	B*	B	B*	B	A*	C	A*	A*	A	B
Jiangsu	B*	B	B*	B	A*	A	A*	C	A*	A
Shanghai	A	A	A*	A	B*	B*	A*	A*	B*	B*
Liaoning	A*	A*	A*	A*	A*	A*	A	A	A*	A*
Guangxi	B*	B	B*	B	B*	B	B*	A	A	B
Sichuan	A	C	B	B	A*	A*	A	A	A*	A
Guizhou	A*	A*	A*	A	B*	B	B*	B*	A	A
Yunnan	B*	B	B	B	B*	C	B*	B	C	A
Shaanxi	A*	A	A*	A	A*	A*	A*	A*	A*	A*
Gansu	B	B	B	B	B	A	B*	B	B*	C
Qinghai	B*	B	B*	B	B*	B*	B*	B*	B*	B
Ningxia	B*	B	B	B	B*	B	B*	B*	B*	B
Xinjiang	B	B	B	B	B*	B*	B*	B*	B*	B*
Shanxi	A*	A	A*	A	A	B	B	B	A	C
Inner Mongolia	A*	A	A	A	B*	B*	B*	B*	A*	A
Jilin	A	A	A	C	A	A	B*	B	A*	A
Heilongjiang	A*	A	A*	A	B*	B	B*	B	B*	B
Anhui	B	A	B*	B	A	A	B	C	A*	A*
Jiangxi	B*	C	B*	B	B	A	A	A	C	A
Henan	A*	A*	A	A	A	A	B	B	B	A
Hubei	A	A	A	A	A*	A*	A*	A	A	A
Hunan	B	A	B	A	B*	C	B*	A	A	A

Notes: A, B, C denote a provincial IRF's being above, below, coincident with the national IRF; a * denotes significance; SR and LR denote short-run and long-run IRFs (at horizons of 2 and 5 respectively).

Table 4: Cross-section regression results

Variable	GDP Shock			Investment Shock		
	Coeff	p-value	R ²	Coeff	p-value	R ²
PROVGDP	0.0003	0.33	0.0363	-0.0012	0.01	0.2473
COAST	0.8394	0.01	0.2190	-1.0863	0.08	0.1118
DISTANCE	-0.0001	0.81	0.0022	-0.0008	0.32	0.0377
INDUSTRY	0.0079	0.41	0.0267	-0.0329	0.05	0.1394
EXPORTS	0.0491	0.06	0.1322	-0.0601	0.21	0.0608
SOE	-0.0520	0.01	0.2290	-0.0240	0.54	0.0149
<u>Four regions</u>						
COAST	1.3385	0.00		-0.4640	0.51	
CENTRE	0.9102	0.03	0.3425	1.6932	0.02	0.3450
NE	0.5615	0.30		1.1882	0.23	
COAST	0.4283	0.25		-2.1572	0.00	
CENTRE	-0.3487	0.50	0.3425	-0.5050	0.59	0.3450
PERIPH	-0.9102	0.03		-1.6932	0.02	

Notes: All regressions have the gap between the provincial IRF and the national IRF at horizon 5 as the dependent variable and all include a constant. The first six regressions have only one regressor (listed in the first column) and the remaining two each have three regional dummy variables. The variable definitions are as follows:

PROVGDP is the provincial GDP in 1980,

COAST is a dummy variable which equals 1 if the province is in the coastal region,

DISTANCE is distance from Beijing,

INDUSTRY is the ratio of non-primary-industry employment in total employment in 1980,

EXPORTS is the ratio of exports to GDP in 1980 and

SOE is the ratio of SOE employment to total employment in 1980.

In the four-region scheme the regions are the coast (COAST), the centre (CENTRE), the north-east (NE) and the periphery (PERIPH).

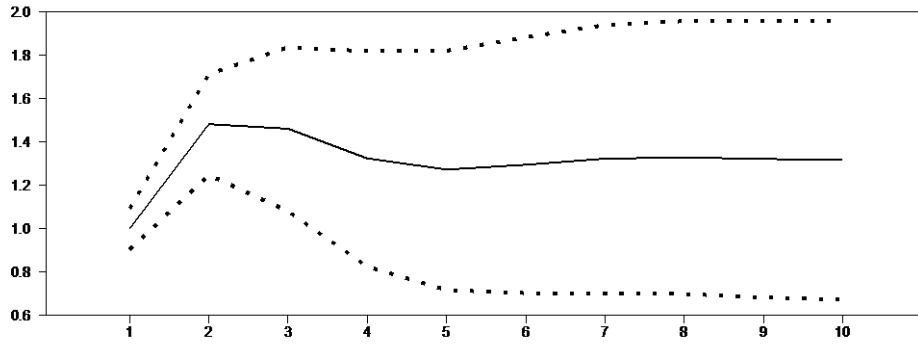


Figure 1: The effects on national GDP of a shock to national GDP in a model with one national variable, two lags, sample 1953-2012.

