Chapter 5

INSTITUTIONAL EFFECT ON CHINESE FOODGRAIN PRODUCTION VARIABILITY

5.1 Introduction

A natural extension to Chapter 4 is to examine changes in the components of total variability of Chinese foodgrain production over time. This extension may help to reveal any patterns in the variability changes. If the periods split for the analysis are largely consistent with major institutional changes or fundamental policy changes, it would also provide some insights into institutional or policy impacts on the variability. These impacts are usually difficult to measure directly.

Previous works in this direction, e.g., Hazell (1984, 1985), Stone and Zhong (1989), involve comparison of components of total variability between two periods. This is probably acceptable if the objective is to discuss the changes in the components of total variability over the two periods. However, to inspect any patterns of changing variability and its components, separating the entire time space into just two parts is potently insufficient, although, in many cases, limited sample size prevents many divisions of a time-series in order to maintain statistical reliability.

The purpose of this chapter is twofold. First, changed variability of Chinese foodgrain production is decomposed into components associated with sown-area and yield changes over three time periods. This may also give some flavour of changing patterns in China's foodgrain variability. Second, institutional or policy effects on the variability are explored. An important step towards obtaining these objectives is to determine the break points in the time-series. This is addressed in section 5.3, after briefly reviewing the variance decomposition technique in section 5.2. The decomposition results can be found in sections 5.4 to 5.6, together with discussion of the effects of policy or institutional changes. Finally, a summary section is provided.

5.2 Analytical Framework

Based on the work of Goodman (1960) and Bohrnstedt and Goldberger (1969), Hazell (1982) developed a variability (indicated by variance) decomposition technique, which decomposes the total output variability into sown-area and yield components of different crops and regions. A useful feature of this technique is that it enables calculation of the changes in the composition of total variability over time. If a sufficient number of periods can be separated, the application of the approach could potentially provide a dynamic picture of the variability and its components.

The basic formula to start with is

$$Q_t = \sum_{k=1}^{nr} \sum_{i=1}^{nc} A_{tki} Y_{tki} \tag{5.1}$$

where Q denotes national foodgrain output, t time-period subscript, A sown-area, and Y yield. The subscripts k, i are for regions and crops and nr and nc represent number of regions and number of crops, respectively. Using h and j as the other subscripts for regions and crops, and letting crop subscripts (i, j) go from 1 to nc and region subscripts (k, h) from 1 to nr, it can be shown that

$$Var(Q_t) = \sum_h \sum_j Var(A_{thj} Y_{thj}) + \sum_h \sum_{i \neq j} \sum_j Cov(A_{thi} Y_{thi}, A_{thj} Y_{thj})$$

$$
\begin{aligned}
&+\sum_{j}\sum_{h\neq k}\sum_{k} Cov(A_{thj}Y_{thj}, A_{tkj}Y_{tkj}) \\
&+\sum_{h\neq k}\sum_{k}\sum_{i\neq j}\sum_{j} Cov(A_{thi}Y_{thi}, A_{tkj}Y_{tkj}), \qquad (5.2)
\end{aligned}
$$

$$
\begin{aligned}
\bar{Q}_t &= \sum_{h}\sum_{j} E(A_{thj}Y_{thj}) \\
&= \sum_{h}\sum_{j} \left[\bar{A}_{thj}\bar{Y}_{thj} + Cov(A_{thj}, Y_{thj})\right]. \qquad (5.3)
\end{aligned}
$$

The covariances in (5.2) can be expressed (Bohrnstedt and Goldberger 1969, p. 1441) as

$$
\begin{aligned}
Cov(A_{thi}Y_{thi}, A_{tkj}Y_{tkj}) &= \bar{A}_{thi}\bar{A}_{tkj}Cov(Y_{thi}, Y_{tkj}) + \bar{A}_{thi}\bar{Y}_{tkj}Cov(Y_{thi}, A_{tkj}) \\
&+ \bar{A}_{tkj}\bar{Y}_{thi}Cov(A_{thi}, Y_{tkj}) + \bar{Y}_{thi}\bar{Y}_{tkj}Cov(A_{thi}, A_{tkj}) \\
&- Cov(A_{thi}, Y_{thi})Cov(A_{tkj}, Y_{tkj}) + R, \qquad (5.4)
\end{aligned}
$$

where $\bar{A}$ and $\bar{Y}$ denote mean of sown-area and mean yield, respectively. R is a residual component containing terms with third or higher moments.

Let t=1, 2, and defining each variable in the second period as its counterpart in the first period plus the change in the variable between the two, represented by δ, e.g., $\bar{A}_{2hi} = \bar{A}_{1hi} + \delta\bar{A}_{hi}$ and $Cov(A_{2hi}, Y_{2kj}) = Cov(A_{1hi}, Y_{1kj}) + \delta Cov(A_{hi}, Y_{kj})$, then

$$
\begin{aligned}
\bar{Q}_2 &= \sum_{h}\sum_{j}(\bar{A}_{1hj} + \delta\bar{A}_{hj})(\bar{Y}_{1hj} + \delta\bar{Y}_{hj}) \\
&+ \sum_{h}\sum_{j} Cov(A_{1hj}, Y_{1hj}) + \sum_{h}\sum_{j} \delta Cov(A_{hj}, Y_{hj}) \\
&= \sum_{h}\sum_{j} \bar{A}_{1hj}\bar{Y}_{1hj} + \sum_{h}\sum_{j} Cov(A_{1hj}, Y_{1hj}) \\
&+ \sum_{h}\sum_{j} \bar{A}_{1hj}\,\delta\bar{Y}_{hj} + \sum_{h}\sum_{j} \bar{Y}_{1hj}\,\delta\bar{A}_{hj} \\
&+ \sum_{h}\sum_{j} \delta\bar{A}_{hj}\,\delta\bar{Y}_{hj} + \sum_{h}\sum_{j} \delta Cov(A_{hj}, Y_{hj}) \qquad (5.5)
\end{aligned}
$$

can be obtained. As the first two terms on the RHS of the above equation are equivalent to $\bar{Q}_1$, the change in the mean production is thus

$$
\begin{aligned}
\delta\bar{Q} &= \bar{Q}_2 - \bar{Q}_1 \\
&= \sum_{h}\sum_{j} \bar{A}_{1hj}\,\delta\bar{Y}_{hj} + \sum_{h}\sum_{j} \bar{Y}_{1hj}\,\delta\bar{A}_{hj}
\end{aligned}
$$

$$+\sum_h \sum_j \delta \bar{A}_{hj}\, \delta \bar{Y}_{hj} + \sum_h \sum_j \delta Cov(A_{hj}, Y_{hj}). \tag{5.6}$$

Equation (5.6) indicates that change in mean production can be attributed to four sources, as described in Table 5.1.

Table 5.1: Components of Changes in Mean Production

Description	Symbols
Change in Mean Yield	$\delta \bar{Y}$
Change in Mean Area	$\delta \bar{A}$
Interaction between Changes in Mean Yield and Mean Sown-area	$\delta \bar{Y}, \delta \bar{A}$
Change in Covariance between Sown-area and Yield	$\delta Cov(A, Y)$

A similar procedure can be applied to derive the components of change in the variance of production. Without duplicating the derivation as given in Hazell (1982, pp. 46-7), Table 5.2 is used to list the sources of change in total production variance.

The third source in Table 5.2 is composed of two parts, one due to changes in intra-crop yield variances and the other due to changes in various yield covariances. The second part can be further disaggregated into three components (Hazell 1982, p. 31), as summarised in Table 5.3. The sixth term in Table 5.2 is also composed of two parts, one due to changes in intra-crop covariances between sown-area and yield, and the other due to changes in inter-crop and inter-region covariances between sown-area and yield. The second part can be further disaggregated as well into three components (Hazell 1982, p. 22), as defined in Table 5.4.

It is feasible to express a variable in the first period as its counterpart in the second period less the changes, and then to find sources of changes in total mean output and output variance. However, as this approach confounds pure and interaction effects (Hazell 1982), it is thus not adopted in this study.

Table 5.2: Components of Change in Variance of Production

Term	Description	Symbols
1	Change in Mean Yield	$\delta\bar{Y}$
2	Change in Mean Sown-area	$\delta\bar{A}$
3	Change in Yield Variance	$\delta Var(Y)$
4	Change in Sown-area Variance	$\delta Var(A)$
5	Interaction between Changes in Mean Yield and Mean Sown-area	$\delta\bar{Y}, \delta\bar{A}$
6	Change in Covariance between Sown-area & Yield	$\delta Cov(A, Y)$
7	Interaction between Changes in Mean Yield & Sown-area Variance	$\delta\bar{Y}, \delta Var(A)$
8	Interaction between Changes in Mean Sown-area & Yield Variance	$\delta\bar{A}, \delta Var(Y)$
9	Interactions between Changes in Mean Sown-area & Yield and Changes in Covariance between Yield & Sown-area	$\delta\bar{Y}, \delta\bar{A}$ & $\delta Cov(A, Y)$
10	Change in Residual	δR

Table 5.3: Components of Change in the Inter-crop and Inter-region Yield Covariances

Description	Symbol
Change in Standard Deviation of Yield	$\delta\sigma_Y$
Change in Correlation Coefficient between Yields	$\delta\rho_{(Y,Y)}$
Change in the Interaction among Standard Deviation of Yield and Correlation Coefficient between Yields	$\delta\sigma_Y, \delta\rho_{(Y,Y)}$

Table 5.4: Components of Change in the Inter-crop and Inter-region Covariances between Sown-area and Yield

Description	Symbol
Changes in Standard Deviations of Sown-area and Yield	$\delta\sigma_Y, \delta\sigma_A$
Change in Correlation Coefficient between Yield and Sown-area	$\delta\rho_{(Y,A)}$
Change in the Interactions among Standard Deviations of Sown-area and Yield and Correlation Coefficient between Yield and Sown-area	$\delta\sigma_Y, \delta\sigma_A, \delta\rho_{(Y,A)}$

It is noted that data used in this chapter were detrended in the way described in section 4.3. The detrended data are split into three sub-periods, as is explained in the following section.

