CHAPTER 4 METHODOLOGY

According to previous literature reviewed, the relationship of growth and inequality could not be one-way, but instead is two-way. Therefore, one purpose of this study is to confirm if the causal relationships between growth and inequality exist. The purpose is similar to Lundberg and Squire (2003), but the most different characteristic of this study from other literature is the former tests an individual economy, China, rather than cross countries. Researching only one economy with time series data has two advantages.

1. Avoiding the problem of ignoring every country's characteristic that has been experienced in cross-section studies, the main argument against cross-section studies is that they assume all countries possess homogeneous economic structure. Forbes (2000) pointed out that the results of cross-section studies were not useful in providing policy implications because they did not show how a change in inequality was related to growth within a given country. Besides, the cross section analysis is very sensitive to a model setting.
2. Time series analysis allows the study to give more attention on explaining China's situation. Although panel data analysis can capture an individual country's characteristic, it focuses on proving an economic theory, which will not tell much about the influential channel between growth and inequality. Actually, the influential channel could not be the same in each country. No only does this study want to confirm their casual relations are positive or negative in China, but it also spends a lot of time explaining why they happen.

This section will be divided into several categories: (i) illustrating the Granger-Causality test; (ii) explaining Toda and Yamamoto procedure; (iii) presenting empirical model of this study and describing data source.

4.1 Traditional Granger-Causality Test

The most common way to test the causal relationships between two variables is the Granger-Causality proposed by Granger (1969). The test involves estimating the following simple *vector autoregressions* (VAR):

$$X_t = \sum_{i=1}^{n} \alpha_i Y_{t-i} + \sum_{j=1}^{n} \beta_j X_{t-j} + \mu_{1t} \tag{4.1}$$

$$Y_t = \sum_{i=1}^{m} \lambda_i Y_{t-i} + \sum_{j=1}^{m} \delta_j X_{t-j} + \mu_{2t} \tag{4.2}$$

where it is assumed that the disturbances μ_{1t} and μ_{2t} are uncorrelated. Equation (4.1) represents that variable X is decided by lagged variable Y and X, so does equation (4.2) except that its dependent variable is Y instead of X.[28]

Granger-Causality means the lagged Y influence X significantly in equation (4.1) and the lagged X influence Y significantly in equation (4.2). In other words, researchers can jointly test if the estimated lagged coefficient $\Sigma\alpha_i$ and $\Sigma\lambda_j$ are different from zero with F-statistic. When the jointly test reject the two null hypotheses that $\Sigma\alpha_i$ and $\Sigma\lambda_j$ both are not different from zero, causal relationships between X and Y are confirmed. The Granger-Causality test is easy to carry out and be able to apply in many kinds of empirical studies, such as export-led growth (Xu, 1996) and money theory (Friedman and Kuttner, 1992). However, traditional Granger-Causality has its limitations.

First, a two-variable Granger-Causality test without considering the effect of other variables is subject to possible specification bias. As pointed out by Gujarati (1995), a causality test is sensitive to model specification and the number of lags. It would reveal different results if it was relevant and was not included in the model. Therefore, the empirical evidence of a two-variable Granger-Causality are fragile

[28] VAR can add constant term, which depends on economic theory.

because of this problem.

Second, time series data are often non-stationary. This situation could exemplify the problem of spurious regression. Gujarati (1995) had also said that when the variables are integrated, the *F*-test procedure is not valid, as the test statistics do not have a standard distribution. Although researchers can still test the significance of individual coefficients with *t*-statistic, one may not be able to use *F*-statistic to jointly test the Granger-Causality. Enders (2004) proved that in some specific cases, using *F*- statistic to jointly test first differential VAR is permissible. First differential VAR also has its limitations, which cannot be employed universally.[29]

To sum up, because of the probable shortcomings of specification bias and spurious regression, this study does not carry out traditional Granger-Causality procedure to test the relationships between growth and inequality in China, but improved Granger-Causality procedure instead.

4.2 Toda and Yamamoto's VAR Procedure

A multivariable VAR model can remedy the first deficiency described above, but it still suffers the non-stationary problem. Besides, the non-stationary problem is worse in multivariable VAR because the probability is low to find that these time series variables have the same stochastic trend. Consequently, the most difficult parts of testing multivariable Granger-Causality are how to confirm the co-integrating relationship and how to estimate the VAR accurately when its system is integrated. The former had been discussed in many papers. Both the Johansen (1988) and the Stock and Watson (1988) procedures are two useful methods to test the co-integration,

[29] Only when the two-variable VAR has lagged length of two periods and only one variable is nonstationary, could it be transformed into first differential form (Enders, 2004; 285~287).

which rely on the relationship between the rank of a VAR model's matrix and its characteristic roots. This co-intergration technique was applied by Johansen and Juselius (1990), which involved transforming VAR into error corrected model (ECM) and identifying the coefficients associated with the causality. However, some researchers' interest is not in the co-integrating relationship, but in the hypothesis test or the significance of coefficients of a VAR model. Although some literatures has tried to discount the possible biases caused by integration (Mosconi and Giannini, 1992; Toda and Phillip, 1993),[30] Rambaldi and Doran (1996) argued that "the virtues of simplicity and ease of application have been largely lost."

