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Regional Resilience in China: The Response of the Provinces to the Growth Slowdown*

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Abstract: This paper focuses on the province-level experience of China's growth slowdown using the notion of regional economic resilience. We first use standard resilience measures based on growth rates and compute the correlation between these measures and a number of determinants. We then decompose growth into national and provincial components and argue that resilience ought to be based only on the former. This extension is important both for ranking provinces and for the correlation analysis. We find that provinces close to the coast with new- rather than old-industry structures were less resilient and suffered greater growth variability.

Keywords: China, growth, provincial growth, provincial response, regional resilience

JEL Codes: E37, O47, O53, R12, R15

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1. INTRODUCTION

The slowdown in China's economic growth rate since its peak in 2007 has received worldwide attention, reflecting the importance of China in the world economy as well as the general interest in the Chinese growth "miracle".[1] While there has been widespread discussion of the sources of the slowdown (e.g., Lin, 2019; Tian, 2019; Chen and Groenewold, 2019a, 2021), much less has been said about the geographical distribution of its effects. Given the considerable regional diversity of the Chinese economy, there is likely to be considerable spatial variation in the impact of the slowdown, and it is this aspect of the slowdown that we examine in this paper.

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[1] It is interesting that the beginning of the slowdown coincided more or less with the Global Financial Crisis (GFC). This is largely coincidence. Most informed commentators (such as Cai, 2016, and Tian, 2019) on the Chinese economy argue that the slowdown was largely the result of domestic factors rather than the contraction of world demand, which followed the GFC.

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We analyze the effects of the slowdown at the level of Chinese provinces within the context of the recent and rapidly-expanding literature on regional economic resilience (see Martin and Sunley, 2015, for a widely-cited exploratory paper), a literature which is concerned with mainly this question: what are the regional consequences of national shocks and what determines the regional resilience or the lack of resilience to such shocks? We argue that this is a worthwhile exercise for China for a number of reasons.

First, there is little work on the way in which the Chinese regions have responded to the growth slowdown. To our knowledge, only three papers (Bian et al., 2020; Tan et al., 2020; He et al., 2021) address this issue, and they overlap very little with our analysis. Only the second and third of these specifically explore the question of resilience; both make use of city-level data (giving them far more cross-section degrees of freedom than we have) and focus on the importance of resilience of a single factor: variety-"resource-based" cities in the case of the second paper and related effects in the last. In contrast, we use provincial-level data and analyze a wide range of factors that have been extensively used in the empirical literature on regional economic resilience.

Second, much of the existing empirical work on regional economic resilience has analyzed the regional effects of national temporary demand shocks; in particular, the effects of the Global Financial Crisis (GFC), which began around 2008.[2] This was an obvious episode to study, given its international nature and the fact that the application of the notion of resilience to regional economies took off at about the same time as the GFC developed. While this is a natural development, it may be presumed but often unstated that resilience is likely to be sensitive to the nature of the initiating shock – a region that is resilient to a demand shock may not be resilient to a supply shock of the same magnitude, or to a demand shock of a larger magnitude. Thus, the examination of regional reactions to a different type of shock would form a useful addition to the literature and we make a contribution in this direction by examining the regional response to China's growth slowdown.

We argue that the slowdown shock differs in two ways from the more conventional national shock. First, it is a supply shock. Second, it is a permanent shock. While this shock differs from the demand shock, which has usually been analyzed, it falls comfortably within the regional resilience notion, which incorporates not only short-run resistance but also the longer-run adaptation to the shock.

A further contribution that we make to the literature is that we do not confine our analysis to the effect of the national shock on the *level* of growth, as is the case in most of the existing literature, but also analyze changes in the *variability* of the growth path along which the provincial economies respond to the slowdown.[3] We argue that, while the sensitivity of a region's level of growth is probably of primary concern to policymakers, regions that react to adverse national shocks with greater volatility in output growth could also be classified as more sensitive, i.e., less resilient.

We carry out our analysis in two stages. In the first stage, we use a conventional approach

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[2] It should be noted that there was discussion after the GFC that this shock would be permanent; see El-Erian (2010). Indeed, the term "The New Normal", which has been used to characterize the Chinese economy after the slowdown, was first used to describe the likely aftermath of the GFC.

[3] Ringwood et al. (2019) also take into account historical variability by adjusting their measure of the extent of the change by historical variability.

based on the (total) provincial growth rates over 2008-2018 and measure the change in provincial growth relative to the national growth as a whole. We use this to compute a sensitivity index. We also define a variability index, which measures the variability of the change in the growth for each province.

In the second stage, we take account of a common observation in the regional economics literature that regional growth is a complicated process that is subject to many different influences (see, e.g., Martin and Sunley, 2015). Only some components of a region's growth experience are relevant for the analysis of regional resilience. Therefore, effects of regional-idiosyncratic shocks should be excluded. The presence of multiple factors operating simultaneously on the regional economy makes it difficult to tease out those components of a region's growth relevant to the proper measurement of resilience. We address this problem by first decomposing each province's growth decline into two components, one being the province's response to national factors and the other the result of province-specific forces. Our view is that it is the first of these components rather than the second or their sum that is the appropriate basis for resilience analysis.

We achieve the decomposition of the growth rate using a sequence of bivariate vector-autoregressive (VAR models), in the spirit of earlier work by Carlino and DeFina (1998, 1999) and more recent applications by Owyang and Zubairy (2013), Ridhwan et al. (2014), Chen and Groenewold (2019b). We then re-compute our indexes based only on the provincial response to national shocks. We compare the resilience characterization of China's provinces using this measure to the more basic one developed in the first stage to gain an indication of the importance of purging the purely regional shocks from the provincial growth rates.

In both stages of our analyses, we also carry out an informal exploration of the possible "determinants" of resilience. In much of the literature, the analysis of the drivers of resilience is based on formal cross-section regression analysis. But in our case, with only thirty cross-section observations (corresponding to the number of provinces) and potentially over twenty possible determinants, there are insufficient degrees of freedom to reasonably use cross-sectional regressions. We, therefore, use less formal analysis based on pair-wise correlation coefficients.[4]

We find that the use of the national component of provincial growth rates rather than the total growth matters, both for ranking provinces according to resilience and for correlations of resilience with determinants capturing provincial characteristics. Broadly, we find that provinces close to the coast with new- rather than old-industry structures are less resilient and tend to have suffered greater variability in growth during the slowdown.

The paper is structured as follows. In the next section, we provide some background information and briefly review the literature on regional economic resilience. In section 3, we discuss the measurement of resilience and explain the method which we use for the time-series decomposition of provincial growth rates into national and provincial components. In section 4, we present the data to be used in the empirical analysis. The results are reported in section 5 for each of the two stages of our analysis: that using conventional measures based on total growth and that based on growth purged of province-specific factors. Conclusions

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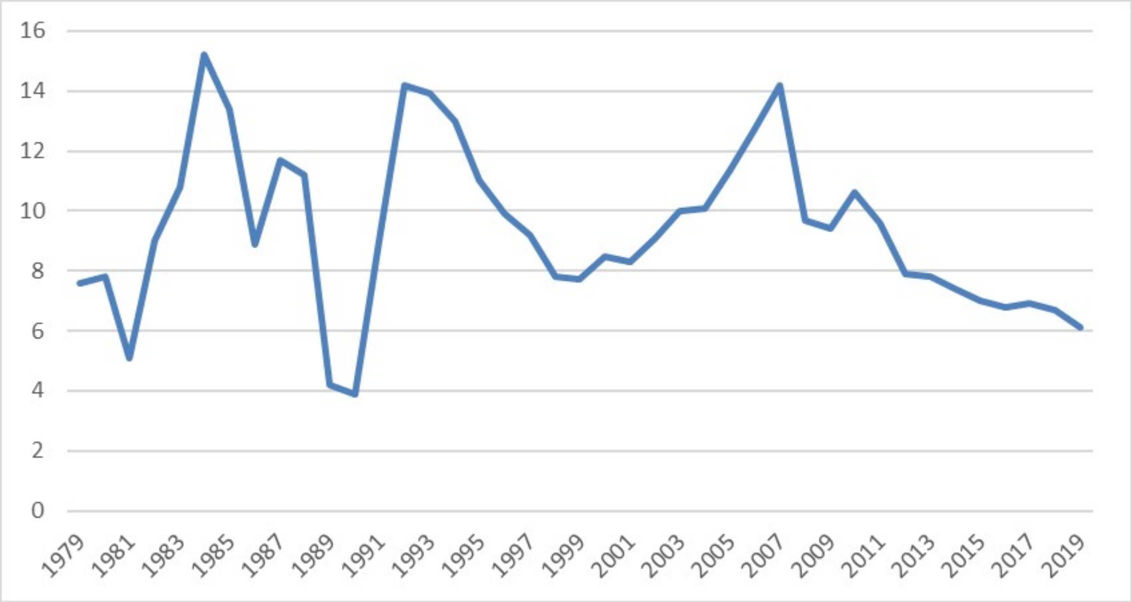
[4] We experimented with cross-sectional regressions but found, not unexpectedly, that the results are very sensitive to included variables, specification search procedures and sample choice.

Figure 1: Real GDP growth rate, China, 1979 to 2019 (%)



are drawn in section 6.