5.3 Determining Time Periods

The split of time periods is important for this kind of analysis because different splits may well lead to different conclusions (Tisdell and Alauddin 1988). Although selection of time periods is inevitably arbitrary, it largely depends on the objectives of the study. To attempt to identify the effects of major institutional changes on Chinese foodgrain production variability, the whole period under study (1949-85) is divided into three sub-periods: 1949-58, 1962-77 and 1978-85.

The first subperiod (1949-58) was dominated by a non-socialist farming system, which includes the first land reform (1949-52) and the cooperative transformation of agriculture (1952-57). The socialist commune system, built on the advanced agricultural production cooperatives, was initiated in August of 1958 and implemented by the end of 1958 (Ma 1982). As far as crop production is concerned, 1958 can be classified into the period with non-socialist farming. Although socialist elements kept increasing in the agricultural sector from 1952 onwards and the foodgrain procurement policy was initiated in 1955, strict government control over agricultural production and marketing was not politically overwhelming. The inclusion of 1958 in the first sub-period is also due to the fact that 1959-61 was an unusual period in China and is excluded from the analysis. The impact of the 'great leap forward' on production in 1958 is probably insignificant. It is noted that 1952-57 is the first five-year plan period.

The second sub-period (1962-77) is characterised by a fully socialist farming system. During this period, a three-tier system of collective farming was in effect. It is the collective farming structure that made it possible for political intervention and a highly centralised command system to be effective. This period includes the infamous 'cultural revolution' (1966-76) when radical politics prevailed. It also includes the 'green revolution' in which modern cereal varieties were widely adopted.

The third sub-period (1978-85) can be characterised as having a family-farming system. In many aspects, it is similar to the system before 1958. However, it differs from the non-socialist farming system because the three-tier production structure still remains, at least nominally. In particular, the procurement policy was fully in operation during 1978-85. This policy was aimed at ensuring the basic needs of national food consumption and restricting large fluctuations in foodgrain production. Since this policy was implemented through a strict control over sown-areas, it could be expected that procurement policy may produce a stabilising effect on foodgrain production. The third sub-period also differs from the collective farming system as the agriculture production responsibility system (APRS) prevails in this period. From 1978 onwards, individual farmers gained certain decision powers and families were directly facing and bearing any risks in both production and marketing.

Analysis of the change in the variability from the first sub-period to the second sub-period can reveal the impact of collective farming on variability. In essence, the impact is from the introduction of the central planning and army-style command system. Conversely, change in the variability between the second and the third sub-period may explore the effect of recent economic reform and APRS on variability. If the first and the third sub-periods are considered, the effect of procurement policy on variability can be examined. It is worth mentioning that the procurement policy might not significantly influence production variability in the first sub-period as the quotas were not very tight and no restrictions on sown-area were directly imposed by the central government.

5.4 Effect of Collective Farming

The transition from private to collective farming was accompanied by a progressive introduction of economic plans. These plans were basically for maintaining and stabilising foodgrain production, largely through control over sown-area. The transition also coincided with the progressive adoption of modern cultivars, which certainly contributed much to the increased foodgrain output, but may possibly also bring about higher variability of foodgrain production (Hazell 1984, 1985). However, the effect of modern cultivars should mainly be associated with crop yields. Thus, change in variance of foodgrain production in China between 1949-58 and 1962-77 is expected to be inversely related to changes in sown-area, but positively related to changes in yield. The change in mean production is expected to be dominated by those components associated with yield.

The decomposition results are largely consistent with the above comments. From 1949-58 to 1962-77, total variance increased by 1.67×10^{14} jin^2. As shown in Table 5.5 (far-right column), this increase consists of some 83.1 per cent due to increase in yield variance

Table 5.5: Components of Change in the Variance of Total Foodgrain Production, All China, from 1949-58 to 1962-77

Component[1]	Sums of Intra-crop Variance	Inter-crop Covariances within Regions	Inter-region Covariances within Crops	Covariances between Crops and Regions	All China
			(per cent)[2]		
$\delta\bar{Y}$	0.2	0.1	0.6	2.3	3.2
$\delta\bar{A}$	-0.1	0.0	0.1	0.1	0.1
$\delta Var(Y)$	3.2	3.3	14.2	62.4	83.1
$\delta Var(A)$	0.4	-0.5	2.2	-3.0	-0.9
$\delta\bar{Y}, \delta\bar{A}$	0.0	0.0	0.0	0.0	0.0
$\delta Cov(A, Y)$	0.3	-0.5	9.7	4.6	14.0
$\delta\bar{A}, \delta Var(Y)$	-0.1	-0.4	1.0	-3.2	-2.7
$\delta\bar{Y}, \delta Var(A)$	0.4	-0.5	1.6	-2.0	-0.5
$\delta\bar{Y}, \delta\bar{A}$ & $\delta Cov(A, Y)$	0.3	-0.1	4.0	1.3	5.5
δR	0.0	0.0	-1.4	-0.5	-2.0
Sum	4.6	1.4	32.0	61.9	100.0

[1] See Table 5.2 for definitions of the symbols.

[2] The percentages are obtained by using the absolute value of change in total variability as denominator. Thus, a negative figure in the table means a stabilising contribution and *vice versa*.

and covariances [$\delta Var(Y)$], 3.2 per cent due to increase in mean yield, and 14.0 per cent due to increase in the covariance between sown-area and yield. The 'pure' yield effect

Table 5.6: Disaggregation of the Contribution due to Changes in Yield Covariances, from 1949-58 to 1962-77

	Components[1]			
	$\delta\sigma_Y$	$\delta\rho_{(Y,Y)}$	$\delta\sigma_Y$ & $\delta\rho_{(Y,Y)}$	Sum
	(per cent)			
Crops within Regions	3.11	0.00	0.00	3.11
Inter-crop within Regions	1.74	-0.02	1.45	3.16
Inter-region within Crops	2.75	0.89	10.04	13.66
Between Crops & Regions	9.36	4.27	46.32	59.97
Sum	16.96	5.14	57.80	79.90

[1] See Table 5.3 for definitions of the symbols.

$(\delta\bar{Y} + \delta Var(Y))$ accounts for 86.3 per cent, while the 'pure' sown-area effect $(\delta\bar{A} + \delta Var(A))$ accounts for a tiny −0.8 per cent. In other words, the changed variability is largely from changes in yield, particularly in yield variance. The contribution by sown-area is probably negative. From the bottom row of Table 5.5, the contribution by sums of regional intra-crop variances is negligible (4.6 per cent). The dominant source of the increased variability is output covariance between crops and regions (61.9 per cent), which is mostly attributable to increase in yield covariances between crops and regions. In fact, the increase in the yield covariances between crops and regions alone contributed more than 62 per cent to the total change in the variance of China's foodgrain production over the two periods under consideration.

Further decomposition of the 79.9 (3.3 + 14.2 + 62.4) per cent contribution due to yield covariances indicates that 17.0 per cent of the contribution is due to changes in standard deviations of yields, 5.1 per cent due to changes in yield correlation coefficients, and the remaining 57.8 per cent due to changes in the interaction of changes in standard deviations and correlation coefficients (Table 5.6). This suggests that concurrent changes in both the standard deviations of and correlation coefficients between yields is the main source of the overall increase in the variance of China's foodgrain production.

Table 5.7: Disaggregation of the Contribution due to Change in Covariance between Sown-area and Yield from 1949-58 to 1962-77

	Components[1]			
	$\delta\sigma_A$ $\delta\sigma_Y$	$\delta\rho_{(Y,A)}$	$\delta\sigma_Y, \delta\sigma_A$ & $\delta\rho_{(Y,A)}$	Sum
	(per cent)			
Crops within Regions	0.09	-0.12	0.28	0.26
Inter-crop within Regions	0.56	-1.00	-0.08	-0.52
Inter-region within Crops	-0.59	0.87	9.25	9.53
Between Crops & Regions	5.24	-5.08	4.26	4.43
Sum	5.32	-5.33	13.72	13.70

[1] See Table 5.4 for definitions of the symbols.

Increase in the covariances between sown-area and yield contributed 13.7 (0.26−0.52 + 9.53 +4.43) per cent to the total variability change (Table 5.7). This is composed of 9.5 per cent due to increase in inter-region covariances within crops (Table 5.7). Increases in standard deviations of sown-area and yield contributed about 5.3 per cent, which is cancelled out by the component due to decreased correlation coefficients between sown-area and yield, thus leaving almost all of the increased covariance between yield and sown-area due to increased interaction among variance of sown-area, yield variance and the correlation coefficients between yield and sown-area.

The 4.6 per cent contribution of the sums of intra-crop variances within regions is composed of 3.2 per cent due to change in yield variance, 0.2 per cent due to change in mean yield and 0.4 per cent due to change in the variance of sown-area (Table 5.5).

The composition of the 4.6 per cent contribution by regions is tabulated in Table 5.8. Recalling that the residual region is artificially defined to allow for successful variance decomposition and thus should be ignored when interpreting the results, the largest contributor is Hunan (12.5 per cent), followed by the other-regions (11.0 per cent). Three regions (Ningxia, Qinghai and Tianjin) contributed nil when rounding to one decimal point.