It is in terms of avoiding integration and complexity that this study adopts the Toda and Yamamoto (1995) procedure to improve the power of the Granger-Causality test. Toda and Yamamoto procedure is a methodology of statistical inference, which makes parameter estimation valid even when the VAR system is not co-integrated. Before making a description of this study's empirical model, this section simply illustrates the rationale of Toda and Yamamoto procedure.

Let $\{y_t\}$ sequence be generated by the following linear function:

$$y_t = \beta_0 + \beta_1 t + \cdots + \beta_q t^q + \eta_t \tag{4.3}$$

Assume $\{\eta_t\}$ sequence is a vector autoregression with k lag length and it can be presented as:

$$\eta_t = J_1 \eta_{t-1} + \cdots + J_k \eta_{t-k} + \varepsilon_t \tag{4.4}$$

It is assumed that k is the lag length is optimal and ε_t is random vector. Transforming (4.3) into $\eta_t = y_t - \beta_0 - \beta_1 t - \cdots - \beta_q t^q$. Then substitute it into (4.4), getting equation (4.5):

[30] Mosconi and Giannini (1992) estimated the co-integrated system by applying likelihood test. Toda and Phillip (1993) requested researcher to transform an ECM to its levels VAR form, and then estimate it with WALD test.

$$y_t = \gamma_0 + \gamma_1 t + \cdots + \gamma_q t^q + J_1 y_{t-1} + \cdots + J_k y_{t-k} + \varepsilon_t \tag{4.5}$$

As order of integration $d>0$, the order of trend γ might be lower than order q. Assume $d=1$ and $q=1$, $\gamma_2 = \gamma_3 = \cdots = 0$ in equation (4.5). Then (4.3) becomes (4.6).

$$y_t = \gamma_0 + \gamma_1 t + J_1 y_{t-1} + \cdots + J_k y_{t-k} + \varepsilon_t \tag{4.6}$$

Toda and Yamamoto procedure is interested in the significance of coefficients of lagged y in (4.6), not the VAR's stationary position. Accordingly, the null hypothesis is to jointly test vector $\boldsymbol{J}$:

$$H_0 : J_1 = J_2 = \cdots = J_k = 0$$

Consider the following VAR:

$$y_t = \hat{\gamma}_0 + \hat{\gamma}_1 t + \cdots + \hat{\gamma}_q t^q + \hat{J}_1 y_{t-1} + \cdots + \hat{J}_k y_{t-k} + \cdots + \hat{J}_p y_{t-p} + \hat{\varepsilon}_t \tag{4.7}$$

where circumflex above coefficients represents estimated value and $p \geqq k+d$. Equation (4.7) includes at least d more lags than k in equation (4.6). Because k is assumed to be optimal lagged length, the coefficients of additional lag are indifferent from zero. Consequently, the null hypothesis is still unchanged. The primary achievement of Toda and Yamamoto (1995) was finding the statistical properties of null hypothesis via estimating equation (4.7). At first, they constructed a Wald statistic to test the null hypothesis. Then they proved that Wald statistic is asymptotically distributed as chi-square with usual degree of freedom if $p \geqq k+d$. What is most important is that the asymptotic property does not depend on whether equation (4.7) is integrated or cointegrated.[31] Furthermore, Toda and Yamamoto (1995) suggested that researchers could estimate a $(k+d_{max})$th-order VAR, where d_{max} is the maximal order of integration, and then jointly test k order lagged coefficients.

[31] See Toda and Yamamoto (1995; p230~233) for proving process.