2. BACKGROUND AND LITERATURE

We begin this section with a little background before briefly reviewing the literature on regional resilience. First, the slowdown at the national level is illustrated in Figure 1 which pictures the annual growth rate of China's real GDP since reforms began in 1978. The graph shows that, while economic growth has fluctuated considerably over the whole period since 1978, it is clear that growth has slowed markedly since the pre-2008 highs of around 10% to a level of less than 7% at the end of the period.[5]

There has been considerable discussion of whether this observed slowdown is permanent or temporary and whether it is demand- or supply-driven. The majority view in this discussion is that it is permanent and that supply factors were the main cause (Lin, 2019; Tian, 2019; Chen and Groenewold, 2019a, 2021). Specific supply factors which have been suggested include a reduction in the rate of growth of urban labor supply (Golley and Meng, 2011; Li et al., 2012; Meng, 2012), the exhaustion of the demographic dividend (Roberts and Cai, 2015; Cai, 2016), a productivity slowdown (Lee and Hong, 2012; Lu, 2017; Bai and Zhang, 2017) and a slowdown in the rate of capital accumulation (Wu, 2016; Lu, 2017). We, therefore, treat the slowdown as mainly a supply effect even though there may be some demand contamination, especially early in the slowdown period.

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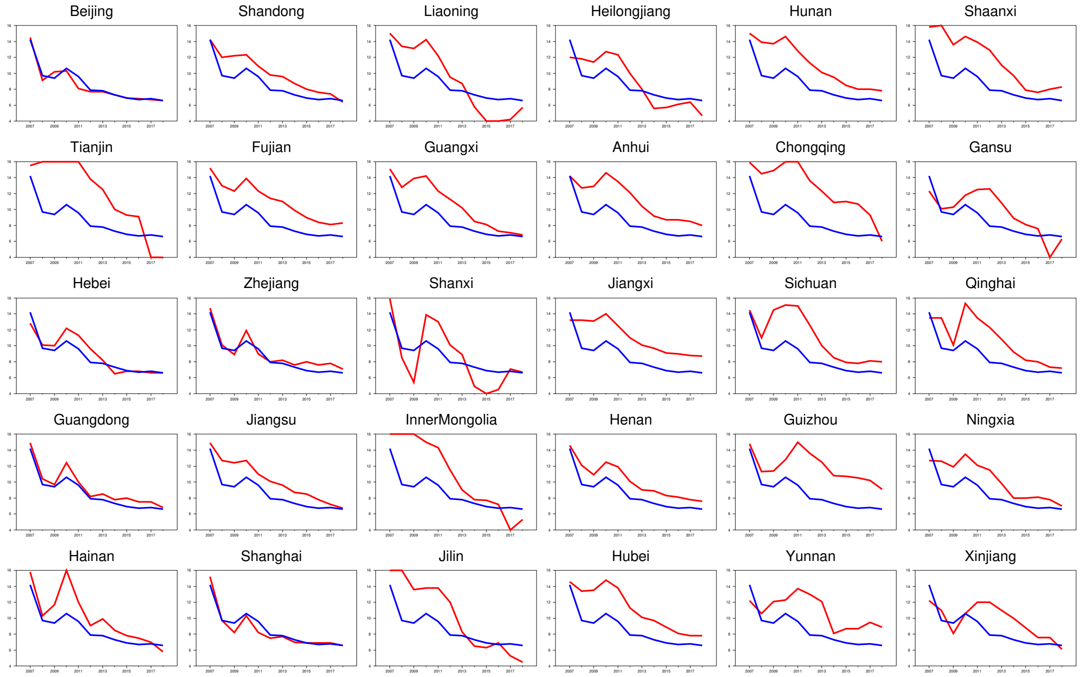
[5] Not surprisingly, there are variations in the dating of the beginning of the slowdown. From the graph, it is clear that there was some recovery in the growth rate in 2010 after the steep decline starting in 2008, but this is commonly seen as a temporary phenomenon, the result of the extraordinary fiscal stimulus that the Chinese government implemented in response to the slowdown in world growth associated with the GFC, rather than a resumption of the pre-slowdown growth pattern. Whatever may be the justification for this view, we focus our analysis on the period after the peak in 2007.

Figure 2: National and provincial growth rates 2007 to 2018 (red line = provincial, blue line = national)



An informal examination of China's provincial growth rates confirms our assertion in Section 1 that China's regional diversity is likely to mean different provincial responses to the slowdown. Figure 2 pictures the growth rates for each province (excluding Tibet for which data are missing) together with the national growth rate over the period of the slowdown, from 2007 to 2018.[6]

It is clear from Figure 2 that all provincial growth rates fell over the period so that the slowdown was, indeed, a national phenomenon. There has been considerable variation in growth rates across provinces which warrants investigation. Nevertheless, it seems reasonable to suppose that the slowdown at the provincial level has also been permanent. Hence, our analysis will be of the resilience of provincial economies to a permanent supply-driven slowdown.

As stated above, we set out to analyze the differences across China's provincial economies in their reaction to the fall in the national growth rate from 2008 using the notion of economic resilience.[7] At a general level, regional economic resilience refers to the way in which a

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[6] It is clear that the provincial growth rates are generally above the national rate. This reflects the fact that the official national growth rate is generally lower than the weighted average of the provincial rates. For the period shown, the gap was over 1.3 percentage points on average but was as high as 2.5 percentage points in 2010. It is interesting that from the beginning of the slowdown, the provincial rates fell more slowly on average than the national rate.

[7] The COVID-19 crisis hit as we were revising this paper. While it is likely to have a major effect on Chinese growth, at least in the short to medium term, and will, no doubt, be the subject of extensive empirical research, our sample period stopped in 2018, so we do not include this episode in this paper.

regional economy reacts to (usually adverse) shocks, and it is common to compare measures of resilience across regions and explore the provincial characteristics which encourage resilience.

The literature on regional economic resilience is a recent and rapidly-growing one; see Martin and Sunley (2015) for a survey paper, Bristow and Healy (2018a) and Wolman et al. (2017) for recent book-length treatments and the *Annals of Regional Science* (2018) and *Regional Studies* (2018) for recent special journal issues on this topic.[8] It is not surprising that in newly-developing literature, the notion of regional economic resilience has been applied in different ways.[9] To clarify the discussion, Martin (2012) has distinguished three types of resilience: engineering resilience, ecological resilience and adaptive resilience, although the empirical literature has focused on the first of these, which assumes that the region will return to its pre-shock state and examines characteristics of the path along which the return is effected. Ecological resilience also assumes the economy to converge to equilibrium but allows for the possibility that the new equilibrium differs from the pre-shock equilibrium.[10] Adaptive resilience is a broader concept which captures the economy's ability to adapt to minimize the impact of a shock.

Within the framework of engineering resilience which we will use for our analysis, we may distinguish, again following Martin (2012), between four phases in the process of return of the regions to their original state: (1) Resistance: short-term reaction to shocks; (2) Recovery: the speed with which the region bounces back from a shock; (3) Re-orientation: structural re-orientation for the region's output and employment; and (4) Renewal: resumption of pre-recession growth paths. As stated, much of the empirical literature presumes engineering resilience and has been focussed on the short-run reaction to the shock, although some papers have also considered recovery (see, e.g., Fingleton et al. (2012); Brakman et al. (2015); Crescenzi et al. (2016); Giannakis and Bruggeman (2017a); Giannakis and Bruggeman (2017b); Faggian et al. (2018); Weinstein and Patrick (2020)). Indeed, with some notable exceptions (see Fingleton et al. (2012) and Cellini and Torrisi (2014)), the empirical analysis of resilience has focussed on the effects at the regional level of the demand-contraction emanating from the GFC. The presumption in this work has been that countries and regions will recover from the GFC to resume their pre-crisis state, so the analysis falls in the engineering resilience category.

A number of variables have been identified in the literature as determinants of resilience and we take guidance from these in our choice of potential determinants in the empirical work reported later. Pre-existing economic conditions are a possible factor since they may potentially constrain or enhance a region's ability to adapt to an adverse shock (Martin

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[8] A much earlier (and continuing) literature related to this issue is that dealing with the relationship between regional and national cycles, which goes back at least to Thirlwall (1966) and includes at least one application to China: Groenewold and Chen (2005). A recent example is Gong and Kim (2018).

[9] For a recent discussion of both definitional and measurement issues, see Ringwood et al. (2019).

[10] Actually, Martin defines ecological resilience as the "scale of shock or disturbance a system can absorb before it is de-stabilized and moved to another stable state or configuration." (Martin (2012), p.5 Table 1), which suggests that it requires the calculation of the maximum shock a system can absorb. In empirical applications of this notion, a system that is resilient in the ecological sense is taken to mean a system that is not resilient in the engineering sense but which will converge to a new equilibrium in response to a shock; see Fingleton et al. (2012); Capello et al. (2015); Diodato and Weterings (2015); Faggian et al. (2018); Kitsos and Bishop (2018); Rizzi et al. (2018).

and Sunley, 2015; Kitsos and Bishop, 2018). Geographic location may also affect resilience in that locations differ in the availability of new jobs with clusters of high-growth firms better able to adapt to adverse external shocks (Diodato and Weterings, 2015; Angulo et al., 2018). The local industrial structure is also regarded as a central determinant of regional resilience since different industries have differing degrees of flexibility in their response to shocks (Martin and Sunley, 2015; Giannakis and Bruggeman, 2017b; Ray et al., 2017; Angulo et al., 2018). Human capital and innovation could have effects on resilience; we might expect high human-capital workers in innovative firms to be more adaptable than those with low skills working in traditional industries (Lee, 2014; Di Caro, 2017; Giannakis and Bruggeman, 2017a; Bristow and Healy, 2018b; Weinstein and Patrick, 2020). Involvement in international trade may also be a determinant of resilience since international trade provides alternatives to shrinking domestic markets in the face of a negative domestic shock (Di Caro, 2017). Finally, the role of cities has been found important in influencing the response to a crisis (Capello et al., 2015; Brakman et al., 2015). Capello et al. (2015) argue that "regions hosting strong, large, dynamic cities might be more resilient to adverse external shocks compared to their rural counterparts (p.952).