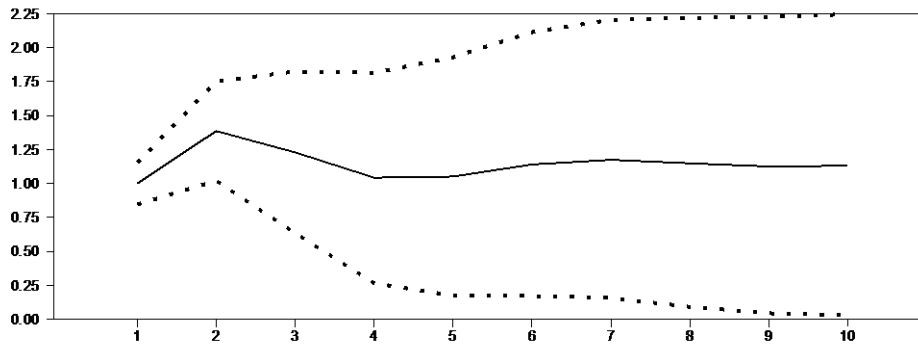


Figure 2: The effects on national GDP of a shock to national GDP in a model with one national variable, two lags, sample 1953-1979.

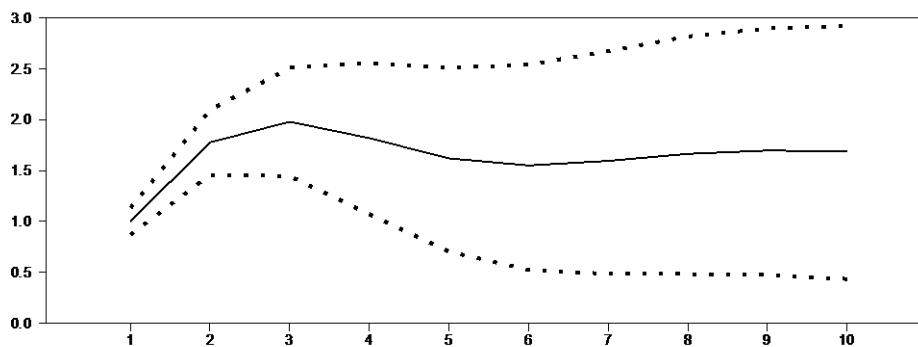


Figure 3: The effects on national GDP of a shock to national GDP in a model with one national variable, two lags, sample 1980-2012.

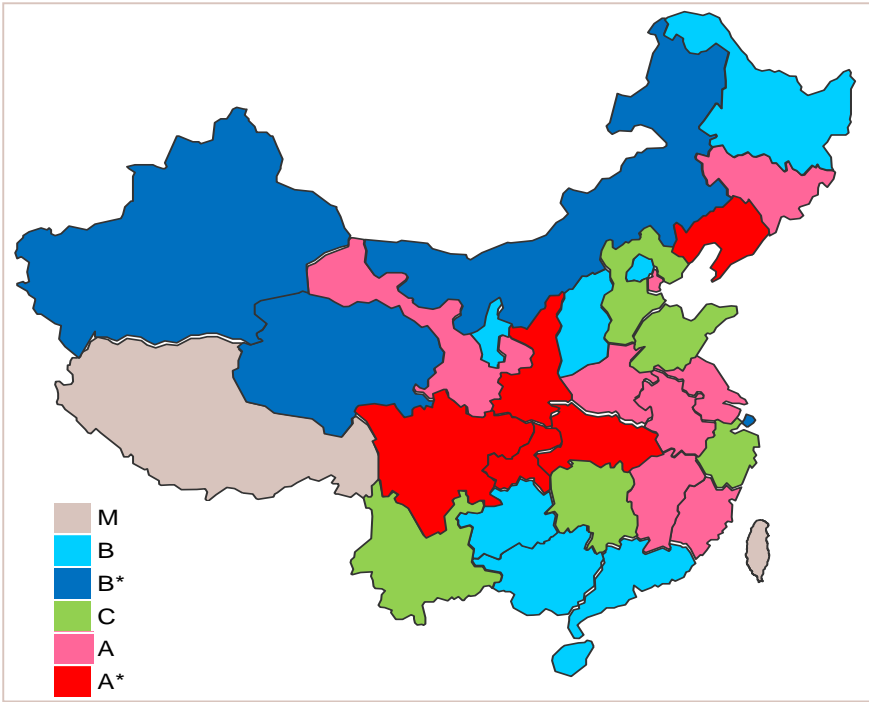


Figure 4: One-variable model, output shock, 1980-2012

Notes: “A” indicates that the provincial IRF is above the national IRF, “B” that it is below, “C” that it is coincident with and “M” that the provincial data are missing so not included in the simulations. An asterisk indicates that the provincial IRF lies outside the bounds of the national IRF for a substantial part of the projection period.