One advantage of Toda and Yamamoto procedure is that it makes Granger-Causality test easier. Researchers do not have to test cointegration or transform VAR into ECM. Rambaldi and Doran (1996) proved that the *VAR* process created by Toda and Yamamoto as applied to the Granger non-causality test could be built into a seemingly unrelated regression (SUR) form. For example, a three-variable (*X*, *Y* and *Z*) VAR can be expressed in the following SUR form:

$$\begin{bmatrix} X_t \\ Y_t \\ Z_t \end{bmatrix} = A_0 + A_1 \begin{bmatrix} X_{t-1} \\ Y_{t-1} \\ Z_{t-1} \end{bmatrix} + \cdots + A_k \begin{bmatrix} X_{t-k} \\ Y_{t-k} \\ Z_{t-k} \end{bmatrix} + A_{k+1} \begin{bmatrix} X_{t-k-1} \\ Y_{t-k-1} \\ Z_{t-k11} \end{bmatrix} + \cdots + A_{k+d} \begin{bmatrix} X_{t-k-d} \\ Y_{t-k-d} \\ Z_{t-k-d} \end{bmatrix} \quad (4.8)$$

Equation (4.8) allows a researcher to test the relationship between any two variables. Suppose one want to see if *Y* affects *X*, he or she has to test the null hypothesis with chi-square statistics:

$$H_0\text{: } \alpha_1^{(12)} = \alpha_2^{(12)} = \ldots = \alpha_k^{(12)} = 0$$

where $\alpha^{(12)}$ are the coefficients of *Y*. If the null hypothesis is rejected, then the one-way effect can be confirmed. The alternative null hypothesis test reverses the influential direction:

$$H_0\text{: } \alpha_1^{(21)} = \alpha_2^{(21)} = \ldots = \alpha_k^{(21)} = 0$$

where $\alpha^{(12)}$ are the coefficients of *X*. As both null hypotheses are rejected, one can say that X and Y have a Causal relationship. Since this methodology has been developed, it was adopted by many econometrics literatures (Shan and Sun, 1998a; Shan and Sun, 1998b; Shan and Wilson, 2001; Huang and Kao, 2003).

Before employing the Granger causality test, the unit root and model selection criteria are necessary to test to select d_{max} and k, respectively. This study employs the augmented Dicky-Fuller (ADF) regression proposed by Dickey and Fuller (1979,

1981) to test if time series variables are stationary. The ADF test is on the following two functions:

$$\Delta y_t = \alpha_0 + \gamma y_{t-1} + \alpha_2 t + \sum \beta_i \Delta y_{t-i} + \varepsilon_t \qquad (4.9)$$

$$\Delta y_t = \alpha_0 + \gamma y_{t-1} + \sum \beta_i \Delta y_{t-i} + \varepsilon_t\ , \qquad (4.10)$$

where ε_t is white noise with zero mean and constant variance. Under the null hypothesis that the unit root exist (γ=1 or not stationary), the conventionally-computed t statistic is known as the τ statistic. If the variable still has a unit root when testing (4.9) and (4.10), then the regressions have to be differentiated once. As the first different ADF regression is stationary, the series variable is called to be integrated of order 1, or $I(1)$, and $d_{max}=1$ means all variables are stationary when they are $I(1)$.

The most general methods of selecting optimal lagged length k are the Akaike Information Criterion (AIC) and the Schwartz Bayesian Criterion (SBC).[32] Their rationales are similar: running the VAR with a different lagged length, and then choosing a lagged length, which makes the VAR have higher explanatory power than other lagged lengths. In other words, the smaller the AIC and SBC, the better the model. However, Enders (2004) reminded that these criterions are not appropriate all the time because it is not possible to find the best model with many data sets. In a time series study, monthly or seasonal data are commonly used, but this study will use annual data sets (This is one weakness of this study). If the lagged length is too long, many will be skeptical about the empirical results because it may not valid that one

[32] AIC and SBC formulas can be expressed as many forms. The followings present their most simple forms:

AIC=T ln(sum of squared residuals)+2n

SBC=T ln(sum of squared residuals)+n ln(T)

where n is number of parameters estimated; T is number of usable observations.

variable from many years ago influences another variable this year. Therefore, this study will select a shorter lagged length, such as 1, 2 or 3.

4.3 Empirical Model and Data Source

After deciding the ways of testing order of integration and selecting lagged length, the next step is to choose an empirical model. This study adopts the augmented production function [33] and adds a proxy variable of inequality to test the causality between growth and inequality. The SUR from an augmented production function can be written as:

$$\begin{bmatrix} GROW_t \\ INEQ_t \end{bmatrix} = \alpha_0 + \beta_1 \times \begin{bmatrix} GROW_{t-1} \\ INEQ_{t-1} \end{bmatrix} + \cdots + \beta_{k+d_{\max}} \begin{bmatrix} GROW_{t-k-d} \\ INEQ_{t-k-d} \end{bmatrix} + \gamma_1 EXP_t + \gamma_2 IMP_t + \gamma_3 LAB_t + \gamma_4 EN_t + \begin{bmatrix} e_{GROW_t} \\ e_{INEQ_t} \end{bmatrix} \tag{4.11}$$