To our knowledge, there are only three papers that analyze the regional effects of the Chinese slowdown. The first is by Bian et al. (2020); their analysis, however, does not focus on resilience and their statistical method is quite different from that used in the majority of resilience studies. They apply dynamic factor analysis with time-varying factor loadings to examine the provincial growth patterns in China before and after 2008 in contrast to the more common cross-sectional analysis in the resilience literature. The second paper is closely related to the present paper. This is a recent one by Tan et al. (2020) which does focus explicitly on regional economic resilience but, in contrast to our analysis, uses data for Chinese cities and has a relatively narrow focus: whether "resource-based" cities have been more resilient to the Asian Financial Crisis and the GFC. The third paper, He et al. (2021) also explicitly analyzes resilience and, like the previous one, uses city-level data and focuses specifically on the effect of related-variety effects on the resilience of regions during the period 2003 to 2013. They find, interestingly, that cities with many related product varieties are less resilient.

3. METHOD

To begin our discussion of methodology, we need to discuss the measurement of regional resilience. Generally, this is done by the use of macroeconomic indicators such as the change in real output or employment, often relative to the change in the corresponding variable for the nation as a whole. There is also some research that uses multidimensional indexes which cover the three broad areas of "economy, society and environment" (Rizzi et al., 2018). In practice, however, most papers use single-dimensional measures. Thus, Fratesi and Rodríguez-Pose (2016), Ezcurra and Rios (2019) for Europe, Fingleton et al. (2012) and Rocchetta and Mina (2019) for the UK, Diodato and Weterings (2015) for the Netherlands, Giannakis and Bruggeman (2017a) for Greece, Holl (2018) for Spain and Faggian et al. (2018) and Cainelli et al. (2019) for Italy all analyze regional resilience in terms of a single variable – employment. In countries with greater institutional rigidity, GDP measures may better reflect economic fluctuations (Cellini and Torrisi, 2014); Annoni et al. (2019) use GDP per capita for European regions. We will focus on output in this paper both because of the importance of GDP growth in Chinese public discourse and because China's labor market still has many rigidities which limit the ability of employment to respond to the shocks in economic growth.

A common measure used to assess regional resilience is what has been called a "sensitivity index" in the literature; see, e.g., Faggian et al. (2018) following Martin (2012). This index simply measures the decline in growth or employment in a particular region over a particular period relative to that in the country as a whole. Some recent empirical papers on resilience, such as Cainelli et al. (2019) and Ezcurra and Rios (2019), have normalized such a measure by dividing by the absolute value of the change in the national variable. A simple difference in growth rates has the useful interpretation of percentage points which the adjusted method does not. Others, such as Ringwood et al. (2019), adjust the difference by the variance of the growth rate to avoid bias in a situation where the period over which the change is measured is potentially different for each region, being based on the regional peak and trough around the national shock. In our application, however, the period over which the change is measured is based on the timing of the national shock and is the same for all regions. Hence we use the simple measure of the difference between the regional and national change in the growth rate over a particular period- the 2007-2018 period in our case. We choose this period since, for reasons explained above, we date the beginning of the slowdown at 2008 so that 2007 is the last pre-slowdown year and 2018 is the last period in our sample.

Define the growth rate for region k at time t as the log-difference of real output between $t-1$ and t, $g_{kt} = \Delta ln(y_{kt})$, and the national growth rate in period t analogously as $g_t = \Delta ln(y_t)$ where y_{kt} and y_t are real output in region k and the nation as a whole in period t; then the sensitivity index, SI, is defined as:

$$SI_k = (g_{k2018} - g_{k2007}) - (g_{2018} - g_{2007}),\ k = 1, \cdots, m. \tag{1}$$

The index may be positive or negative. In our application, the change in the national growth rate is negative so SI_k will be negative if the fall in the provincial growth rate between 2007 and 2018 exceeds that in national growth. Hence the more negative is SI_k, the less resilient is province k.[11]

If it is the case that the slowdown in China's growth rate is a permanent change, it is not possible to see our analysis of its regional effects within the context of engineering resilience since a permanent slowdown in China's growth rate will require a permanent change in at least some of the provincial growth rates and, therefore, not all regions can return to their pre-shock state. We could, however, define engineering resilience in this case as a situation where a region converges to a new long-run growth path that bears the same relation to the new national growth path as it did before the shock and, in that sense, the sensitivity index defined above can be used to inform us about engineering resilience.

As pointed out in the introductory section, we not only assess resilience in terms of growth level effects but also in terms of growth variability effects. While it is likely that private

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[11] Early in our research, we also experimented with the ratio rather than the difference in the provincial and national growth changes but found little difference in the results. The cross-section correlation between the two series is 96.5%. We, therefore, proceeded with just the difference measure.

agents and policymakers are most concerned with a region's growth response to an adverse national shock, there are also costs to more variable responses to shocks since variability makes for greater uncertainty which, in turn, makes it more costly to adapt employment and investment decisions for both firms and workers.

We measure the variability of the slowdown using a variability index, *VI*, which is defined in a similar way to *SI*, i.e. as the difference between the standard deviation of the provincial growth rate over the period 2007 to 2018 and the comparable measure for the country as a whole. We de-trended growth rates over the 2007-2018 period before the standard deviations are calculated. We make this adjustment because we wish to measure the variability of the path to the new equilibrium, which would be artificially inflated by a large fall in growth even if the path to the new growth rate were very smooth. Thus the variability index, VI_k, for region k is defined as

$$VI_k = sd_{2007,2018}(gdt_k) - sd_{2007,2018}(gdt), k = 1, \cdots, m \tag{2}$$

where $sd_{2007,2018}$ is the standard deviation over the period 2007-2018 and gdt_k and gdt represent the de-trended growth rate series for province k and the national as a whole. Both standard deviations are positive so that a positive VI value means that the provincial standard deviation exceeds the national standard deviation over the slowdown period, suggesting less resilience.

It was argued in the introductory section of the paper that regional growth is a complex process reflecting the influence of a large number of factors. Hence, the change in provincial growth rates during the slowdown will reflect not only the effect of the factors driving the slowdown but also province-specific forces. For a clearer comparison of resilience across provinces, we should attempt to purge the provincial growth rates of the province-specific factors. Hence, after applying the indexes above to the growth rates as indicated in the formulae, we go on to decompose the growth rates into two components: (1) a response to present and past national shocks (the national component) and (2) a response to present and past provincial shocks (the provincial component). We then apply the index formulae to both of these components but focus our discussion on the national component since that is the basis of our analysis of resilience. A comparison of the indexes based on the growth rates to those based on the national component of the growth rates will provide an indication of the extent to which the use of the total growth rate is misleading.

We accomplish our decomposition using a time-series approach. Ideally, we would model all the provincial growth rates and the national growth rate simultaneously. But with 30 provinces and approximately 40 years of annual data, this approach would quickly run into degrees-of-freedom problems. There are at least two ways in which this difficulty may be resolved, each of which involves restricting the possible interaction between all the variables. An early approach by Carlino and DeFina (1998, 1999) is to use a sequence of models (henceforth, the SoM approach) in which a sequence of independent vector-autoregressive (VAR) models is estimated, one for each province which includes a number of provincial as well as some national variables. The approach has been used in more recent work on regional issues by Owyang and Zubairy (2013), Ridhwan et al. (2014) and Chen and Groenewold (2019b). The advantage of this approach is that the modeling, the estimation procedure, and simulation methods are all straightforward. However, it comes at the cost of strongly implied restrictions on the interdependence of the provincial economies as well as questions about whether the estimated national shocks are, in fact, similar in all models as they should be.

A more recent approach byLastrapes (2005) uses a restricted VAR model, which also has strong restrictions on provincial interdependence but ensures that the national shocks are common to all provinces. Recent applications of this approach include Lastrapes (2006), Fraser et al. (2014), Chen and Groenewold (2018, 2019b). The last of these papers show that in an application to China, the weakness of the SoM approach that national shocks are not constrained to be identical across the sequence of models is not an empirically serious one.

As neither of the methods is clearly superior to the other, we propose to use the SoM approach. It has the advantage of being the simpler of the two, and it is also suitable for the historical decomposition procedure, which we use to separate the provincial growth rates into a component measuring the provincial response to current and past national shocks and one which captures the accumulated effects on the provincial growth rate of idiosyncratic provincial shocks. The historical decomposition of the growth rate is based on a standard VAR model. The SoM approach involves, as we shall see, a series of standard VAR models, but the Lastrapes procedure is based on a transformed VAR model, which results in a sequence of non-VAR models (see, e.g., equations (10a) and (10b) in Lastrapes (2005)) the structure of which is not immediately amenable to the application of the historical decomposition method.

In general, then, the SoM approach uses a sequence of VAR models, each with a number of national variables (which are the same for each model) and a number of provincial variables (which are specific to the model). There are, therefore, as many models in the sequence as there are provinces. In our case, we use the simplest possible form of the model with just one national variable and one provincial variable, the variables being the national and provincial growth rates. The reduced-form version of the model for the kth province is:

$$g_{k,t} = \alpha_{1k} + \sum \beta_{1kj} g_{k,t-j} + \sum \gamma_{1kj} g_{t-j} + \varepsilon_{1kt} \tag{3a}$$

$$g_t = \alpha_{2k} + \sum \beta_{2kj} g_{k,t-j} + \sum \gamma_{2kj} g_{t-j} + \varepsilon_{2kt} \tag{3b}$$

where the summation operators all run over $j = 1, 2, \cdots, p$. Each of the sequence of models is a standard VAR model and can be estimated and simulated as such.