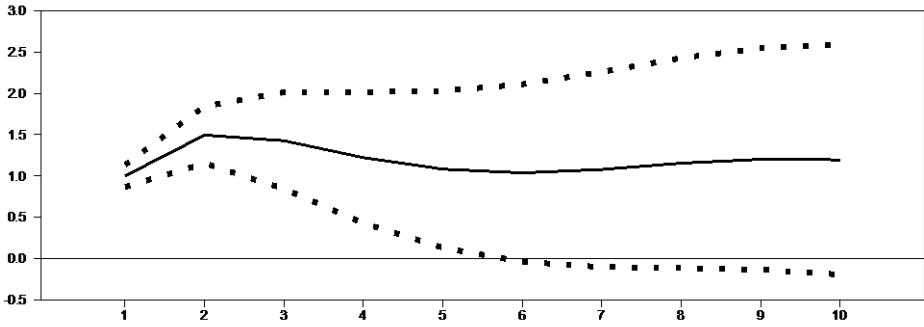


Figure 5: The effects on national GDP of a shock to national GDP in a model with two national variables, two lags, sample 1980-2012.

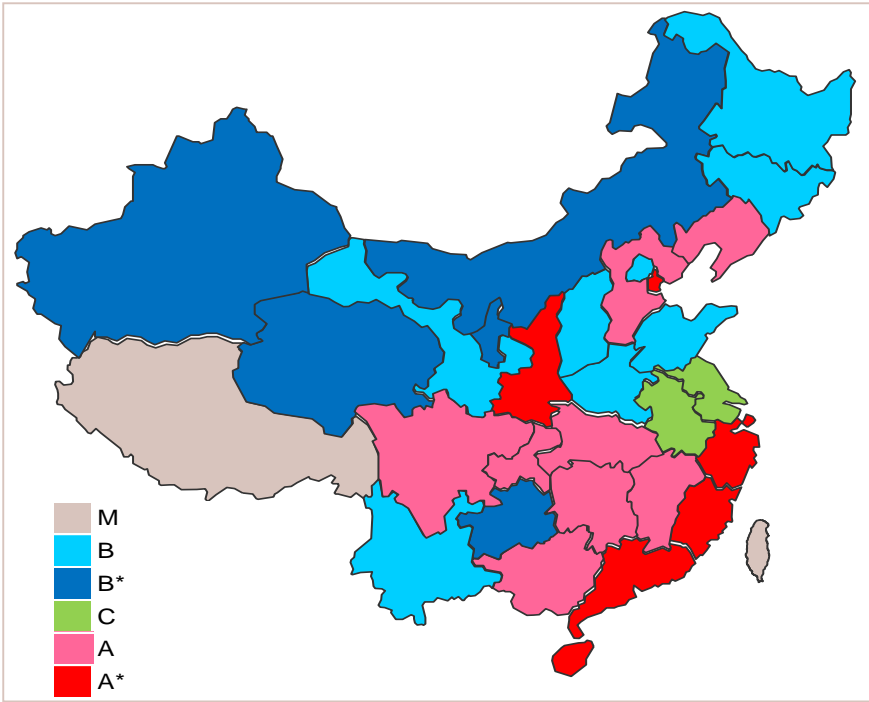


Figure 6: Two-variable model, output shock, 1980-2012

Notes: “A” indicates that the provincial IRF is above the national IRF, “B” that it is below, “C” that it is coincident with and “M” that the provincial data are missing so not included in the simulations. An asterisk indicates that the provincial IRF lies outside the bounds of the national IRF for a substantial part of the projection period.