The composition of the 4.6 per cent contribution is also presented by crops in Table

Table 5.8: Components of Changes in the Sums of Intra-crop Variances, by Region, from 1949-58 to 1962-77

Region	Components[1] $\delta\bar{Y}$	$\delta\bar{A}$	$\delta Var(Y)$	$\delta Var(A)$	$\delta\bar{Y}$ $\delta\bar{A}$	$\delta Cov(A,Y)$	$\delta\bar{A}$ & $\delta Var(Y)$	$\delta\bar{Y}$ & $\delta Var(A)$	$\delta Cov(A,Y)$ & $\delta\bar{Y},\delta\bar{A}$	δR	Sum[3]
						(per cent)[2]					
Anhui	9.5	-1.6	55.6	3.0	0.1	28.9	-8.6	1.4	11.4	0.2	4.6
Hubei	1.1	1.0	14.4	22.3	0.1	30.1	7.2	11.0	16.7	-3.8	6.[illegible]
Hunan	1.3	0.4	26.9	13.0	0.0	36.8	3.2	8.5	13.9	-4.1	12.5
Guangdong	1.5	-0.1	99.1	-0.8	0.0	11.6	-12.9	-0.7	3.7	-1.4	4.7
Gansu	0.9	0.4	63.5	6.1	0.0	12.0	4.3	3.2	10.1	-0.5	0.4
Guangxi	0.4	0.0	44.8	5.6	0.0	34.0	0.6	5.3	13.4	-4.1	3.7
Guizhou	1.7	-1.0	85.3	6.5	0.0	17.2	-5.1	0.9	0.0	-5.4	0.2
Heilongjiang	5.1	0.6	40.0	2.5	0.0	21.8	11.3	4.0	15.1	-1.3	1.6
Henan	10.7	-0.6	112.7	0.2	-0.2	-9.7	-10.4	-2.5	-2.0	1.7	6.2
Jiangsu	3.1	0.3	40.2	18.0	0.0	16.0	-0.6	14.2	12.8	-3.9	8.9
Liaoning	21.6	0.1	91.8	-4.0	0.0	-2.9	-15.0	-6.4	14.2	0.5	1.5
Ningxia	6.9	5.4	44.8	0.5	-0.3	17.7	16.1	-4.1	13.9	-0.8	0.0
Qinghai	0.2	2.2	27.9	9.9	0.1	19.5	13.6	8.0	19.2	-0.4	0.0
Shaanxi	1.5	-0.1	105.6	4.7	0.0	-11.4	-2.7	3.4	-2.5	1.3	0.6
Sichuan	6.7	-3.2	84.2	4.2	-0.1	8.7	-4.8	3.6	7.6	-7.0	4.3
Shandong	4.8	-0.8	75.5	3.6	-0.1	3.1	-1.0	4.3	12.1	-1.4	6.7
Shanghai	1.2	1.7	10.5	36.9	-0.1	24.7	2.5	11.7	13.8	-2.9	0.1
Shanxi	4.8	-1.1	76.0	3.4	-0.1	3.1	-0.8	3.7	9.7	1.4	0.5
Tianjin	7.5	1.8	24.8	12.6	0.6	20.4	4.1	13.3	11.5	3.5	0.0
Xinjiang	0.4	9.0	7.6	6.8	-1.7	40.1	4.4	3.4	33.4	-3.4	0.2
Zhejiang	0.3	0.5	40.0	6.4	0.0	33.3	4.7	4.7	13.6	-3.5	3.6
Other-regions	5.3	-2.4	115.5	-1.9	0.3	-21.1	-3.1	7.6	-5.4	5.2	11.0
Residual Region	6.5	-3.8	87.6	13.4	-0.2	-20.1	-6.4	16.1	0.8	6.2	22.8
China	4.8	-1.2	69.3	8.5	-0.0	5.7	-2.7	8.2	7.3	0.3	100.0

1 See Table 5.2 for definitions of the symbols.

2 The percentages are obtained by using the absolute value of change in the sum of intra-crop variances of each region as denominator. Thus, components in each row sum to 100.0 or -100.0. A negative figure in the table means a stabilising contribution and *vice versa*.

3 The sum indicates the regional contribution to the sums of intra-crop variances.

Table 5.9: Components of Changes in the Sums of Intra-crop Variances, by Crop, from 1949-58 to 1962-77

Component[1]	Rice	Wheat	Maize	Tubers	Soy-beans	Sor-ghum	Millet	Other-Grains	Residual Grain	All China
					(per cent)[2]					
$\delta\bar{Y}$	1.9	8.9	1.9	-185.7	125.0	64.7	26.7	5.3	18.6	4.8
$\delta\bar{A}$	0.5	0.2	2.7	-228.6	-75.0	-23.5	-60.0	-28.0	-4.9	-1.2
$\delta Var(Y)$	37.4	95.4	27.9	1528.57	325.0	500.0	113.3	24.0	255.5	69.3
$\delta Var(A)$	11.7	1.3	6.7	-871.4	-100.0	23.5	60.0	39.3	6.3	8.5
$\delta\bar{Y},\delta\bar{A}$	0.0	-0.2	-0.1	14.3	0.0	0.0	0.0	0.7	-0.2	-0.0
$\delta Cov(A,Y)$	30.7	1.2	23.3	-828.6	-475.0	-311.8	-266.7	16.7	-120.5	5.7
$\delta\bar{A},\delta Var(Y)$	1.7	-6.4	8.2	114.3	-100.0	-194.1	-53.3	-17.3	-31.6	-2.7
$\delta\bar{Y},\delta Var(A)$	7.6	-1.3	10.5	42.9	0.0	5.9	40.0	35.3	8.4	8.2
$\delta\bar{Y},\delta\bar{A},\delta Cov(A,Y)$	12.9	0.8	21.2	242.9	50.0	-11.8	20.0	8.0	-51.9	7.3
δR	-4.4	0.2	-2.4	71.4	150.0	47.1	20.0	16.0	20.3	0.3
Sum[3]	52.2	13.1	21.5	-0.2	-0.1	0.4	-0.3	3.2	10.2	100.0

1 See Table 5.2 for definitions of the symbols.

2 The percentages are obtained by using the absolute value of change in the sum of intra-crop variances of each crop as denominator. Thus, components in each column sum to 100.0 or -100.0. A negative figure in the table means a stabilising contribution and *vice versa*.

3 The sum indicates the contribution of the crop to the sums of intra-crop variances.

5.9. Rice accounts for 52.2 per cent of the 4.6 per cent contribution. Three crops (tubers, soybeans and millet) had reductions in their variances from 1949-58 to 1962-77. However, their combined effect is only −0.6 (−0.2 − 0.1 − 0.3) per cent, thus it can hardly be seen as significant.

5.4.1 Changes in mean production

Total average output of China's foodgrain increased by 1242 billion *jin* from 1949-58 to 1962-77. Reduction in the mean of total sown-area led to a reduction of 42.6 billion *jin*, or a negative 3.4 per cent contribution to the total change in mean output (Table 5.10). This reduction is matched by the increase in the mean production due to changes in the covariances between sown-area and yield. The effect of change in the interaction of mean sown-area and mean yield is relatively negligible. Thus, about 100 per cent of the increase in the total mean output is from the increases in mean yield. It is worth noting that all regions increased their mean yields from 1949-58 to 1962-77. Moreover, increase in mean yield contributed more than 100 per cent to increase in regional mean output for 12

Table 5.10: Components of Change in Mean Production of Total Foodgrain, by Region, from 1949-58 to 1962-77

Region	Components[1]				Contribution to Total Change
	$\delta\bar{Y}$	$\delta\bar{A}$	$\delta\bar{Y}.\delta\bar{A}$	$\delta Cov(A,Y)$	
	(per cent)				
Anhui	148.4	-34.3	-17.3	3.2	5.3
Hubei	52.8	35.1	8.0	4.1	7.2
Hunan	76.2	13.5	3.1	7.2	7.0
Guangdong	131.9	-24.5	-8.9	1.5	5.0
Gansu	115.2	-15.6	-3.2	3.5	1.1
Guangxi	92.0	-3.0	-0.3	11.4	3.8
Guizhou	102.4	-3.8	-0.7	2.1	0.9
Heilongjiang	66.1	17.1	7.5	9.3	4.0
Henan	136.2	-25.3	-7.8	-3.1	7.1
Jiangsu	103.0	5.6	-4.7	-3.8	10.1
Liaoning	128.6	-23.7	-8.1	3.3	3.1
Ningxia	53.1	33.9	9.3	3.6	0.4
Qinghai	48.0	30.0	10.1	12.0	0.3
Shaanxi	107.5	-2.9	-1.6	-3.1	2.6
Sichuan	118.4	-19.6	-2.9	4.2	7.3
Shandong	128.5	-25.8	-4.0	1.2	7.8
Shanghai	51.1	44.5	2.7	1.8	1.1
Shanxi	106.9	-6.4	-0.9	0.4	2.7
Tianjin	99.8	-15.5	0.5	15.2	0.5
Xinjiang	33.6	46.5	11.7	8.2	2.0
Zhejiang	88.9	4.1	0.7	6.3	4.4
Other-regions	108.2	-5.0	-0.8	-2.3	16.4
Residual Region	5113.3	-945.6	-1538.0	-2529.6	-0.1
All China	100.8	-3.4	-1.0	3.5	100.0

[1] See Table 5.1 for definitions of the symbols.

out of 22 regions (residual region excluded). On the other hand, more than half of the regions experienced reductions in their expected sown-area. For instance, yield increase contributed from 34 per cent (Xinjiang) to 148 per cent (Anhui) to regional increase in mean production. Conversely, reduction in mean sown-area decreased the mean of Anhui's foodgrain production by more than 34 per cent, but lifted Xinjiang's output by 47 per cent (Table 5.10). Regions such as Ningxia, Qinghai, Heilongjiang and Xinjiang increased their sown-areas possibly by reclamation, while other regions that increased most likely did so through intensification of cropping, e.g., Jiangsu, Zhejiang.