The reduced-form errors, ε_{ikt}, are linear combinations of the structural errors (the provincial shocks and the national shocks). These structural errors need to be identified since it is the accumulation of these that we wish to compute. We make the common identification assumption based on the Cholesky decomposition of the error covariance matrix in such a way that the national shocks are identified as one which affects the national and provincial growth rates contemporaneously, but the provincial shock affects only the provincial growth rate within the period of the shock although it will, of course, feedback into the national rate with a lag.[12] Once the structural errors have been identified, the estimated model can

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[12] Note that the national growth rate also includes the effect of the growth rate of the province in question. An alternative to our specification would be to exclude province i's growth rate from the national growth

be used to decompose the provincial growth rates into two components by repeated substitution for the lagged growth rates. After an infinite number of substitutions, the provincial growth rate can be written as a constant (the accumulation of the intercept term), an infinite weighted sum of past provincial errors (the provincial component of the growth rate) and an infinite weighted sum of the national errors (the national component of the growth rate). This is the historical decomposition approach. In matrix form, the model for province k in equations (3a) and (3b) can be written as:

$$y_{kt} = \alpha_k + Ay_{kt-1} + \varepsilon_{kt}, \tag{4}$$

where $y_{kt} = (g_{kt}, g_t)'$, α_k is the vector of intercepts, A is the matrix of slope coefficients and ε_{kt} is the vector of error terms. This can be re-written as:

$$y_{kt} = (I - AL)^{-1}\alpha_k + (I - AL)^{-1}\varepsilon_{kt}, \tag{5}$$

from which the equation for the provincial growth rate for province k can be written as:

$$g_{kt} = constant + \sum \delta_{1j}\varepsilon_{1kt-j} + \sum \delta_{2j}\varepsilon_{2kt-j}, \tag{6}$$

where the summation operators now run from 0 to infinity. Substituting in for the reduced-form errors in terms of the structural errors, u_{ikt-j}, the growth rate for province k can be written as:

$$g_{kt} = constant + \sum \pi_{1j}u_{1kt-j} + \sum \pi_{2j}u_{2kt-j}. \tag{7}$$

The first summation term is the provincial component and the second is the national component of province k's growth rate. The constant component can be ignored since the growth rates are used in a differenced form in which case the constant cancels.

4. DATA

We require time-series data for two variables: national and provincial real output. All data are annual from 1978 to 2018.[13] National real output was measured by real GDP (RGDP), which was taken from the *China Statistical Yearbook* (NBSC, various issues). The regional variables are provincial RGDP which are taken from Wu (2004) and the *China Statistical Yearbook* (NBSC, various issues). We use data for 30 of China's 31 provinces (including the "city-provinces" of Beijing, Shanghai, Chongqing and Tianjin), with Tibet excluded due to missing data.

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rate in the model for province i. This possibility was discarded, however, because it would mean defining a national shock as one which did not contemporaneously affect province i. Besides, to the extent that the removal of the provincial growth rate from the national growth rate has an appreciable effect, it would mean that the identified national shock would differ across models and, so, would cease to be a national shock.

[13] Note that there were recent data revisions by National Bureau of Statistics of China (NBSC) for about half of the provincial growth rates for 2018. Our data does not include these revisions. We did, however, check the effect on the *SI* index and found that the graphs of the indexes with and without the revision were almost indistinguishable; the correlation between them was 99.91%.

In the discussion of the resilience results, we make use of a number of provincial characteristics, data for which we use in informal correlation analysis to gain insight into the possible sources of differences in resilience across provinces. The province-specific variables used in this exploratory analysis were chosen on the basis of the existing empirical literature. They may be grouped into the following broad categories:

1. Geography: regional dummy variables (based on three regions, coast, centre and west) and distance from the coast,[14]
2. Lagged growth, RGDP and RGDP per capita,
3. Economic structure which consists of various sub-groups:
    i. The state-owned-enterprise share in urban employment, investment share of GDP, a marketization index and an index of energy consumption per unit of output,
    ii. A selection of human capital measures: the shares of the population with primary, senior high and college education,
    iii. A number of demographic indicators: the urban share of population and the share of migrants in the population, and
    iv. Measures of openness: the import and export shares of output.

All cross-sectional data are an average for the years 2004 to 2006 except for the migrant share of the population (which is based on the 2000 census data). Data before the start of the slowdown period (2007 to 2018) were chosen to avoid the possible problem of endogeneity and an average of three years was used to avoid undue dependence on a particular year. The data were taken from the *China Statistical Yearbook* (NBSC, various issues) except for the marketization index, which is taken from Fan et al. (2011) and the migrants variable, which was derived from the population census of 2000. The precise definitions of the variables as well as summary statistics are given in Table 1.

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[14] The coastal region is comprised of Beijing, Tianjin, Hebei, Guangdong, Hainan, Shandong, Fujian, Zhejiang, Jiangsu, Shanghai, Liaoning and Guangxi; the central region consists of Shanxi, Inner Mongolia, Jilin, Heilongjiang, Anhui, Jiangxi, Henan, Hubei and Hunan, and the western region is formed from the remaining provinces.

Table 1: Definition and Description of Variables

Group	Variables	Definition	mean	Std. Dev	min	max
Geography	COD	Regional dummy for the coast	0.39	0.50	0	1
	CED	Regional dummy for the central	0.32	0.48	0	1
	WED	Regional dummy for the west	0.29	0.46	0	1
	DIS1	Distance to the nearest coast major port (kilometers)	533.90	548.37	0	2505.89
	DIS2	Distance to the coast (kilometers)	524.73	527.35	0.17	2463.29
	DIS3	Distance to the nearest major port (kilometers)	352.47	466.93	0	2302.87
Initial condition	G2006	Provincial output growth rate in 2006(%)	13.04	1.44	11.00	18.00
	G2004-06	Provincial output growth rate, 2004-2006(%)	12.94	1.86	10.73	20.77
	RGDP2004-06	Real provincial output (billion yuan, 1953 price)	155.62	127.93	11.74	449.73
	RGDPpc2004-06	Real provincial output per capita (yuan, 1953 price)	4381.66	4835.40	841.51	26274.60
Economic structure	SOESH	Share of SOE in urban employment (%)	40.65	10.45	19.50	57.85
	INVSH	Share of total investment in output(%)	46.53	8.95	30.68	70.37
	MKT	Marketisation index	6.45	1.70	3.16	9.90
	ENESH	Energy consumption (thousand ton coal/10 thousand yuan)	1.64	0.82	0.78	4.12
	PRIM	Share of population with primary education(%)	32.12	7.33	14.18	46.67
	SENH	Share of population with senior high school education(%)	13.73	4.23	6.84	26.11
	COLL	Share of population with college or above education(%)	7.03	4.83	3.44	25.91
	URBSH	Share of urban population(%)	46.61	15.14	27.16	88.90
	MIG	Share of migrants in population(%)	4.09	5.31	0.39	19.11
	IMPSH	Share of imports in output(%)	18.43	27.36	1.65	110.23
	EXPSH	Share of exports in output(%)	19.64	23.45	3.62	87.02

Notes: The data are taken from Wu (2004), Fan et al. (2011), the population census of 2000, and the China Statistical Yearbook (NBSC, various issues). For Beijing, import exceeds total output so the maximum value of IMPSH is larger than 1.

5. RESULTS

Our empirical work proceeds in two stages, both of which examine the resilience of the Chinese provinces in the wake of the national growth slowdown which China has experienced since 2007. In the first stage, we use a more conventional measure of provincial response based on their (total) growth rate. In this stage, we examine both the change in the level of growth as well as its variability, both measured relative to the nation as a whole. In the second stage, we extend this analysis by using the SoM approach to decompose provincial growth rates into the provincial response to the national slowdown and an idiosyncratic provincial component (called the national and provincial components, respectively).

We have argued earlier in the paper that the national component is a more appropriate basis for the analysis of regional resilience than the overall growth and we repeat the analysis of the level and variability effects using this national component. We compare the results to those obtained in the first stage to gauge the importance of removing the effects of province-specific factors and, in both stages, provide some informal analysis of the results based on correlations with a number of provincial characteristics. In the literature reviewed earlier in the paper, it is common to carry out a cross-sectional regression analysis of the resilience measures across the regions. We do not report such results. The literature has suggested many possible explanations, and, with only 30 cross-section observations, it is impossible to clearly distinguish between the effects of 20 or so possible regressors that can be identified as being potentially useful at the cross-section stage.

5.1. Resilience Based on Regional Growth Rates

Recall that we measure the extent of the growth slowdown in province k by the sensitivity index, *SI*, and the *variability* of the decline for each province by the variability index, *VI*, both defined in section 3. The time period for which we measure the indexes is from 2007 to 2018. For reasons discussed in section 2, we date the beginning of the slowdown from 2008 so that 2007 is the last pre-slowdown year. While shorter horizons might be appropriate for the investigation of temporary shocks such as the GFC (where often windows of three to four years are used), this would not be appropriate for the long-term nature of the Chinese slowdown, which many would argue was still continuing in 2018, the end of our sample period. The values of the sensitivity index can be gauged from Figure 3 where the height of the bars (the provincial growth decline) above (or below) the red line (the national growth decline) represent the negative (or positive) of *SI*. The actual numbers are reported in the first two columns of figures in Table 2.