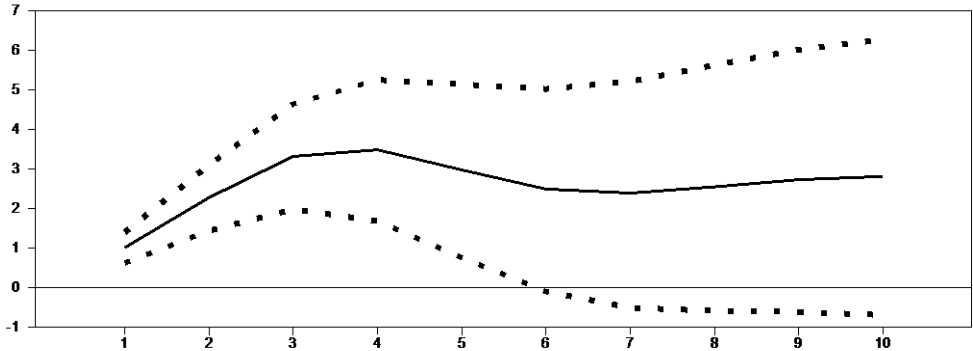


Figure 7: The effects on national GDP of a shock to national investment in a model with two national variables, two lags, sample 1980-2012.

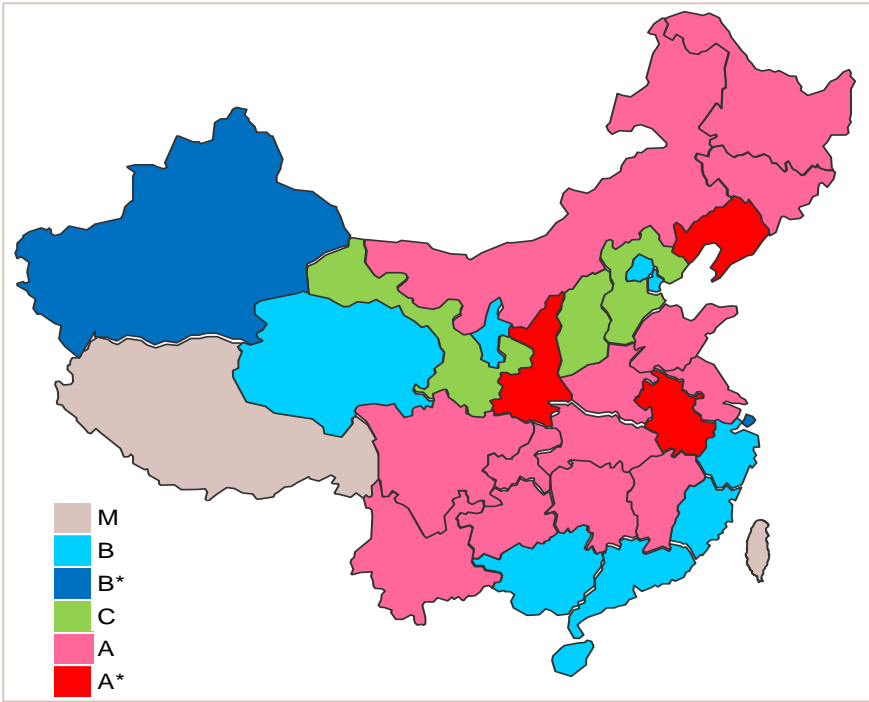


Figure 8: Two-variable model, investment shock, 1980-2012
 Notes: “A” indicates that the provincial IRF is above the national IRF, “B” that it is below, “C” that it is coincident with and “M” that the provincial data are missing so not included in the simulations. An asterisk indicates that the provincial IRF lies outside the bounds of the national IRF for a substantial part of the projection period.