By crop, nearly 46 per cent of the increase in the overall mean production is from rice; some 49 (24.0 + 24.9) per cent is from wheat and maize (Table 5.11). Crops such as millet,

Table 5.11: Components of Change in Mean Production of Total Foodgrain, by Crop, from 1949-58 to 1962-77

Crop	Components[1]				Contribution to Total Change
	$\delta\bar{Y}$	$\delta\bar{A}$	$\delta\bar{Y},\delta\bar{A}$	$\delta Cov(A,Y)$	
	(per cent)				
Rice	77.3	10.8	2.8	9.1	45.5
Wheat	90.0	7.3	0.3	2.4	24.1
Maize	69.3	13.3	6.6	10.7	24.9
Tubers	110.2	-7.8	2.8	-5.2	5.9
Soybeans	-312.5	263.5	64.5	84.5	-0.8
Sorghum	-3264.1	1955.5	698.3	710.3	-0.2
Millet	-134.6	164.2	38.4	32.0	-2.3
Other-grains	362.6	-155.8	-69.0	-37.7	2.6
Residual Grain	-21.0	67.4	86.4	-32.8	0.2
All China	100.8	-3.4	-1.0	3.5	100.0

[1] See Table 5.1 for definitions of the symbols.

soybeans and sorghum decreased their mean production. The decreases are entirely due to decreases in their mean yields, reflecting the fact that the Chinese governments neglected production of coarse grains, as argued in Chapter 4. However, these decreases are basically cancelled out by the increases in the mean production of the other-grains.

5.5 Effect of the APRS and Economic Reform

The major feature of the APRS and economic reform in general is the gain of decision power of local organisations and individuals. From 1978 onwards, there has also been the gradual removal of direct political intervention by the central and provincial governments. Resource allocation, particularly of land, has become more rational or more in accordance with local conditions than hitherto. Therefore, any concurrent changes in either crop yield or sown-area should be less in 1978-85. In addition, as farmers have taken on full responsibility in their farming, care is given to every phase of the production process and every means is used to secure the yield. As individual farmers, rather than the community (production team, brigade or commune) have become the decision-makers, they may have tended to be more risk-averse, rather than risk-neutral or even risk-preferring. These changes have probably helped to reduce yield variability. On the other hand, as average yield increases, perhaps resulting from continued expansion of modern cultivars, it may still contribute positively to production variability.

These assertions are broadly supported by the decomposition results, as presented in Table 5.12. From 1962-77 to 1978-85, total variance of China's foodgrain production reduced remarkably by an amount of 1.72×10^{14} jin^2, 75.0 per cent of which came from reduced variability of yield. The changes in yield and sown-area covariance contributed some 25.7 per cent of this reduction. The interaction of changes in mean yield, mean sown-area and covariances between sown-area and yield contributed 10.3 per cent of the reduction. Conversely, increase in average yield continued to be the main source of enhancing the production variability (+11.5 per cent). and the second most important positive contribution is from the changes in the mean of sown-area (+3.4 per cent). The change in the covariances between crops and regions is the dominant source in the reduction of the yield variability (−55.5 per cent).

Overall, change in the inter-region covariances within or not within crops contributed a −92.8 (−30.7 − 62.1) per cent to the change in the total variability. Changes in the inter-crop covariances within regions contributed a small −2.2 per cent. The sums of intra-crop variance of all regions shared only −5.0 per cent (Table 5.12).

Further decomposition of the −71.8 (−2.9 − 13.4 − 55.5) per cent contribution due to changes in yield covariances shows that changes in standard deviations of yields shared −60.0 per cent and changes in the correlation coefficients of yields shared another −55.2 per cent. The remaining 43.4 per cent is due to change in the interaction between yield standard deviations and correlation coefficients of yields (Table 5.13). These results consistently suggest the importance of reducing central planning in the context of stabilising China's foodgrain production.

Table 5.14 presents the results from the disaggregation of the covariances between yield

Table 5.12: Components of Change in the Variance of Total Foodgrain Production, All China, from 1962-77 to 1978-85

Component[1]	Sums of Intra-crop Variance	Inter-crop Covariances within Regions	Inter-region Covariances within Crops	Covariances between Crops and Regions	All China
			(per cent)[2]		
$\delta\bar{Y}$	0.8	-0.1	6.0	4.8	11.5
$\delta\bar{A}$	0.4	-0.2	3.0	0.3	3.4
$\delta Var(Y)$	-3.2	-2.9	-13.4	-55.5	-75.0
$\delta Var(A)$	-1.1	0.8	-4.6	2.9	-2.0
$\delta\bar{Y}, \delta\bar{A}$	0.1	0.0	0.2	-0.1	0.2
$\delta Cov(A, Y)$	-0.8	-0.1	-14.2	-10.6	-25.7
$\delta\bar{A}, \delta Var(Y)$	-0.1	0.0	-1.9	-0.9	-2.8
$\delta\bar{Y}, \delta Var(A)$	-0.5	0.3	-2.4	0.9	-1.7
$\delta\bar{Y}, \delta\bar{A}$ & $\delta Cov(A, Y)$	-0.6	0.0	-4.9	-4.8	-10.3
δR	0.0	0.1	1.4	0.9	2.4
Sum	-5.0	-2.2	-30.7	-62.1	-100.0[3]

1 See Table 5.2 for definitions of the symbols.

2 The percentages are obtained by using the absolute value of change in total variability as denominator. Thus, a negative figure in the table means a stabilising contribution and *vice versa*.

3 The negative value indicates decrease in the total variability over the two periods; cf. note 2 to this table.

Table 5.13: Disaggregation of the Contribution due to Changes in Yield Covariances, from 1962-77 to 1978-85

	Components[1]			
	$\delta\sigma_Y$	$\delta\rho_{(Y,Y)}$	$\delta\sigma_Y$ & $\delta\rho_{(Y,Y)}$	Sum
	(per cent)			
Crops within Regions	-3.06	0.00	0.00	-3.06
Inter-crop within Regions	-2.25	-2.25	1.77	-2.73
Inter-region within Crops	-11.19	-8.59	6.83	-12.96
Between Crops & Regions	-43.52	-44.37	34.83	-53.05
Sum	-60.02	-55.21	43.43	-71.80

[1] See Table 5.3 for definitions of the symbols.

and sown-area, which is the second most important component in reducing the overall variability (Table 5.12). It indicates that reduction in the correlation coefficients between yield and sown-area is the most influential factor in contributing to change in this covariance (−23.5 per cent), followed by standard deviation of yield and sown-area (−18.8 per cent). The remaining influence is from the interaction effect (+17.4 per cent).

Turning to change in the sum of intra-crop variance of individual crops (Table 5.15), it is found that all crops had a lower variability in the second period. This is primarily due to reductions in variances of yield and sown-area, and possible reductions in the interactive effect of mean yield and variance of sown-area, and/or in the covariance between sown-area and yield. A similar pattern emerges for change in the sum of intra-crop variance of individual regions as shown in Table 5.16.

5.5.1 Changes in mean production

As for the previous case, sources of change in mean production are dominated by yield increment (Table 5.17). On average, China's foodgrain production increased by 1195 billion *jin* from 1962-77 to 1978-85. About 97 per cent of this increase is from mean yield increase, and 5.3 per cent from increase in the mean of sown-area (Table 5.17). Also, every region

Table 5.14: Disaggregation of the Contribution due to Change in Covariance between Sown-area and Yield from 1962-77 to 1978-85

	Components[1]			
	$\delta\sigma_A$ $\delta\sigma_Y$	$\delta\rho_{(Y,A)}$	$\delta\sigma_Y, \delta\sigma_A$ & $\delta\rho_{(Y,A)}$	Sum
	(per cent)			
Crops within Regions	-0.52	-0.82	0.39	-0.95
Inter-crop within Regions	-0.08	0.04	-0.07	-0.11
Inter-region within Crops	-11.37	-15.57	13.05	13.88
Between Crops & Regions	-6.83	-7.16	4.03	-9.96
Sum	-18.79	-23.51	17.40	-24.90

[1] See Table 5.4 for definitions of the symbols.

Table 5.15: Components of Changes in the Sums of Intra-crop Variances, by Crop, from 1962-77 to 1978-85

Component[1]	Rice	Wheat	Maize	Tubers	Soy-beans	Sor-ghum	Millet	Other-Grains	Residual Grain	All China
					(per cent)[2]					
$\delta\bar{Y}$	23.0	10.8	27.6	2.6	33.3	-0.0	60.0	-1.2	-10.8	16.5
$\delta\bar{A}$	8.1	5.4	29.9	2.6	16.7	-44.4	-0.0	-13.9	-17.8	7.1
$\delta Var(Y)$	-36.0	-88.6	-40.0	-69.1	-133.3	-177.8	-240.0	-57.4	-208.9	-64.3
$\delta Var(A)$	-21.0	-6.8	-18.1	-8.9	-150.0	-92.6	-380.0	-39.1	-31.0	-21.8
$\delta\bar{Y}, \delta\bar{A}$	0.6	1.4	2.8	0.0	0.0	14.8	20.0	1.2	1.5	1.3
$\delta Cov(A,Y)$	-47.7	-10.0	-47.8	-13.1	183.3	207.4	640.0	-2.3	151.6	-15.9
$\delta\bar{A}, \delta Var(Y)$	-4.8	0.8	-16.6	-2.1	33.3	88.9	60.0	14.8	24.6	-1.2
$\delta\bar{Y}, \delta Var(A)$	-11.4	-5.2	-11.5	-0.5	-50.0	-40.7	-160.0	-3.2	-11.5	-10.2
$\delta\bar{Y}, \delta\bar{A}, \delta Cov(A,Y)$	-15.0	-8.2	-28.0	-0.5	-33.3	-25.9	-80.0	2.0	14.9	-12.0
δR	4.3	0.4	1.6	-11.0	0.0	-29.6	-20.0	-0.9	-12.7	0.40
Sum[3]	-49.2	-10.0	-18.6	-3.8	-0.1	-0.6	-0.1	-6.9	-10.6	-100.0[4]

[1] See Table 5.2 for definitions of the symbols.