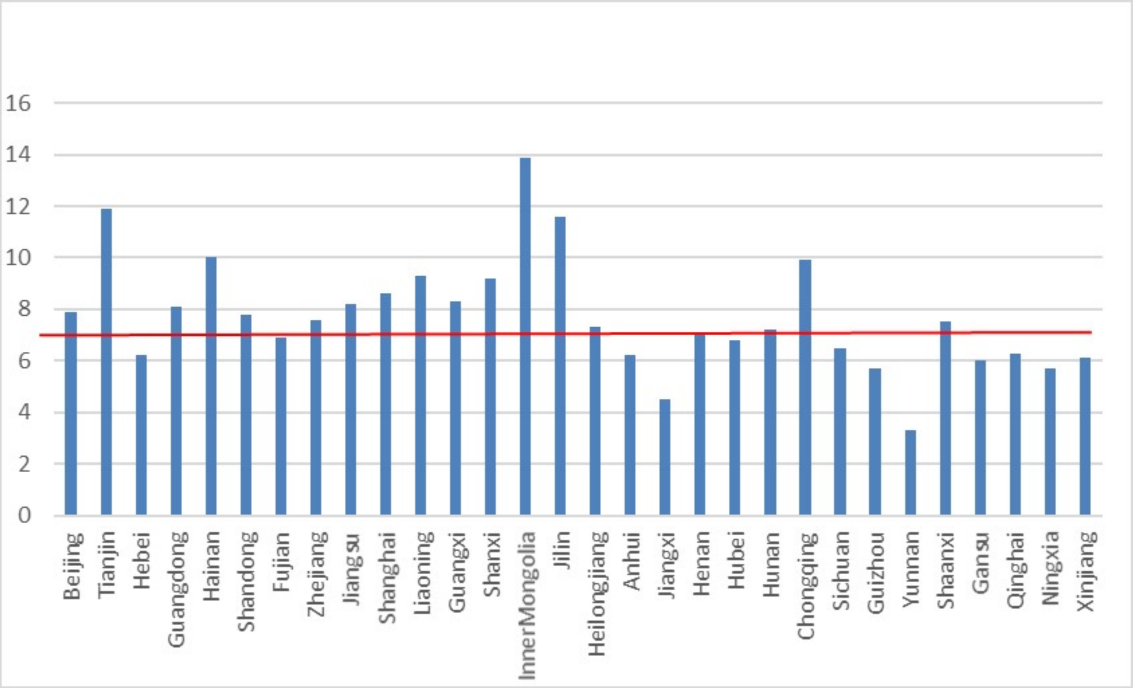
There is clearly considerable variation in both the *SI* and *VI* across provinces which makes an analysis of the resilience of China's provincial economies in the face of the national growth slowdown worthwhile. It can be seen from Figure 3 that almost one-half of the provinces experienced growth declines in excess of the nation as a whole (blue bars above the red line), and this is reflected in the negative values for the index *SI* in Table 2. Similarly, about one-half of the *VI* values in Table 2 are positive, which indicates that the growth variability was greater over the period 2007 to 2018 for approximately half of the provinces. There does not seem to be systematic variation in *VI* across provinces. There is a weak

Table 2: Sensitivity Indexes and Variability Indexes (percentage points)

Province	SI	VI	SI-N	SI-P	VI-N	VI-P
Beijing	-0.30	0.38	0.55	-0.49	0.49	0.00
Tianjin	-4.30	2.36	-2.49	-1.45	-0.46	4.45
Hebei	1.40	-0.02	-0.10	1.86	0.61	0.45
Guangdong	-0.50	0.36	-1.54	1.40	0.60	0.45
Hainan	-2.40	1.78	1.94	-3.98	4.44	2.53
Shandong	-0.20	-1.00	0.82	-0.66	0.54	0.51
Fujian	0.70	-0.76	-1.56	2.62	0.72	0.55
Zhejiang	0.00	0.70	-3.18	3.54	1.33	0.13
Jiangsu	-0.60	-0.98	-2.00	1.76	1.51	1.29
Shanghai	-1.00	1.15	3.47	-4.10	-0.64	1.50
Liaoning	-1.70	6.05	-4.68	3.34	0.71	7.41
Guangxi	-0.70	-0.59	2.12	-2.46	-0.24	0.32
Shanxi	-1.60	8.81	1.41	-2.65	1.05	5.69
Inner Mongolia	-6.30	-0.23	3.74	-9.68	-0.41	0.87
Jilin	-4.00	0.08	-1.03	-2.61	0.21	2.41
Heilongjiang	0.30	0.44	1.29	-0.63	-0.60	1.02
Anhui	1.40	-0.29	1.20	0.56	0.51	2.25
Jiangxi	3.10	-0.71	2.32	1.14	0.01	1.00
Henan	0.60	-0.58	1.05	-0.09	0.12	-0.06
Hubei	0.80	-0.42	-0.25	1.41	-0.08	0.58
Hunan	0.40	-0.70	2.14	-1.38	-0.69	0.35
Chongqing	-2.30	0.95	1.59	-3.54	-0.39	2.47
Sichuan	1.10	1.75	2.29	-0.83	-0.23	1.93
Guizhou	1.90	0.56	3.52	-1.26	0.48	1.92
Yunnan	4.30	0.86	2.47	2.19	0.01	1.61
Shaanxi	0.10	-0.25	-1.24	1.70	0.25	1.18
Gansu	1.60	1.71	0.02	1.94	-0.58	2.84
Qinghai	1.30	1.00	3.63	-2.00	-0.55	1.67
Ningxia	1.90	-0.44	2.60	-0.34	-0.16	0.90
Xinjiang	1.50	0.82	5.98	-4.12	-0.40	2.64

Notes: The indexes are defined as follows: $SI_k = (g_{k2018} - g_{k2007}) - (g_{2018} - g_{2007})$, and $VI_k = sd_{2007,2018}(gdt_k) - sd_{2007,2018}(gdt)$, where g_t and g_{kt}, are the growth rates for province k year t and the nation as a whole in year t, $sd_{2007,2018}$ is the standard deviation over the period 2007-2018 and gdt_k and gdt represent the de-trended growth rates for province k and the nation as a whole. $SI-N$, $SI-P$, $VI-N$ and $VI-P$ are the corresponding indexes based on the national (N) and provincial (P) components of the provincial growth rates.

Figure 3: Growth Decline (in percentage points) from 2007 to 2018, by Province (blue bars) and the National Growth Decline (red line)



negative correlation (-0.23) between *SI* and *VI*, suggesting that provinces with larger falls in growth tended to have higher variability relative to the nation as a whole. Recall that *SI* is negative (positive) if the province's fall in growth exceeds (falls short of) that of the country as a whole, in which case the province is said to be non-resilient (resilient). Hence, there is weak evidence that the less resilient provinces also suffer greater variability in their growth slowdown.

We now proceed to a more systematic exploration of the indexes, starting with *SI*. As a preliminary matter, we examine the possibility of spatial autocorrelation in *SI* by computing Moran's I, which can be used to test the significance of the relationship between *SI* and its spatial lag. The value for the statistic is 0.143 with a p-value of 0.148, suggesting that there is weak but insignificant positive spatial autocorrelation.

Next, we turn to a more formal analysis of the relationship between *SI* and a number of provincial characteristics. As we pointed out earlier, there are too few cross-section observations relative to the potential determinants to carry out a formal cross-sectional regression analysis. Instead, we compute correlations between the index and individual provincial characteristics. For this purpose, we group the potential determinants into three groups – geographic, economic, and structural. In the first group, we include three regional dummy variables as well as several variables which measure the distance of each province from the coast. In the second, we include provincial RGDP averaged over the period of 2004 to 2006 as a measure of economic size, RGDP per capita averaged from 2004 to 2006 as a measure of development and two measures of lagged growth – one for 2006 and the other an average of 2004 to 2006. In the third group, we include two summary measures of a large number of variables capturing provincial economic structure. In particular, we considered the following variables (see Table 1 for variable definitions): SOESH, INVSH, MKT, ENESH, EXPSH, IMPSH, PRIM, SENH, COLL, URBSH and MIG and examined their correlations. We found that they naturally divided into two groups, each group having high positive correlations with each other but negative correlations with the members of the other group. The correlations are shown in the Appendix, Table A1.

The first group consisted of SOESH, INVSH and ENESH, while the second group included the remaining variables: MKT, EXPSH, IMPSH, EDUYR, URBSH, and MIG. High values of the first group tend to be associated with provinces with traditional manufacturing structures, while the second group characterizes provinces with urban, educated, high-tech industry structures.[15] We combined each group into a single index by averaging the normalized variables and called the first INDEXOLD and the second INDEXNEW (for old and new industry structure).

The correlations of each of these with SI are reported in the first column of figures in Table 3.

Table 3: Correlations of indexes and determinants

Determinant	SI	VI	SI-N	SI-P	VI-N	VI-P
Geography:						
COD	-0.2572	0.0105	-0.5028	0.2190	0.4450	-0.0305
CED	-0.1425	-0.0159	0.1271	-0.2178	-0.1743	-0.0502
WED	0.4174	0.0046	0.4104	-0.0164	-0.3015	0.0828
DIST1	0.3429	0.0099	0.5732	-0.2109	-0.4272	0.0795
DIST2	0.3365	-0.0081	0.5602	-0.2050	-0.4297	0.0749
DIST3	0.2603	0.0288	0.5342	-0.2427	-0.3237	0.0857
Economic:						
G2006	-0.6547	-0.1926	-0.3247	-0.2418	-0.0608	-0.0803
G2004-06	-0.6479	-0.0749	-0.1474	-0.3847	0.0783	-0.0942
RGDP2004-06	-0.1141	-0.0825	-0.4581	0.2941	0.1251	-0.1466
RGDPpc2004-06	-0.2899	0.1043	-0.1068	-0.1374	-0.1001	0.0609
Structure:						
Indexnew	-0.3400	0.0510	-0.3410	0.0193	0.0973	-0.0406
Indexold	0.1837	0.1407	0.5326	-0.3020	-0.2477	0.1737

Notes: The figures in the body of the table are correlation coefficients of the index at the head of the column with the relevant determinant. The variables are defined in Table 1. The 5% critical value is 0.35.