APPENDIX

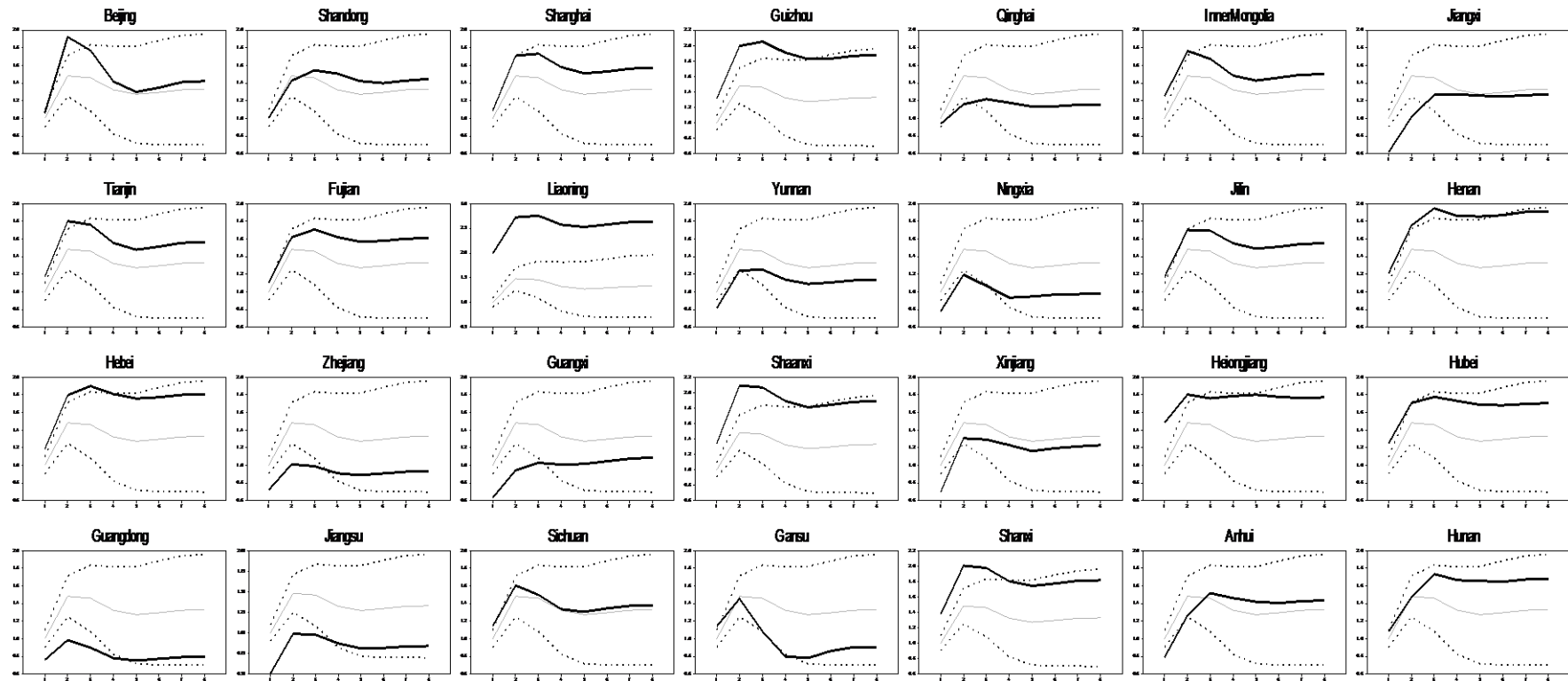


Figure A1: The effects on provincial GDP of a shock to national GDP in a model with one national variable and two lags; sample 1953-2012. Note: the provincial IRF is the dark solid line, the national IRF is the light solid line and the national confidence bounds are the dotted lines