[2] The percentages are obtained by using the absolute value of change in the sum of intra-crop variances of each crop as denominator. Thus, components in each column sum to 100.0 or -100.0. A negative figure in the table means a stabilising contribution and *vice versa*.

[3] The sum indicates the contribution of the crop to the sums of intra-crop variances.

[4] The negative value means that the sums of intra-crop variances decreased over the two periods under consideration.

Table 5.16: Components of Changes in the Sums of Intra-crop Variances, by Region, from 1962-77 to 1978-85

Region	Components[1]										
	$\delta\bar{Y}$	$\delta\bar{A}$	$\delta Var(Y)$	$\delta Var(A)$	$\delta\bar{Y}$ $\delta\bar{A}$	$\delta Cov(A,Y)$	$\delta\bar{A}$ & $\delta Var(Y)$	$\delta\bar{Y}$ & $\delta Var(A)$	$\delta Cov(A,Y)$ & $\delta\bar{Y},\delta\bar{A}$	δR	Sum[3]
	(per cent)[2]										
Anhui	16.8	10.1	-43.3	-21.4	1.1	-38.3	-3.7	-9.9	-13.4	2.0	-4.2
Hubei	34.9	0.4	-6.4	-35.6	0.1	-61.4	0.1	-20.0	-16.2	4.1	-5.1
Hunan	21.6	16.6	-30.8	-24.0	1.4	-50.4	-8.5	-10.6	-19.6	4.3	-11.4
Guangdong	5.3	-0.9	-79.5	0.2	-0.0	-22.6	0.7	0.1	-5.2	1.9	-3.7
Gansu	10.9	10.4	-70.3	-10.1	0.5	-22.9	-7.6	-3.5	-8.4	0.9	-0.3
Guangxi	18.2	11.9	-45.3	-12.9	0.8	-48.3	-6.9	-6.3	-15.4	4.2	-3.1
Guizhou	11.6	6.0	-66.3	-16.9	0.2	-26.0	-1.9	-5.5	-5.3	4.0	-0.1
Heilongjiang	29.1	30.7	-60.6	-22.9	2.6	-37.7	-10.6	-11.1	-21.7	2.1	-0.7
Henan	2.9	0.1	-99.4	-8.8	1.2	7.6	4.4	-4.5	-2.6	-1.0	-5.4
Jiangsu	34.0	-5.9	-23.5	-34.3	0.1	-44.2	2.7	-23.2	-10.0	4.2	-7.6
Liaoning	35.1	34.2	-70.9	-34.3	6.8	-4.0	-0.3	-20.1	-33.5	-12.9	-1.0
Ningxia	23.1	21.8	-68.4	-11.4	1.6	-32.0	-10.5	-9.5	-16.1	1.4	-0.0
Qinghai	21.9	22.8	-46.5	-18.8	2.3	-36.5	-13.1	-9.8	-23.1	0.8	-0.0
Shaanxi	1.6	6.1	-110.5	-10.0	-0.2	18.4	-4.3	-2.7	4.6	-3.0	-0.3
Sichuan	20.3	12.1	-77.9	-12.7	1.2	-22.0	-7.1	-8.3	-12.8	7.3	-3.8
Shandong	20.9	15.6	-73.4	-14.8	2.5	-17.0	-7.0	-9.1	-19.4	1.8	-5.1
Shanghai	23.9	-5.0	7.6	-61.7	-0.5	-52.2	-1.4	-13.1	-3.7	6.1	-0.1
Shanxi	21.0	2.4	-72.4	-14.1	1.6	-17.3	-0.6	-7.0	-13.7	0.2	-0.2
Tianjin	45.4	-1.7	-18.9	-51.6	0.6	-47.1	7.9	-20.7	-17.7	3.7	-0.0
Xinjiang	20.6	18.6	-33.3	-22.4	1.3	-51.7	-8.6	-9.4	-13.0	2.9	-0.1
Zhejiang	20.1	13.7	-43.4	-13.0	1.1	-49.4	-7.5	-7.4	-17.9	3.8	-3.0
Other-regions	12.9	5.2	-83.0	-17.0	1.1	1.0	-0.3	-8.0	-8.5	-3.4	-17.5
Residual Region	9.8	6.1	-83.3	-27.9	1.9	12.7	2.5	-9.6	-9.9	-2.3	-27.0
China	16.5	7.1	-64.3	-21.8	1.3	-15.9	-1.2	-10.2	-12.0	0.4	-100.0[4]

1 See Table 5.2 for definitions of the symbols.

2 The percentages are obtained by using the absolute value of change in the sum of intra-crop variances of each region as denominator. Thus, components in each row sum to 100.0 or -100.0. A negative figure in the table means a stabilising contribution and *vice versa*.

3 The sum indicates the regional contribution to the sums of intra-crop variances.

4 The negative value means that the sums of intra-crop variances decreased over the two periods under consideration.

Table 5.17: Components of Change in Mean Production of Total Foodgrain, by Region, from 1962-77 to 1978-85

Region	Components[1]				Contribution to Total Change
	$\delta\bar{Y}$	$\delta\bar{A}$	$\delta\bar{Y},\delta\bar{A}$	$\delta Cov(A,Y)$	
	(per cent)				
Anhui	101.7	0.2	-0.3	-1.5	4.7
Hubei	123.4	-12.1	-2.5	-8.8	4.9
Hunan	59.5	37.4	8.9	-5.8	7.8
Guangdong	108.3	-4.3	-1.0	-3.0	5.0
Gansu	96.1	6.1	0.2	-2.4	1.2
Guangxi	80.5	23.7	5.5	-9.7	3.6
Guizhou	81.9	18.6	2.2	-2.6	1.9
Heilongjiang	68.6	31.8	4.7	-5.1	3.9
Henan	117.0	-17.8	-2.5	3.3	6.4
Jiangsu	140.0	-31.0	-12.0	3.0	7.4
Liaoning	88.9	4.8	7.9	-1.7	3.9
Ningxia	74.0	23.3	3.7	-0.9	0.4
Qinghai	84.1	21.4	7.8	-13.3	0.2
Shaanxi	100.2	-3.8	0.4	3.2	2.2
Sichuan	90.4	10.5	2.9	-3.8	11.6
Shandong	109.3	-9.7	1.7	-1.3	8.5
Shanghai	197.0	-92.2	-1.8	-3.1	0.2
Shanxi	128.7	-23.8	-5.2	0.3	1.8
Tianjin	105.5	13.0	-2.8	-15.8	0.4
Xinjiang	64.8	35.6	7.2	-7.6	1.4
Zhejiang	80.3	19.8	5.0	-5.1	5.6
Other-regions	95.2	4.0	3.8	-3.0	17.3
Residual Region	281.0	-355.4	-166.7	341.1	-0.3
All China	96.7	5.3	2.5	-4.5	100.0

[1] See Table 5.1 for definitions of the symbols.

Table 5.18: Components of Change in Mean Production of Total Foodgrain, by Crop, from 1962-77 to 1978-85

Crop	Components[1]				Contribution to Total Change
	$\delta\bar{Y}$	$\delta\bar{A}$	$\delta\bar{Y},\delta\bar{A}$	$\delta Cov(A,Y)$	
	(per cent)				
Rice	88.2	17.7	3.9	-9.9	47.0
Wheat	89.3	11.4	2.8	-3.5	26.4
Maize	69.8	32.0	9.5	-11.3	23.4
Tubers	86.7	13.9	2.6	-3.2	6.25
Soybeans	342.7	-315.0	-45.7	118.0	0.5
Sorghum	-257.4	373.2	76.0	-91.8	-1.3
Millet	-449.8	564.8	123.6	-138.6	-0.5
Other-grains	-137.8	262.8	36.8	-61.8	-2.0
Residual Grain	-19.8	52.6	24.1	43.1	0.4
All China	96.7	5.3	2.5	-4.5	100.0

[1] See Table 5.1 for definitions of the symbols.

raised its mean yield and output in the second period. As shown in the far right column of Table 5.17, the largest contributor besides the other-regions is Sichuan (11.6 per cent), followed by Shandong (8.5 per cent).

From Table 5.18, it is apparent that important crops continued to surge in output and unimportant crops continued to decrease. The main factor lies in the mean yields. The first four crops in the table gained their increase mainly through increase in yields, supplemented by increase in sown-area. Conversely, the rest of the crops would have lost more ground through reductions in mean yields if their sown-area had not been considerably increased. The increases in the sown-areas for less important crops in 1978-85 were likely due to the reduction in procurement quotas for fine grains and due to relaxation of macro-control over sown-areas, which enabled farmers to cultivate according to local conditions.

To sum up, the introduction of APRS and economic reform have had a tremendous effect on raising crop yields, presumably through motivating farmers' initiatives. Further expansion of modern cultivars in the second period may also have helped to lift yields. The increases in crop yields are largely responsible for the jump in total mean production.