The variables representing geography show some significant correlations with the sensitivity index; in particular, it appears that the western provinces exhibited smaller falls in growth than the coastal and central provinces or, alternatively, that the closer to the

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[15] Note that in Table A1 we have three education variables: PRIM, SENH and COLL. Not surprisingly, PRIM is highly negatively correlated with the other two, which are, in turn, highly positively correlated with each other. We, therefore, combined these three variables into a single one that measured: average years of education, EDUYR, which is what we included in our new-industry index.

coast is a province, the less resilient it was to the growth slowdown. This is also evident in Figure 3 where the western provinces (the right-hand end of the horizontal axis) generally show smaller falls in growth. This distance effect is rather surprising since one might have supposed that the coastal provinces, being more advanced and flexible and being more integrated into the world market and so having alternative avenues for selling output, would have suffered less as a result of the slowdown. A possible explanation is that the coastal provinces have traditionally been highly dependent on the migration of labor from the interior to the coast and one of the commonly-cited drivers of the slowdown is the drying–up of the surplus agricultural labor (see, e.g., Golley and Meng (2011); Meng (2012); Roberts and Cai (2015); Cai (2016); Lou (2016); Chen and Groenewold (2021)). He et al. (2021) argues that regions (cities in their case) with high levels of foreign investment are likely to be more sensitive, although they consider the effects of demand shocks rather than the supply shocks which we consider. To the extent that foreign investment is concentrated in the coastal provinces in China, this would provide some indication of why the coastal provinces would be less resilient.

The correlation with lagged growth is significant and negative – the higher the pre-slowdown growth rate, the larger the fall in growth when the slowdown hit. This is true whether we use the 2006 growth rate or, to reduce reliance on a particular year, the average of the growth rates for 2004, 2005 and 2006. The high-growth provinces were, therefore, less resilient in the face of the slowdown. The correlations with the level of RGDP and RGDP per capita were also negative but smaller and insignificant. Thus, economic size (as measured by RGDP) and economic development (as measured by RGDP per capita) are only weakly related to a provincial response to the slowdown. The negative effect of per capita RGDP is consistent with the finding of He et al. (2021).

Finally, the correlations of SI with the industry-structure summary measures show that the new-industry provinces tend to be less resilient and the old-industry provinces more resilient. This is consistent with the other correlations: new-industry provinces tend to be near the coast and to be high growth and *vice versa*. It is also potentially consistent with the evidence presented in He et al. (2021) that regions with many related products are less resilient since it is likely that these are more prevalent in new industries than old industries. It appears in contrast to the findings by Tan et al. (2020) that cities dominated by secondary and tertiary industries tend to be more resilient, but, as for He et al. (2021), they consider cities rather than provinces and demand rather than supply shocks.

Turning briefly to the correlations of the variability index with the province-specific determinants, which are reported in the second column of figures in Table 3, we find that, in contrast to the previous results, there are only very weak correlations between VI and the provincial characteristics. In fact, none of the correlations is significant, so little can be said about the "determinants" of the differences in variability across provinces. As noted earlier, there is a weak negative correlation between the SI and VI indexes, suggesting that provinces with a larger growth fall also suffered greater growth volatility in the transition to the new low-growth state.

We now turn to the second stage of our investigation, in which we first decompose growth rates into national and provincial components and then focus on the national component as the appropriate measure to use for resilience analysis.

5.2. Resilience Based on the National Component of Growth

Recall that we use an SoM approach to distinguish between national and provincial shocks driving provincial growth rates and then compute the national component of each provincial growth rate as the accumulative effects of past and present national shocks and similarly for the provincial component. We then recompute the *SI* and *VI* indexes for each component, labelling them *SI-N*, *SI-P*, *VI-N* and *VI-P* where "*N*" and "*P*" denote that the indexes are computed from national and provincial components of growth. We report the numbers in the relevant columns of Table 2 above. The underlying estimated VAR models are reported in Appendix Table A2.

Before analyzing the relationship between the indexes and the various determinants, we present some preliminary properties of the indexes. First, we also computed Moran's I statistic for SI-N to assess spatial autocorrelation in these variables; the value of the statistic is 0.051 with a p-value of 0.485. Thus, again, there is (very) weak and insignificant positive spatial autocorrelation. Second, since we argued that it is the national component of growth that should be the basis for the analysis of the resilience of Chinese provinces, it is important to ask whether there is a substantial difference between total growth and the national component of growth. In Figure 4 we picture adjusted total growth and its national component for each of the provinces for the period 2007-2018.[16]

Several aspects of the graph stand out. First, the general shape of the national component is similar across provinces, although there are noticeable variations. Second, it appears that more of the growth decline over the period is driven by the national than the provincial component and this is borne out in Figure 5 in which we picture the change in the *N* component between 2007 and 2018 as a proportion of the change in the adjusted growth rate over the same period.[17]

It can be seen that, with few exceptions, the national component accounts for a large proportion of the change in total growth (the mean of the ratio is 0.92). The correlation between total growth and the national component over the period 2007-2018 averages 0.82 across the provinces while that with the provincial component averages 0.56. It is interesting that there appears to be some similarity between the *N* proportion of adjusted growth across provinces and the *SI* index itself although the correlation is only 0.47. We have included the value of *SI* for each province in Figure 5 to illustrate this relationship.

Third, from Figure 4 it is clear that there is far more variation across the provinces in the adjusted growth curve than there is in the national component, reflecting the fact, not surprisingly, that the provincial component varies more from province to province and this accounts for much of the cross-province variation in growth as a whole. Again, this is borne

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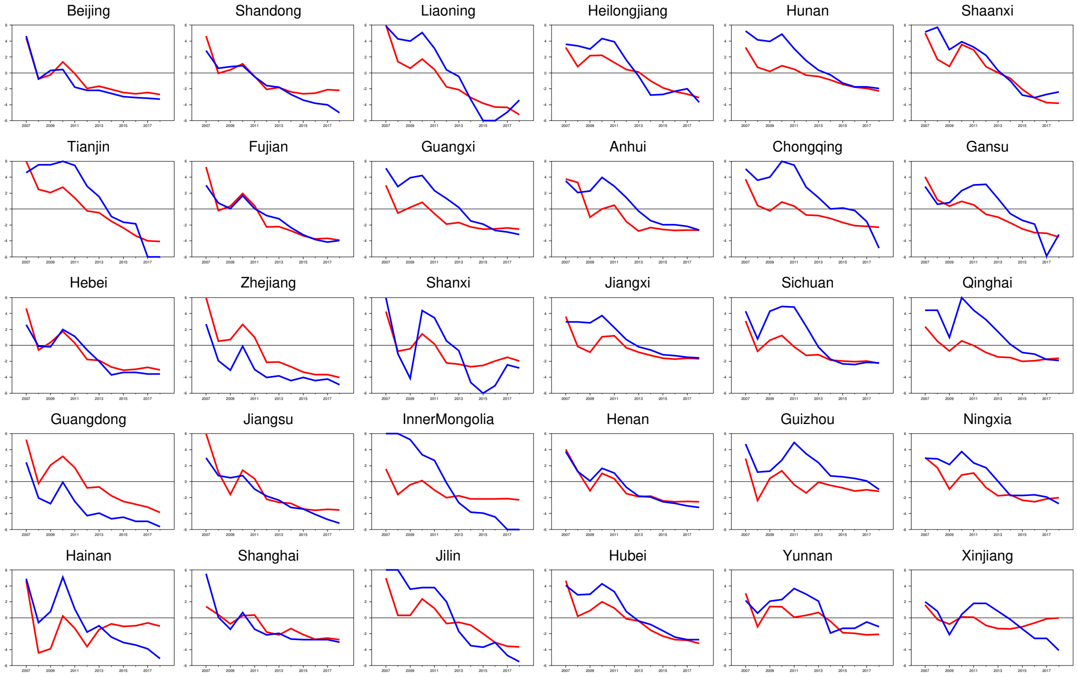
[16] We make an adjustment to the growth rate by subtracting the mean because the decomposition procedure also produces a third component which captures the deterministic part of the VAR model, in our case just the intercept and so is constant over time. The adjusted growth lines omit this component to ensure the comparability of the scales of the two variables. An almost identical graph is produced if we use the sum of the N and P components instead of adjusted growth.