The empirical study starts from 1978 because China carried out its economic reforms in this year and this study is confined to China during the post reform period. Nevertheless, the annual data sets for period 1978 to 2002 are not long enough to make all variables endogenous, this study sets all variables exogenous except growth and inequality to make sure the degree of freedom is large enough. Here, *GROW* represents the per capita GDP growth rate or GDP growth rate; *INEQ* represents the logarithm of the income inequality level. This study uses four inequality indicators (Gini coefficient, Generalized entropy, coefficient of variation, and Max/Min) introduced in the previous section as a proxy variable of the inequality level. Other real variables coming from the augmented production function are export value *(EXP)*, import value *(IMP)*, labor numbers *(LAB)*, and energy consumption *(EN)*.[34]

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[33] See Shan and Sun (1998b).
[34] Real capital is a variable included in augmented production function but not in this study. Some literature disserted that inequality would influence accumulation (Venieris and Gupta, 1986; Persson

The ***China Statistical Yearbook*** (various year) and ***Comprehensive Statistical Data and Materials on 50 Years of New China*** provide most of the data variables for the period from1978-2002. The proxy variable of labor is the number of employees (unit: 10,000 persons). The unit of energy consumption is 10,000 tons and the unit of import and export values is 100 million RMB. The basic statistical properties and definitions of all variables are shown in Table 4.1. It is in term of various units that the mean, variances and standard deviation of labor, energy consumption and trade are not comparable. But it reveals exports and imports have a higher value of coefficient of variation than labor and energy consumption do. This implies that the trade sector expands rapidly due to the reform and open policy.

Earlier data are available in ***Comprehensive Statistical Data and Materials on 50 Years of New China***, but some data is only in other official statistical books. For instance, Tibet's data of population and GDP for early reform period are reported in ***Tibet Statistical Yearbook***. Which price index is suitable to use to transform nominal term into real term is another difficulty. The GDP deflator is a better price index, but it cannot be found in an official statistical yearbook.[35] Therefore, this study will adopt the consumer price index (CPI) as a deflator. The shortcoming of CPI is it fails to reveal the market price in China because the government still controls some prices of commodities, especially agricultural purchase prices. This price control of necessary goods will directly distort real consumer price.

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and Tabellini, 1994). If both variables are included in equation (11), it will cause misspecification and estimation bias. Besides, statistical test reveals the relationship inequality and capital investment in post-reform China is highly correlated. The correlation coefficient is about 0.7 when Gini coefficient or generalized entropy is used as inequality indicators. Therefore, this study throws real capital away from the empirical model.

[35] In fact, GDP deflator is reported in ***China Statistical Yearbook*** implicitly. One can calculate GDP deflator from the data of nominal GDP and real growth rate. Keidel (2001) pointed out that although China's statistical authority revised the national GDP level, it did not adjust real growth rate as well. Due to this, the self-calculated GDP deflator is far from correct.

Table 4.1 Descriptive Statistics and Definitions of Explanatory Variables

Variable	Definition	Mean	Std.
Economic growth (Adjusted)	Per capita GDP growth rate.	7.38	3.60
Gini coefficient	Income inequality index. Its value is confined to [0,1]. The higher the value, the higher the inequality.	0.24	0.02
Generalized Entropy	Income inequality index. Its value is confined to [0,1]. The higher the value, the higher the inequality.	0.095	0.01
Coefficient of Variation	Measurement of deviation level within a group of observations. The higher the value, the higher the deviation level.	0.550	0.07
Max/Min	The ratio of the richest provincial per capita GDP to the poorest provincial per capita GDP.	10.08	1.83
Import	Total value of commodities imported into the boundary of China.	1829.08	1500.22
Export	Total value of commodities exported from the boundary of China.	1968.85	1734.25
Labor	Number of employed persons.	58766.48	11721.79
Energy consumption	Standard coal consumption.	100017.88	30469.47

Source: *China Statistical Yearbook* (various year) and *Comprehensive Statistical Data and materials on 50 Years of New China*.

Although China has had remarkable economic growth rate since 1978, its credibility of statistics on growth magnitude have been suspect. Many literatures claimed China's statistical officials overestimated its growth rate, and the problem was more serious during 1990s. Wang and Meng (2001) indicated that not only did local industries over-report their output, but also local administration had incentives to falsify statistical data. Rawski (2001) speculated the exaggeration has increased since 1997.[36] The second reason of overestimating growth rate was statistical officials undervalued price index. Maddison (1998) pointed out China's comparable price estimates for industry are likely to understate inflation, whereas the problem is not significant for agriculture. Keidel (2001) also found a notable difference between value-add and expenditure GDP growth rate because of use of a different deflator.