Surprisingly, this jump is accompanied by a rather substantial decrease in total variability. It is quite clear that relaxation of macro-control over both the agricultural sector and the whole economy eliminated, to some extent, the concurrent shifts in sown-areas and/or input applications across regions. This is the major source of reduction in variability. The reduction in simultaneous changes across regions is evidenced by the decreases in the correlation coefficients of yields and correlation coefficients between yield and sown-area. It is noted that intra-crop variance of sown-area decreased for all regions except Guangdong, Liaoning and the other-regions over the two periods (Table 5.8). The major reason behind this may lie in the fact that the procurement policy was still in force in the second period, which may have prevented a large swing of area among different crops, and that farmers were able to follow a rational rotational farming system, which normally cannot be easily changed unless by political force, as happened in 1962-77.

5.6 Effect of Procurement Policy

As argued previously, procurement as practised in China should be useful in stabilising foodgrain production, particularly in terms of sown-areas, although the basic aim of the policy was to obtain sufficient foodgrain for urban residents and non-grain producing regions. However, the results in section 5.4 indicate that the stabilising effect of procurement policy seems very small. This is possibly because procurement policy was implemented without due regard to its impact on production covariabilities. Frequent changes in procurement quotas often meant a proportional increase or decrease of sown-area for a crop for most, if not all, regions. This may well enhance inter-region covariability of sown-area within crops, as seen in Table 5.5. Worse still, quotas were normally tied to input allocations and this could, in turn, lead to stronger yield covariabilities. Further, the absolute decrease in total variance of China's foodgrain production due to change in sown-area variability is 1.49×10^{12} jin^2 from 1949-58 to 1962-77. This value is quite large. However, the overwhelming increases in other components outweighed the variability-reducing effect of procurement policy. Thus, the relative or percentage contribution from decreased sown-area variability turned out to be very small (–0.9 per cent). It was previously argued that most of the increase in foodgrain production variability from 1949-58 to 1962-77 was due to the highly centralised command system in China in the latter period. A secondary factor may be the narrower genetic base of modern cultivars, in comparison with traditional varieties. These assertions were proven, at least partially, by the results in section 5.5.

To see the effect of procurement policy on variability, the comparison of changes in the components of China's foodgrain production variability between 1949-58 and 1978-85 may be more informative. This is because the centralised system was gradually removed after the economic reform of 1978 and blind commands were no longer accepted. Also, the quotas were reduced and imposed more in line with regional production capacities in 1978-85. As far as institutional form is concerned, these two periods are somewhat similar. As production technology has improved substantially over the two periods, its effects are presumed to be mainly on yields. The strict implementation of procurement policy in the second period is perhaps the most important institutional factor in distinguishing the two periods. It is hypothesised that the comparison will indicate both a 'green revolution' effect on yield variability and a procurement effect on sown-area variability.

Table 5.19 shows that, from 1949-58 to 1978-85, variability of yield increased drastically, while variability of sown-area decreased substantially. The effect of the 'green revolution' on variability seems strong, as indicated by the large contribution due to mean yield and variance of yield. The "pure" yield effect contributed 324.3 (222.9 + 101.4) per cent to the total change in the variability of China's foodgrain production. However, any risk-inducing effect of the 'green revolution' is seemingly outweighed by the risk-reducing effect of procurement policy, which is reflected by the negative contributions associated with sown-area, e.g., $\delta Var(A)$, $\delta\bar{Y}$ and $\delta Var(A)$. These resulted in a modest decrease in the variance of China's foodgrain production by an amount of 4.96×10^{12} jin^2 from 1949-58 to 1978-85. The procurement policy seemingly succeeded in reducing the variance of sown-area, which led to a decrease in total variability by 66.4 per cent. The policy was also useful in reducing the contribution made by the components of changes in the covariance between sown-area and yield (–165.6 per cent), in the interaction of mean yield and variance of sown-area

Table 5.20: Disaggregation of the Contribution due to Changes in Yield Covariances, from 1949-58 to 1978-85

	Components[1]			
	$\delta\sigma_Y$	$\delta\rho_{(Y,Y)}$	$\delta\sigma_Y$ & $\delta\rho_{(Y,Y)}$	Sum
	(per cent)			
Crops within Regions	-7.66	0.00	0.00	-7.66
Inter-crop within Regions	6.08	-6.50	1.24	1.34
Inter-region within Crops	14.28	7.35	13.42	35.06
Between Crops & Regions	45.23	-1.50	20.72	64.45
Sum	57.93	-0.64	35.82	93.10

[1] See Table 5.3 for definitions of the symbols.

have gone up. This is indeed the case. The increase in inter-region yield correlation coefficients contributed a positive 7.4 per cent to the change in total variability of China's foodgrain production (Table 5.20). The inter-crop correlation coefficients of yields and yield correlation coefficients between crops and regions were marginally lower in the second period. Therefore, overall change in the correlation coefficients of yields, if significant, is not destabilising total foodgrain production. Thus, one may doubt if the impact of the 'green revolution' on foodgrain variability is of real concern in China. The contribution of yield covariances (93.1 per cent) is mainly from increases in standard deviation of yields (57.9 per cent) and the interaction between changes in yield standard deviations and correlation coefficients among yields (35.8 per cent) (Table 5.20).

The large negative contribution due to change in covariance between yield and sown-area (−158.9 per cent) is made up of −88.4 per cent from changes in yield and/or sown-area standard deviations, −118.2 per cent from changes in the correlation coefficients between yield and sown-area, and the remaining +47.7 per cent from the interaction (Table 5.21). All the correlation coefficients decreased from 1949-58 to 1978-85, as shown in the third column of Table 5.21.

The components of change in the sums of intra-crop variances within regions are presented by crops in Table 5.22. It is found that output variances of most crops decreased

Table 5.21: Disaggregation of the Contribution due to Change in Covariance between Sown-area and Yield from 1949-58 to 1978-85

	Components[1]			
	$\delta\sigma_A$ $\delta\sigma_Y$	$\delta\rho_{(Y,A)}$	$\delta\sigma_Y, \delta\sigma_A$ & $\delta\rho_{(Y,A)}$	Sum
	(per cent)			
Crops within Regions	-4.39	-8.60	5.72	-7.26
Inter-crop within Regions	-15.33	-17.29	10.49	-22.13
Inter-region within Crops	-9.30	-18.29	8.36	-19.24
Between Crops & Regions	-59.40	-73.98	23.10	-110.28
Sum	-88.43	-118.16	47.67	-158.90

[1] See Table 5.4 for definitions of the symbols.

from 1949-58 to 1978-85 except for wheat and maize. These two crops are presumed to be influenced more by seed-fertiliser technology than other crops are. In particular, all crops experienced a large decrease in sown-area variance. This may imply the stabilising effect of procurement policy. Scanning Table 5.22, change in mean yield is generally the major factor. Other-crops (or other-grains) reduced variability to a larger extent than any of the explicitly considered crops. This is consistent with the result that the other-regions, which are mainly engaged in other-grains production, had a large decrease in its variability (−338 per cent), as shown in Table 5.23. From Table 5.23, a majority of the regions increased their sum of intra-crop variances. The results in Table 5.23 indicate that 18 out of 22 regions (excluding the residual region) decreased their sown-area variances, while 17 regions increased their yield variances. Increase in mean yields led to increase in regional variability for all regions. This pattern is consistent with the earlier assertion that the 'green revolution' may have brought about higher yield variance, but procurement policy possibly had a stabilising effect on sown-area.

5.6.1 Changes in mean production

The decrease in total variance is accompanied by an increase in mean production, thus the relative variability (often measured by CV) may have decreased drastically from 1949-58

Table 5.22: Components of Changes in the Sums of Intra-crop Variances, by Crop, from 1949-58 to 1978-85

Component[1]	Rice	Wheat	Maize	Tubers	Soy-beans	Sor-ghum	Millet	Other-Grains	Residual Grain	All China
					(per cent)[2]					
$\delta\bar{Y}$	117.9	139.9	99.7	-1.2	73.7	172.1	39.7	6.8	202.5	100.5
$\delta\bar{A}$	46.3	6.9	163.3	-13.6	-37.4	-61.8	-74.1	-42.2	-62.6	-12.4
$\delta Var(Y)$	16.6	94.0	-28.3	-14.9	-4.5	43.7	9.2	-113.1	-120.7	-51.2
$\delta Var(A)$	-40.8	-9.8	-2.2	-39.3	-77.6	-76.2	-14.5	-6.8	-59.0	-43.2
$\delta\bar{Y}, \delta\bar{A}$	2.0	-1.8	-10.0	0.8	-4.5	0.2	-7.8	1.5	-4.4	-1.0
$\delta Cov(A, Y)$	-107.7	-24.9	-7.4	-42.1	-52.8	14.2	-21.1	11.3	7.3	-41.1
$\delta\bar{A}, \delta Var(Y)$	2.8	3.8	-57.0	7.3	9.5	-32.3	-26.0	40.4	24.0	18.0
$\delta\bar{Y}, \delta Var(A)$	-53.5	-73.4	-0.5	-1.4	-53.5	-159.8	-17.9	-9.0	-132.8	-55.4
$\delta\bar{Y}, \delta\bar{A}. \delta Cov(A, Y)$	-83.9	-37.2	-39.7	12.5	2.7	2.6	2.1	0.9	7.4	-21.0
δR	0.3	2.6	-17.7	-8.2	44.4	-2.6	10.6	10.3	38.2	6.9
Sum[3]	-20.3	19.4	9.3	-42.0	-2.7	-2.8	-4.0	-42.3	-14.5	-100.0[4]

1 See Table 5.2 for definitions of the symbols.

2 The percentages are obtained by using the absolute value of change in the sum of intra-crop variances of each crop as denominator. Thus, components in each column sum to 100.0 or -100.0. A negative figure in the table means a stabilising contribution and *vice versa*.