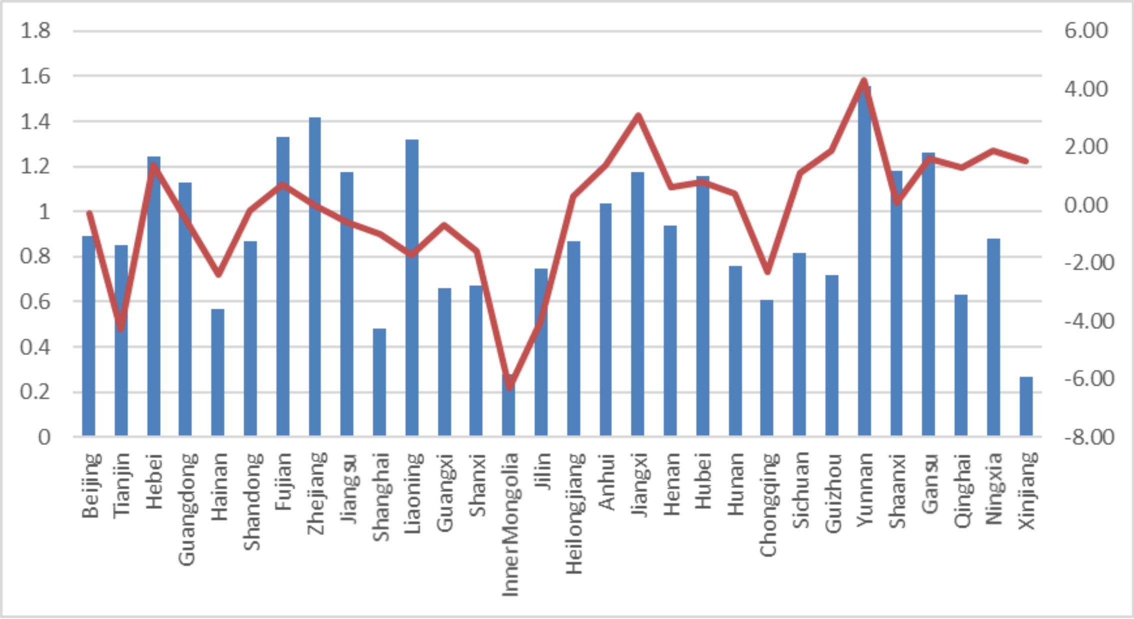
[17] Note that since the adjustment is to remove a constant it does not affect the change over time so Figure 5 might as well use the change in the total growth rate; we continue to use the adjusted growth rate to emphasize the link to Figure 4: the bars in Figure 5 are simply the proportion of the change between the endpoints in the blue line accounted for by the corresponding change in the red line in Figure 4.

Figure 4: National component and adjusted growth by province, 2007 to 2018



Notes: red = national component, blue = adjusted growth

Figure 5: Proportion of the change in adjusted growth accounted for by the change in the national component (blue bars, left-hand axis) and SI (red line, right-hand axis)



out by the fact that, on average, the correlation between the deviation of provincial growth from Chinese national growth rate and the provincial component is 0.80, while it is only 0.12 for the national component. Thus analyzing resilience using provincial growth rather than the national component of the provincial growth rates is likely to inject significant spurious elements into the analysis.

More importantly, perhaps, we should consider the differences in the sensitivity indexes based on the two growth measures – *SI* and *SI-N* – since these are the basis for deciding whether a province has been resilient or not in the face of the growth slowdown. Considering the relevant columns in Table 2, it is clear that there are numerous changes in sign if we move from using *SI* to using *SI-N*. Indeed, there are 13 such changes – almost one-half of the provinces switch categories. Eight change from non-resilient to resilient, and five switch in the opposite direction. The cross-province correlation between *SI* and *SI-N* is only 0.24 although the (Spearman) rank correlation is somewhat higher at 0.33.

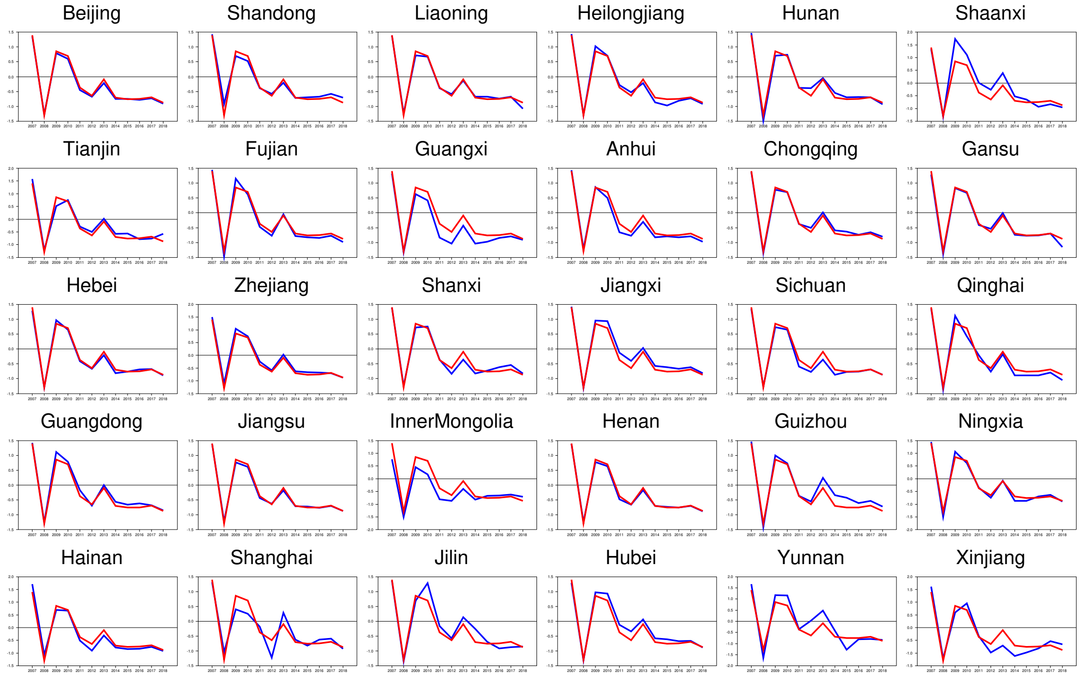
Thus, very different conclusions regarding the resilience of provinces will be reached depending on whether this is based on the change in total provincial growth or on the change in the national component of provincial growth. So, for example, Gansu province is ranked 5^{th} most resilient on the basis of SI, but only 20^{th} on the basis of *SI-N* and Inner Mongolia is ranked last on the basis of *SI* but 2^{nd} on the basis of *SI-N*. At the very least, this indicates the sensitivity of the rankings to the underlying measure of growth and the importance of careful consideration of how this underlying measure should be defined.

A final preliminary aspect of the decomposed growth rates is prompted by a question raised by our earlier evaluation of the SoM approach to the modeling of provincial growth rates. The underlying notion of each province's growth rate having a national component is that the forces driving this component are the same for all provinces (although provinces may respond differently). But, as we pointed out in our discussion of the model, this is not guaranteed by the SoM approach, which re-defines the national shocks in each iteration. To check whether there are important differences between the implied national shocks, we compare the national shock series generated by each iteration of the VAR model in Figure 6 and include in each graph the RGDP-weighted average of all 30 shock series. It is clear from this figure that the shocks are very similar across provinces – the average correlation between the national shocks and the average of these shocks across all provinces is 0.98. Thus we can conclude that the weakness of the SoM approach that the national shocks are not constrained to be identical across provinces is not very serious in this particular application.

Consider now the relationship between the *SI-N* and *SI-P* indexes and the "determinants" we used above in our exploration of the factors which might underlie the cross-provincial variation in the *SI* index. We include correlations for *SI-N* and *SI-P* and the same set of determinants used previously in Table 3. For the geography factors (regional dummy variables and distance from the coast) the correlations with *SI-N* are generally stronger than for *SI*. In particular, the distance variables are more important once the sensitivity measure has been purged of province-specific influences so that the use of *SI* rather than *SI-N* significantly underplays the importance of distance from the coast as a factor in resilience.

The opposite is true for the lagged growth variables. In this case the strong negative correlations we found previously for *SI* are more the result of autocorrelation in *SI-P* than

Figure 6: National component for each province and the national average of these components, 2007-2018



Notes: blue=national component for each province, red=average of national components

in *SI-N*. It follows that the inappropriate use of a measure based on total growth substantially exaggerates the effects of lagged growth on resilience. In contrast, size now matters – the lagged RGDP variable is now significantly correlated with *SI-N* where it was not so for *SI*. Surprisingly, greater economic size makes a province less resilient.

Finally, the correlation with the structure indexes are also sensitive to whether total growth or its national component is used as a basis for the measurement of sensitivity. In particular, using the national component makes the old structure index significantly positively correlated with sensitivity – the greater the concentration of old rather than new industries in a province, the more resilient the provincial economy was to the slowdown. This effect was previously masked by a strong effect of the opposite sign through the provincial component of growth.

Consider now the variability indexes in Table 2. When the index was based on total growth, we found weak evidence that the less resilient provinces also had greater variability in the transition to the slower growth rate. This effect is strengthened when the national component of growth is used, although it is still weak. A comparison of all three versions of the index – *VI*, *VI-N* and *VI-P* – shows that most of the cross-province variation in the index is associated with the provincial component – the correlation between *VI* and *VI-N* is only 0.17 but between *VI* and *VI-P* it is 0.85.

As to the correlation between the *VI* index and the determinants, previously, we concluded that none of the variables we considered had a significant correlation with the variability index based on total growth. However, an inspection of the results in Table 3 based on the decomposition of the growth rates shows that for the geography variables, this was an artifact of the underlying data. In particular, if the variability index is based on the national component of provincial growth, as we argue it should be, there are strong geographical effects that were previously masked by the opposite effects of province-specific shocks. Now it appears that provinces closer to the coast have shown greater variability in their path to the new slower growth rate and that this is particularly true for the coastal provinces. Moreover, the signs of the correlation with the structure indexes suggest that new-industry provinces suffered greater variability than old-industry provinces. On the other hand, the economic variables continue to have no significant correlation with the variability index.