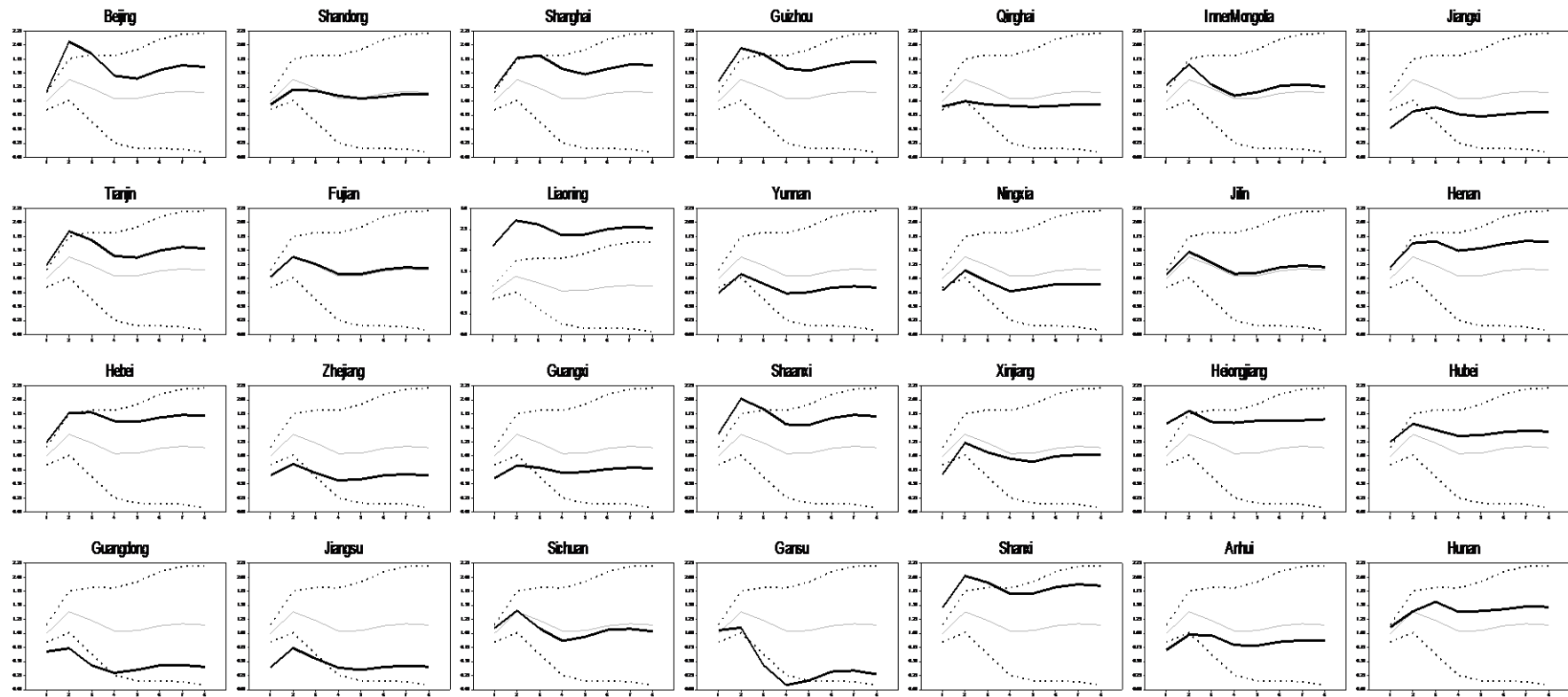


Figure A2: The effects on provincial GDP of a shock to national GDP in a model with one national variable and two lags; sample 1953-1979. Note: the provincial IRF is the dark solid line, the national IRF is the light solid line and the national confidence bounds are the dotted lines