3 The sum indicates the contribution of the crop to the sums of intra-crop variances.

4 The negative value means that the sums of intra-crop variances decreased over the two periods under consideration.

to 1978-85. According to Table 5.24, every region (excluding the residual region) raised its mean output. About half of the regions experienced a decrease in sown-area. Increase in mean yield dominated the sources of the increased mean output. For nearly half of the regions, more than 100 per cent increase in output was from increase in mean yields. Taking China as a whole, the mean production increased by some 2 437 billion *jin*, 99 per cent of which came from yield changes, with less than 2 per cent from interaction between changes in mean yields and mean of sown-area. The other components contributed almost nothing.

From Table 5.25, it is clear that most of the increase in mean production is from major or important crops. As in Table 5.24, contributions from change in covariance between sown-area and yield are negligible. Decreases in coarse grain outputs were the result of decreases in their mean yields, just as the increase in mean yield is responsible for increase in outputs for the important crops.

Table 5.23: Components of Changes in the Sums of Intra-crop Variances, by Region, 1949-58 to 1962-77

Region	Components[1]										Sum[3]
	$\delta\bar{Y}$	$\delta\bar{A}$	$\delta Var(Y)$	$\delta Var(A)$	$\delta\bar{Y}$ $\delta\bar{A}$	$\delta Cov(A,Y)$	$\delta\bar{A}$ & $\delta Var(Y)$	$\delta\bar{Y}$ & $\delta Var(A)$	$\delta Cov(A,Y)$ & $\delta\bar{Y},\delta\bar{A}$	δR	
	(per cent)[2]										
Anhui	991.5	-34.4	139.9	-372.7	3.3	73.3	4.1	-982.9	-31.6	109.5	-0.9
Hubei	36.1	12.4	132.1	5.0	1.5	-83.3	69.9	1.3	-74.3	-0.8	4.5
Hunan	385.9	227.4	-119.1	-259.0	13.1	10.1	-55.1	-331.1	-13.5	41.2	-0.7
Guangdong	25.4	-1.1	150.3	-5.9	0.3	-25.9	-20.1	-9.3	-15.4	1.7	5.8
Gansu	17.2	7.9	56.9	1.9	0.4	11.2	-10.1	3.7	9.0	1.9	0.4
Guangxi	11.4	3.6	46.3	-8.0	-0.7	27.5	7.9	-6.7	21.0	-2.3	3.1
Guizhou	30.3	5.3	151.3	-27.0	-0.4	-20.3	-10.7	-13.6	-3.4	-11.4	0.3
Heilongjiang	21.1	2.8	33.8	-7.1	-0.1	26.4	13.3	-9.2	19.5	-0.4	[illegible]
Henan	505.1	-22.2	179.4	-91.0	-13.2	-55.1	-17.4	-328.1	-74.4	16.8	2.7
Jiangsu	134.7	2.5	253.3	13.4	-1.1	-119.9	-12.6	-41.6	-129.7	1.2	5.4
Liaoning	176.6	5.0	91.8	-55.4	-0.5	18.1	20.5	-150.9	25.2	-30.2	4.0
Ningxia	45.9	25.2	47.6	-5.9	-2.2	21.3	0.6	-53.0	20.3	0.2	0.0
Qinghai	177.5	733.1	-789.1	-268.0	87.9	580.9	-339.4	133.6	-289.8	73.3	0.0
Shaanxi	8.9	0.4	89.8	2.3	0.1	-4.5	1.5	4.5	-1.0	-2.0	1.8
Sichuan	578.1	-129.7	-67.8	-137.8	-7.0	-160.9	92.6	-140.4	-145.9	19.8	1.1
Shandong	69.3	-6.3	87.4	-15.4	-0.7	4.2	-3.5	-33.4	-2.3	0.8	9.6
Shanghai	5.9	3.8	33.8	17.8	-0.2	6.6	14.7	9.5	4.4	3.8	0.3
Shanxi	23.0	-4.1	95.6	-2.4	-0.7	3.1	-22.9	-0.4	5.2	3.6	1.8
Tianjin	34.6	-0.4	32.3	-12.6	-1.1	22.2	16.3	-4.9	-2.6	16.1	0.1
Xinjiang	12.6	114.4	-55.3	-47.3	-38.3	123.1	-122.3	-61.0	180.9	-6.8	0.2
Zhejiang	11.2	17.0	54.7	-7.9	-1.3	11.1	17.8	-13.8	10.3	0.9	2.5
Other-regions	22.5	-1.0	-46.5	-28.1	1.5	-35.3	1.9	-10.7	-3.2	-1.1	-79.8
Residual Region	35.1	-18.1	-101.5	-10.9	-2.5	-4.6	20.0	-17.8	-10.1	10.3	-67.3
China	100.5	-12.4	-51.2	-43.2	-1.0	-41.1	18.0	-55.4	-21.0	6.9	-100.0[4]

1 See Table 5.2 for definitions of the symbols.

2 The percentages are obtained by using the absolute value of change in the sum of intra-crop variances of each region as denominator. Thus, components in each row sum to 100.0 or -100.0. A negative figure in the table means a stabilising contribution and *vice versa*.

3 The sum indicates the regional contribution to the sums of intra-crop variances.

4 The negative value means that the sums of intra-crop variances decreased over the two periods under consideration.

Table 5.24: Components of Change in Mean Production of Total Foodgrain, by Region, from 1949-58 to 1978-85

Region	Components[1]				Contribution to Total Change
	$\delta\bar{Y}$	$\delta\bar{A}$	$\delta\bar{Y},\delta\bar{A}$	$\delta Cov(A,Y)$	
	(per cent)				
Anhui	133.7	-18.4	-16.3	1.0	5.0
Hubei	73.6	17.6	9.7	-1.0	6.0
Hunan	65.3	21.9	12.3	0.5	7.4
Guangdong	124.3	-14.1	-9.5	-0.7	5.0
Gansu	107.1	-4.7	-2.9	0.6	1.1
Guangxi	86.5	6.4	5.7	1.3	3.7
Guizhou	89.2	10.7	1.2	-1.1	1.4
Heilongjiang	65.4	20.7	11.6	2.3	3.9
Henan	130.5	-20.7	-9.6	-0.2	6.7
Jiangsu	120.5	-4.9	-14.6	-1.0	8.8
Liaoning	106.8	-8.6	1.2	0.6	3.5
Ningxia	57.3	28.3	13.0	1.3	0.4
Qinghai	58.7	22.2	18.5	0.6	0.3
Shaanxi	104.1	-3.0	-0.9	-0.2	2.4
Sichuan	103.7	-3.9	0.8	-0.6	9.4
Shandong	120.5	-18.2	-2.2	-0.1	8.1
Shanghai	72.5	24.5	2.1	0.9	0.7
Shanxi	116.1	-9.9	-6.6	0.4	2.2
Tianjin	98.6	-2.8	1.2	3.0	0.4
Xinjiang	39.4	39.0	19.7	1.9	1.7
Zhejiang	84.1	10.1	5.7	0.1	5.0
Other-regions	100.9	-0.6	2.4	-2.7	16.9
Residual Region	964.3	-229.5	-642.6	7.7	-0.1
All China	98.8	0.0	1.6	-0.4	100.0

[1] See Table 5.1 for definitions of the symbols.

Table 5.25: Components of Changes in Mean Production of Total Foodgrain, by Crop, from 1949-58 to 1978-85

Crop	Components[1]				Contribution to Total Change
	$\delta\bar{Y}$	$\delta\bar{A}$	$\delta\bar{Y},\delta\bar{A}$	$\delta Cov(A,Y)$	
	(per cent)				
Rice	81.0	12.2	7.2	-0.4	46.2
Wheat	89.4	8.0	3.1	-0.6	25.2
Maize	66.5	16.9	16.4	0.3	24.2
Tubers	98.0	0.4	5.8	-4.2	6.1
Soybeans	-1204.8	875.2	385.9	43.7	-0.2
Sorghum	-648.0	459.3	291.8	-3.1	-0.7
Millet	-227.4	217.2	109.1	1.0	-1.4
Other-grains	1869.9	1081.6	-715.7	27.5	0.4
Residual Grain	-21.3	43.7	58.2	19.4	0.3
All China	98.8	0.0	1.6	-0.4	100.0

[1] See Table 5.1 for definitions of the symbols.

5.7 Summary

To examine the effect of institutional changes on variability, a variance decomposition technique was applied to the Chinese foodgrain production data for the period from 1949 to 1985 with 1959-61 excluded. It is found that the total variability, as indicated by variance, of Chinese foodgrain production increased from 1949-58 to 1962-77 by 1.67×10^{14} jin^2, and then decreased from 1962-77 to 1978-85 by 1.72×10^{14} jin^2. Therefore total variability decreased by some 4.96×10^{12} jin^2 between 1949-58 and 1978-85. Meanwhile, average production kept increasing from 1949-58 to 1962-77 and from 1962-77 to 1978-85. It can be concluded that relative variability in 1978-85 was lower than in the earlier periods considered in this chapter.

Changes in the mean values of yield and sown-area have always destabilised Chinese foodgrain production. That was particularly so between 1949-58 and 1978-85. Changes in yield variance and covariances were the major determinants of the changed (increased or decreased) total variability. Changes in the variance and covariances of sown-area created a stabilising effect on Chinese foodgrain production. In general, changes in yield mean, yield variance and covariances, covariance between sown-area and yield, and interaction among mean yield, mean sown-area and covariance between yield and sown-area were the most influential components of the changes in the total variability. Conversely, changes in mean production were dominated by the source of changes in mean yield, either at the national level or at the regional level.