[36] Rawski (2001) conjectured the official reported cumulative GDP growth rate more than two-third of real rate during 1997~2001.

It is possible to adjust the problem of falsification and understating inflation. Wang and Meng (2001) provided four methods to correct falsification of China's industrial output. However, their suggestions can estimate average growth rate for a period of time, and are not suitable to adjust growth rate year by year. Maddison (1998) and Keidel (2001) advised alternative ways to eliminate the shortcoming of official price index. This study adopts latter method to adjust China's growth rate from 1979 to 2002.

Keidel (2001) thought expenditure measure would be a more preferred GDP reporting method than value add measure, but it is still immature in China's statistical system. The official statistical yearbooks only provide a nominal GDP expenditure level so Keidel (2001) tried to convert it into real term by employing different deflators. In ***China Statistical Yearbook***, total expenditure GDP is decomposed into several parts: rural consumption, urban consumption, government, capital formation, and trade balance; Keidel used rural CPI, urban CPI, national CPI, official investment deflator and retail price index to deflate them, respectively.[37] After adding the deflated parts together, one can get real expenditure GDP. Comparing the annual official growth rate and real expenditure GDP growth rate, this study finds the latter are smaller than the former in most 1990s. Accordingly, this study will replace the official growth rate with expenditure GDP growth rate in empirical model to check if it would alter results.

Figure 4.1 compares the official and adjusted GDP growth rate. Figure 4.1 shows that their moving trends are similar, but it seems adjusted data are more intense

[37] The formula of real expenditure GDP proposed by Keidel (2001) can be written as follows:

Real GDP = (rural consumption / rural CPI) + (urban consumption / urban CPI) + (government consumption / CPI) + (capital formation / investment deflator) + (trade balance/ retail price)

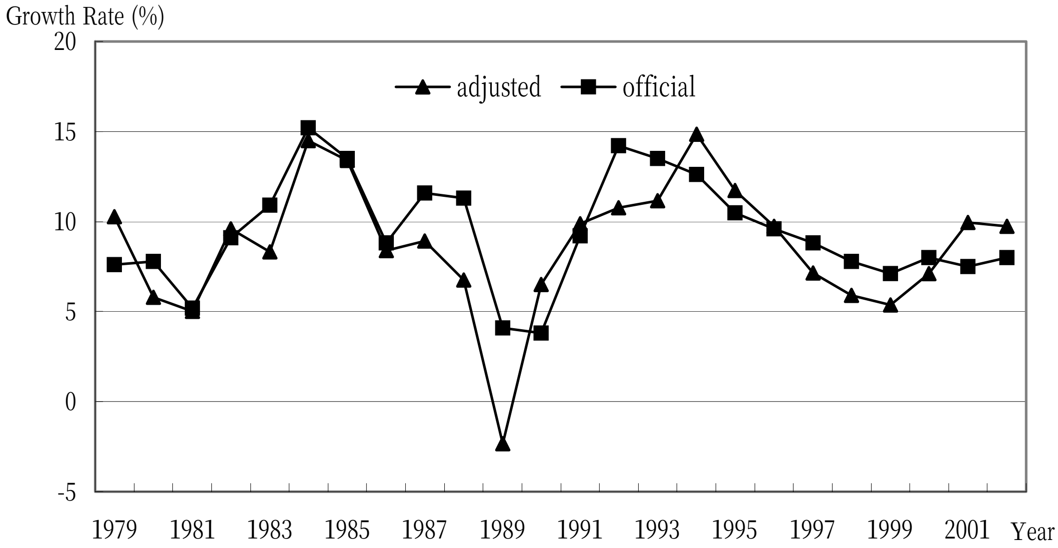

Figure 4.1 Comparison of Adjusted and Official GDP Growth Rate

Source: *China Statistical Yearbook* (various year), *Comprehensive Statistical Data and materials on 50 Years of New China* and Keidel (2001).

than official data, especially in 1989 and 1994. And in most years the adjusted GDP growth rates are lower than official. Although this study has an adjusted growth rate, it could not remedy all of China's statistical problems because the original data comes from official statistical publications.

To sum up this study's empirical process: (i) collecting and treating data from official statistical publications (ii) choosing the maximal order of integration with unit root test; (iii) testing the Granger causality. Process (ii) can be employed in many econometric packages, such as Eviews. Section (iii) involves the special chi-square test procedure, and so programming is necessary. Rambaldi and Doran (1996) showed how to use the SUR routines in SHAZAM, SAS, and RATS to obtain the chi-square test. This study follows their method of programming.