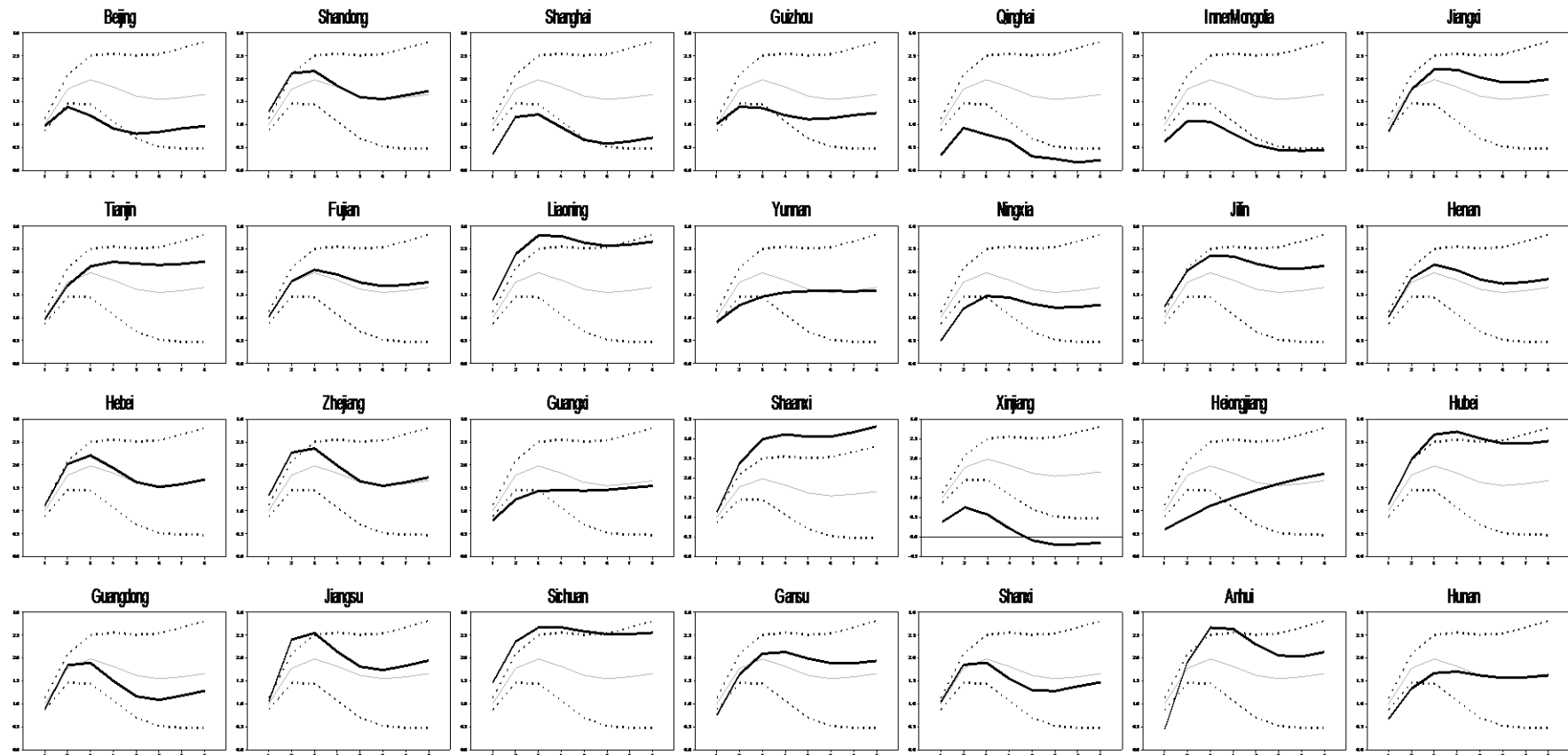


Figure A3: The effects on provincial GDP of a shock to national GDP in a model with one national variable and two lags; sample 1980-2012. Note: the provincial IRF is the dark solid line, the national IRF is the light solid line and the national confidence bounds are the dotted lines

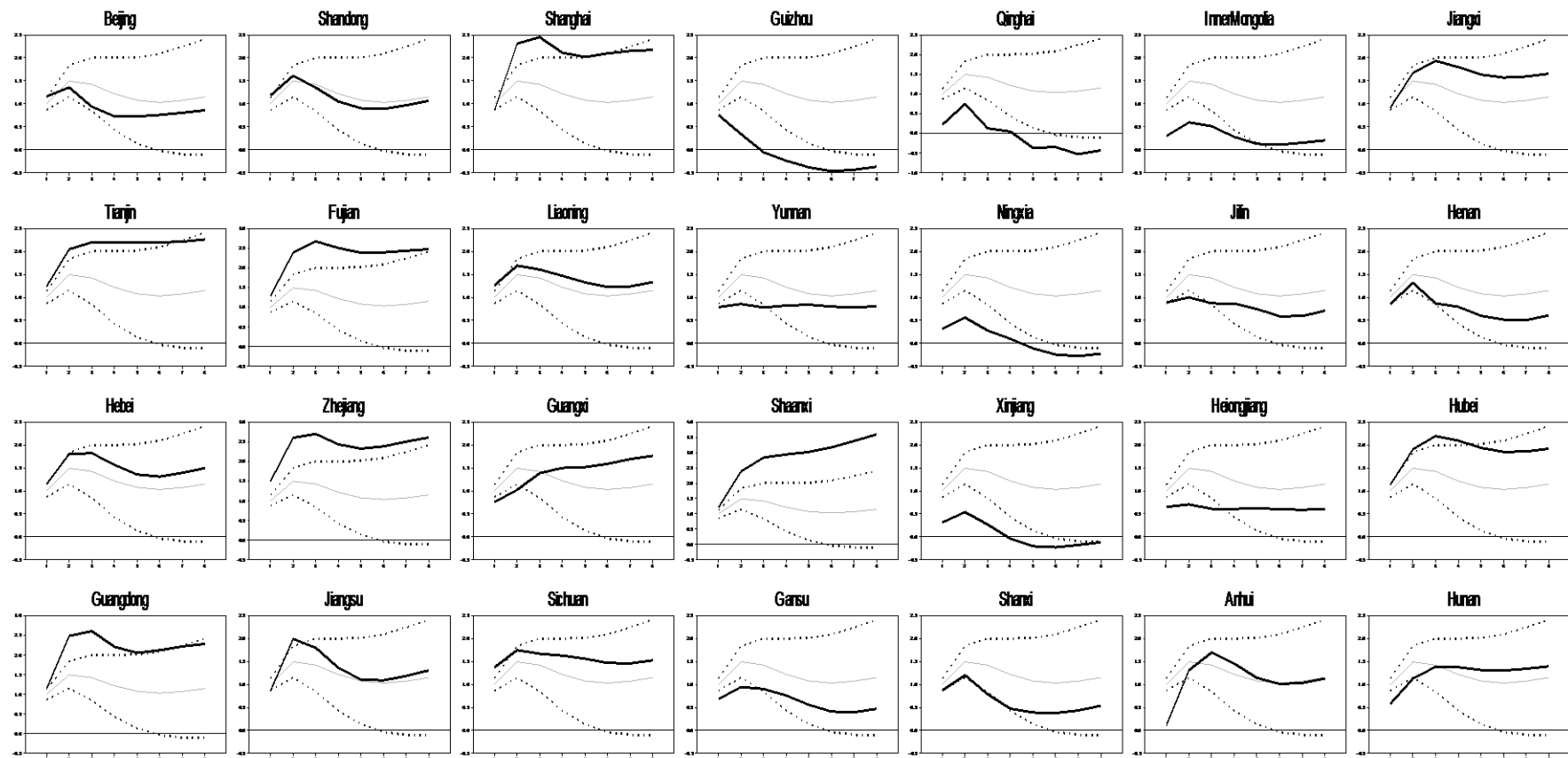


Figure A4: The effects on provincial GDP of a shock to national GDP in a model with two national variables, two lags, sample 1980-2012. Note: the provincial IRF is the dark solid line, the national IRF is the light solid line and the national confidence bounds are the dotted lines