In conclusion, we can say that the measure of growth underlying the resilience index calculations matters. When we use just the national component, as we argue we should, the ranking of the provinces according to their resilience is very different from the ranking based on more traditional total growth measures. Further, the correlations with province-specific variables also change when we remove the effects of province-specific shocks from the underlying growth rate. This is true both for the sensitivity index and for the variability index. Generally, the finding is that provinces closer to the coast and with the new-industry structure were less resilient and experienced greater variability in the transition to the new lower growth levels.

6. CONCLUSIONS

In this paper, we have reported an empirical analysis of the resilience of China's provinces in the face of the growth slowdown which China has experienced since 2007. We initially reported results for resilience based on traditional measures of economic growth and found that, surprisingly, resilience is greater for provinces distant from the coast, with lower pre-slowdown growth rates and with an old industry rather than a new-industry structure. In several cases, the signs of the relationship between resilience and the "determinants" contrasted with those found in the limited existing literature on China, although the comparison is made difficult by the fact that the two most closely-related papers (Tan et al., 2020; He et al., 2021) use city-level data and appear to focus on demand shocks in contrast to our work which uses province-level data and analyzes supply shocks.

We argued that these traditional measures were less than satisfactory, however, in that the observed growth rates changed not only as a result of the national slowdown but also in response to province-specific factors and that the latter should be purged from the growth rates to provide more satisfactory measures of resilience. We achieved this purging by using a sequence of VAR models and re-computed the resilience indexes, and found that the new measures produced a very different ranking of the provinces in terms of their resilience. We found that the use of the national component rather than total growth also had a substantial effect on the correlations with the "determinants" which we explored. In particular, both the distance effects and the structure effects were strengthened when we removed the province-specific shocks from the underlying growth rates.

We also computed a variability index which measured the variability of each province's transition to the new lower growth regime. These were found to be weakly correlated with the sensitivity index and once we used the national component of the growth rate, they were strongly negatively correlated with distance from the coast – provinces close to the coast experienced greater variability in the process of slowing growth. There was also weak evidence that variability was greater for new-industry provinces than for old-industry provinces.

All in all, the use of the national component of provincial growth rates rather than total growth matters, both for ranking provinces according to resilience and for correlations of resilience with determinants capturing provincial characteristics. Generally, we found that provinces close to the coast with new- rather than old-industry structures are less resilient and tended to suffer greater variability in growth during the slowdown. These results are surprising in the light of the existing literature and worthy of further detailed research.

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Table A1: Correlations of main determinants

	SOESH	INVSH	MKT	ENESH	EXPSH	IMPSH	PRIM	SENH	COLL	URBSH	MIG
SOESH		0.20	-0.87	0.55	-0.76	-0.67	0.30	-0.42	-0.41	-0.66	-0.61
INVSH	0.20		-0.45	0.67	-0.44	-0.41	0.31	-0.35	-0.17	-0.32	-0.35
MKT	-0.87	-0.45		-0.70	0.80	0.68	-0.41	0.49	0.40	0.67	0.60
ENESH	0.55	0.67	-0.70		-0.47	-0.47	0.28	-0.39	-0.24	-0.42	-0.35
EXPSH	-0.76	-0.44	0.80	-0.47		0.81	-0.46	0.60	0.50	0.76	0.82
IMPSH	-0.67	-0.41	0.68	-0.47	0.81		-0.68	0.79	0.84	0.88	0.91
PRIM	0.30	0.31	-0.41	0.28	-0.46	-0.68		-0.91	-0.80	-0.79	-0.54
SENH	-0.42	-0.35	0.49	-0.39	0.60	0.79	-0.91		0.87	0.90	0.69
COLL	-0.41	-0.17	0.40	-0.24	0.50	0.84	-0.80	0.87		0.85	0.76
URBSH	-0.66	-0.32	0.67	-0.42	0.76	0.88	-0.79	0.90	0.85		0.80
MIG	-0.61	-0.35	0.60	-0.35	0.82	0.91	-0.54	0.69	0.76	0.80	

Notes: The variables mnemonics are defined in Table 1. The 5% critical value for the correlation coefficients is 0.35.

Table A2: Estimation Results for 30 Provinces

Variables	BJ	TJ	HB	GD	HI	SD	FJ	ZJ	JS	SH
g_{-1}	0.57	0.05	0.21	0.22	0.23	-0.03	0.66	0.47	1.58	1.24
	(0.34)	(0.31)	(0.39)	(0.39)	(0.57)	(0.48)	(0.32)	(0.49)	(0.40)	(0.28)
g_{-2}	-0.09	0.01	-0.33	-0.58	-1.00	-0.54	-0.36	-0.61	-0.84	-1.45
	(0.32)	(0.30)	(0.39)	(0.39)	(0.54)	(0.42)	(0.33)	(0.47)	(0.42)	(0.28)
$g_{k,-1}$	0.13	0.85	0.54	0.50	0.25	0.64	0.33	0.51	-0.17	-0.11
	(0.23)	(0.22)	(0.29)	(0.24)	(0.20)	(0.33)	(0.19)	(0.26)	(0.25)	(0.23)
$g_{k,-2}$	-0.33	-0.18	-0.02	0.30	0.04	0.19	-0.12	-0.03	0.06	0.95
	(0.23)	(0.22)	(0.29)	(0.24)	(0.18)	(0.31)	(0.19)	(0.26)	(0.24)	(0.23)
C	7.27	3.02	6.16	5.79	15.51	7.35	6.67	7.37	6.36	3.65
	(2.15)	(2.28)	(1.92)	(2.34)	(4.25)	(2.18)	(2.35)	(2.71)	(2.23)	(1.43)
Adj. R^2	0.16	0.48	0.30	0.36	0.12	0.28	0.30	0.33	0.43	0.62

Variables	LN	GX	SA	IM	JL	HL	AH	JX	HN	HU
g_{-1}	0.52	-0.06	0.31	0.04	0.52	0.04	1.10	0.45	1.24	0.70
	(0.45)	(0.26)	(0.38)	(0.33)	(0.38)	(0.17)	(0.27)	(0.23)	(0.27)	(0.32)
g_{-2}	-0.29	-0.13	-0.42	-0.25	0.18	0.01	-0.48	-0.31	-0.42	-0.26
	(0.45)	(0.26)	(0.36)	(0.32)	(0.37)	(0.17)	(0.32)	(0.23)	(0.29)	(0.32)
$g_{k,-1}$	0.52	0.67	0.38	0.55	0.30	0.59	0.16	0.33	-0.32	0.08
	(0.27)	(0.20)	(0.20)	(0.18)	(0.20)	(0.19)	(0.17)	(0.19)	(0.18)	(0.22)
$g_{k,-2}$	-0.11	0.05	0.00	0.19	-0.44	0.13	-0.04	-0.17	-0.04	0.05
	(0.26)	(0.19)	(0.20)	(0.18)	(0.20)	(0.18)	(0.15)	(0.17)	(0.18)	(0.21)
C	3.22	4.59	7.15	5.24	4.93	1.85	3.62	7.39	6.85	4.92
	(2.76)	(2.03)	(2.72)	(2.61)	(2.78)	(1.53)	(2.36)	(1.80)	(2.21)	(2.20)
Adj. R^2	0.37	0.36	0.14	0.38	0.20	0.40	0.35	0.29	0.33	0.18

Variable	HA	CQ	SC	GZ	YN	SX	GS	QH	NX	XJ
g_{-1}	0.10	0.33	-0.02	-0.20	0.39	1.24	0.82	0.53	0.80	0.07
	(0.18)	(0.24)	(0.25)	(0.26)	(0.25)	(0.33)	(0.30)	(0.16)	(0.21)	(0.18)
g_{-2}	-0.19	-0.52	-0.19	-0.10	-0.09	-0.74	-0.35	-0.75	-0.70	-0.23
	(0.18)	(0.24)	(0.25)	(0.26)	(0.26)	(0.36)	(0.32)	(0.16)	(0.22)	(0.16)
$g_{k,-1}$	0.81	0.51	0.51	0.45	-0.13	-0.10	-0.01	0.24	0.25	0.65
	(0.22)	(0.21)	(0.23)	(0.20)	(0.20)	(0.19)	(0.19)	(0.10)	(0.18)	(0.18)
$g_{k,-2}$	-0.07	0.24	0.22	0.06	0.08	0.41	0.22	0.62	0.30	-0.07
	(0.21)	(0.21)	(0.23)	(0.19)	(0.20)	(0.22)	(0.18)	(0.07)	(0.17)	(0.18)
C	3.54	4.42	4.77	7.91	7.85	2.71	3.15	3.52	3.53	5.75
	(1.29)	(1.80)	(1.86)	(2.27)	(2.32)	(2.36)	(2.41)	(1.39)	(1.70)	(1.73)
Adj. R^2	0.55	0.45	0.26	0.12	-0.02	0.30	0.17	0.69	0.43	0.34

Notes: Standard errors are in parentheses. BJ, TJ, HB, GD, HI, SD, FJ, ZJ, JS, SH, LN, GX, SA, IM, JL, HL, AH, JX, HN, HU, HA, CQ, SC, GZ, YN, SX, GS, QH, NX, XJ are abbreviations for Beijing, Tianjin, Hebei, Guangdong, Hainan, Shandong, Fujian, Zhejiang, Jiangsu, Shanghai, Liaoning, Guangxi, Shanxi, Inner Mongolia, Jilin, Heilongjiang, Anhui, Jiangxi, Henan, Hubei, Hunan, Chongqing, Sichuan, Guizhou, Yunnan, Shaanxi, Gansu, Qinghai, Ningxia, Xinjiang.