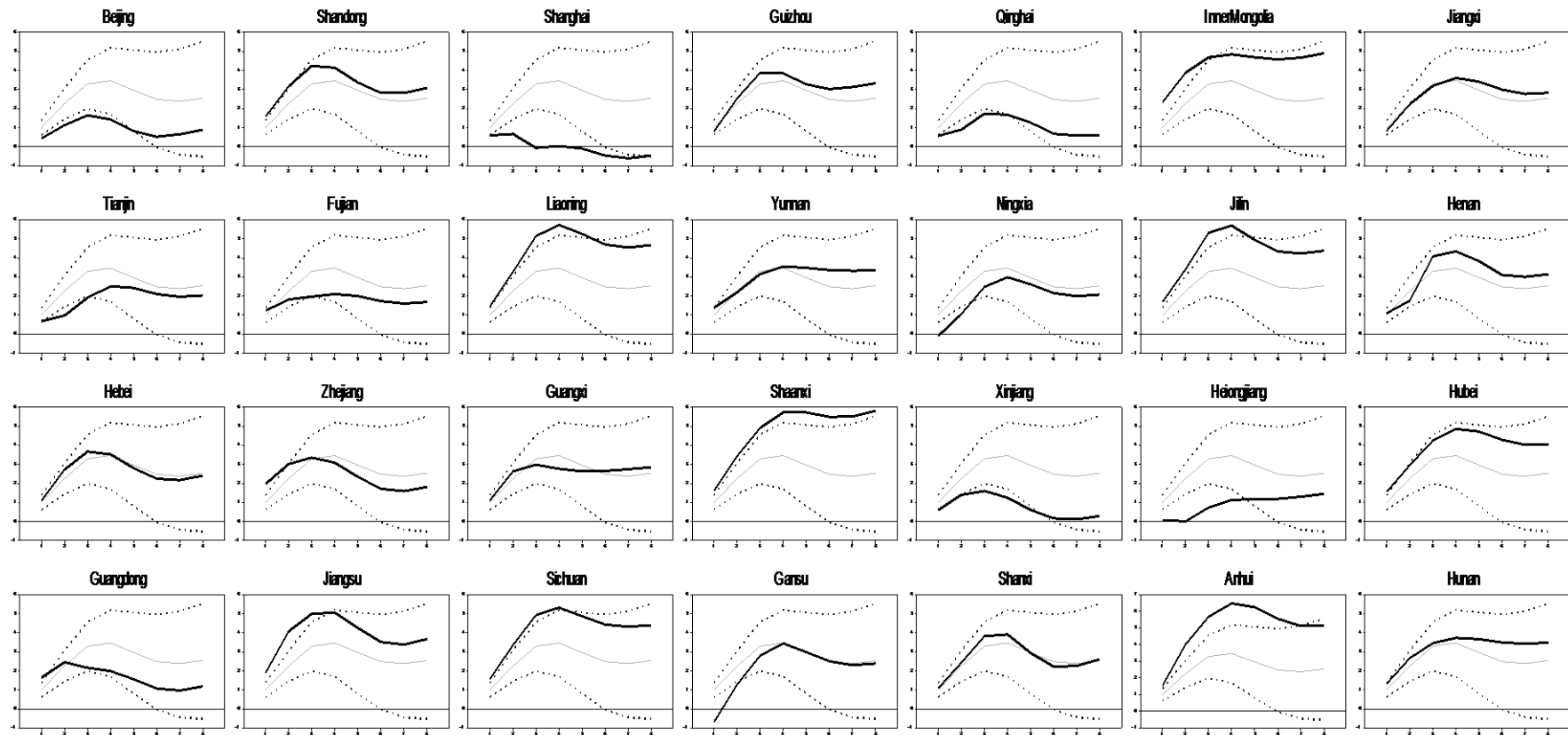


Figure A5: The effects on provincial GDP of a shock to national investment in a model with two national variables, two lags, sample 1980-2012. Note: the provincial IRF is the dark solid line, the national IRF is the light solid line and the national confidence bounds are the dotted lines