It seems that the highly centralised planning system when coupled with the commune structure led to a very unstable period of China's foodgrain production in 1962-77. The centralised system might be useful in stabilising regional intra-crop sown-areas, but it probably increased inter-region covariabilities of both sown-area and yield. These covaribilities were most important in contributing to the changes that have occurred in the variability of Chinese foodgrain production since 1949.

Chapter 6

INPUT APPLICATIONS AND CHINESE FOODGRAIN PRODUCTION VARIABILITY

6.1 Introduction

After analysing intra-crop and intra-region variability in Chapter 3 and inter-crop and/or inter-region variability in Chapter 4, the institutional effect on China's foodgrain production variability was broadly discussed in Chapter 5. It is time to search for the root causes of the variabilities. Restrained by the available data, effort will be devoted to discover the relationship between quantitative factors and instabilities of rice, maize and wheat outputs.

In a world in which risk is captured in a mean-variance framework, a factor can assert its impact on yield or area sown variability in two ways, namely, through its mean changes and through changes in its variation. The relationship between changes in variability of yield or area sown and changes in mean level of a production factor, termed a output-variance function here, can quite flexibly be described by a so-called Just-Pope model, which allows for positive, negative or zero marginal variability (Just and Pope 1978, Griffiths and Anderson 1982). However, the relationship between changes in variability of yield or area sown and changes in variation of a production factor, called a variability-variability function, seems not to have been explicitly discussed in the literature. These two relationships are entirely different and both of them are useful in the context of policy-making. Taking government investment in capital construction in agriculture as one example, its mean changes are expected to be inversely related to production variations, while its fluctuations are positively related to production instability. As another illustration, changes in the mean prices of a product will enhance the production variability, but within a relevant range, changes in the variation of price could create a stabilising effect on production, at least in the long-run. This is because price and production are usually negatively correlated if supplies confront a downward-sloping demand curve. It is in this sense that a frozen price, practised in China for more than 30 years, might have reinforced agricultural production variability.

The plan of this chapter is as follows. In section 6.2, the output-variance function will be discussed in detail, and an extension of the model considered by Griffiths and Anderson (1982) into seemingly unrelated regressions will be undertaken. Subsequently, the extended model will be used to estimate marginal variabilities using Chinese foodgrain production data in section 6.3. Finally, a summary of the chapter is presented in section 6.4.

6.2 Output Variability and Mean Levels of Inputs

It is reasonable to propose that changes in some inputs, e.g., investment in improving environmental conditions, are inversely or negatively related to changes in the riskiness of crop output. However, a positive relationship may exist between other inputs, e.g., areas sown with modern cultivars (Anderson, Findlay and Wan 1989), and output variabilities of agricultural crops. Just and Pope (1978) show that these relationships cannot be correctly taken into account by the commonly-used functions, no matter whether the function is of additive error or multiplicative error and no matter whether the function is linear or nonlinear. For example, the widely-used Cobb-Douglas, transcendental and CES functions, restrict the marginal product and marginal variability to be of the same sign, normally positive. Other restrictions of these functions are detailed by Just and Pope (1978).

To relax these restrictions, models such as (6.1) to (6.3) are proposed:

$$Y = f(X) + h(X)\epsilon, \tag{6.1}$$

$$Y = f(X) + h(X, \epsilon), \tag{6.2}$$

$$Y = f(X, \epsilon), \tag{6.3}$$

where Y and X are dependent and independent variables, respectively. ϵ is usually a vector of random disturbance with certain properties, and h, f represent functional forms.

As equations (6.2) and (6.3) are rather too general to discuss their estimation insightfully (Just and Pope 1978), equation (6.1) is taken here for further discussion. More concrete specifications of (6.1), together with their risk implications and econometric estimation procedure, will be made in section 6.2.1. In section 6.2.2, a seemingly unrelated regression(SUR) which consists of Cobb-Douglas type models as f and h, and models which have composite errors will be developed. Also, the computational procedure will be outlined.

6.2.1 Estimating marginal variability via a single equation

Assuming a linear functional form for both f and h, equation (6.1) can be expressed as

$$Y = \sum_{k=0}^{K} \beta_k X_k + \epsilon \sum_{k=1}^{K} \alpha_k X_k, \tag{6.4}$$

where β_k and α_k are parameters to be estimated, X_k is the k-th exogenous variable, and normally X_0 contains identical constants.

It can be shown that

$$\frac{\partial E(Y)}{\partial X_j} = \beta_j, \tag{6.5}$$

$$\frac{\partial Var(Y)}{\partial X_j} = 2\alpha_j \sigma_\epsilon^2 \sum_{k=1}^{K} \alpha_k X_k. \tag{6.6}$$

where σ_ϵ^2 is the assumed constant variance of ϵ which has zero mean. If a power function for f and h is assumed, equation (6.1) becomes

$$Y = \prod_{k=0}^{K} X_k^{\beta_k} + \epsilon \prod_{k=1}^{K} X_k^{\alpha_k}, \tag{6.7}$$

With respect to equation (6.7),

$$\begin{aligned}
\frac{\partial E(Y)}{\partial X_j} &= \frac{\beta_j}{X_j}\prod_{k=0}^{K} X_k^{\beta_k} \\
&= \beta_j E(Y)/X_j, \qquad (6.8) \\
\frac{\partial Var(Y)}{\partial X_j} &= 2\frac{\alpha_j\sigma_\epsilon^2}{X_j}\prod_{k=1}^{K} X_k^{2\alpha_k} \\
&= 2\alpha_j Var(Y)/X_j. \qquad (6.9)
\end{aligned}$$

If Y represents production volume, the marginal products as expressed by equations (6.5) and (6.8) take the same sign as β_k and normally are positive. However, the sign of marginal variability as expressed by equation (6.6) depends on the αs and that by equation (6.9) on α_j only. It is apparent that variance is used to represent variability in this chapter.

If the stochastic terms in the above functions are replaced by a well-behaved residual, marginal variability would be always zero. In passing, it is noted that most of the commonly-used production functions imply positive marginal variability (Griffiths and Anderson 1982, Just and Pope 1978). This does not sit well with either casual empiricism or reflective intuition as to how some factors operate in influencing variability. Thus, application of models such as equations (6.4) and (6.7) has justification both theoretically and empirically, especially in the context of variability studies.

Using time-series data, the estimation of equation (6.7) normally takes four steps: (a) a nonlinear least-squares regression of Y on the deterministic part of the equation. This will produce inefficient estimates of β, namely $\hat{\beta} = (\hat{\beta}_0, \hat{\beta}_1, \hat{\beta}_2, \cdots, \hat{\beta}_K)'$. However, the estimates denoted by $\hat{\beta}$ are consistent and thus enable the computation of consistent residuals, denoted by $\hat{\mu}$; (b) a linear least-squares regression of $ln|\hat{\mu}|$ on the logarithm of the stochastic part of the equation with ϵ suppressed. This will result in a biased estimate of the constant (α_0) and inefficient estimates of α, namely $\hat{\alpha} = (\hat{\alpha}_0, \hat{\alpha}_1, \cdots, \hat{\alpha}_K)'$; (c) modifying $\hat{\beta}$ as follows

$$\begin{aligned}
\tilde{\beta} &= \hat{\beta} + \left[\sum_{t=1}^{T} Z_t Z_t' exp\left(2Z_t'(\hat{\beta} - \hat{\alpha})\right)\right]^{-1} \\
&\quad \times \sum_{t=1}^{T} \hat{\mu}_t Z_t exp[Z_t'(\hat{\beta} - 2\hat{\alpha})], \qquad (6.10)
\end{aligned}$$

where $Z_t = (\ln X_{t0}, \ln X_{t1}, \ln X_{t2}, \cdots, \ln X_{tk})'$, and the t subscript refers to the t-th observation; (d) modifying $\hat{\alpha}$ as follows:

$$\begin{aligned}\tilde{\alpha} &= \hat{\alpha} + 1.2704e_1 - \frac{1}{2}\left[\sum_{t=1}^{T} Z_t Z_t'\right]^{-1} \\ &\quad \times \sum_{t=1}^{T} Z_t \left[1 - \hat{\mu}_t^2 exp[-2Z_t'(\hat{\alpha} + e_1)]\right], \end{aligned} \tag{6.11}$$

where $e_1 = (1\ 0\ 0\ \cdots)'$. It is noted that the last two steps given by Just and Pope (1978) are incorrect.

After obtaining $\tilde{\alpha}$ and $\tilde{\beta}$, marginal variability can be estimated, for instance, according to equations (6.6) and (6.9).

6.2.2 Estimating marginal variability via SUR with error components

Complications arise when a time-series of cross-sectional data is used to estimate a function similar to equation (6.7) (see Griffiths and Anderson 1982). Further complications appear to arise when a system of equations is specified. The intention in this subsection is to develop a seemingly unrelated regression model which carries variability implications and allows for the use of a time series of cross-sectional data.

For combining time-series and cross-sectional data, one specification is that of a composite error structure for the models in question. This will take a section effect and a time effect into account in addition to the usual random disturbance (Judge et al. 1982, chapter 16). Thus, if there are N cross-sectional firms over T time periods, a set of M nonlinear stochastic equations of the form

$$Y_m = \gamma_m \coprod_{k=1}^{K} X_{mk}^{\beta_{mk}} + \epsilon_m \circ \coprod_{k=1}^{K} X_{mk}^{\alpha_{mk}} \tag{6.12}$$

can be established, where $m = 1, 2, \cdots, M$, Y_m is the $NT \times 1$ vector of observations on the dependent variable, ϵ_m is a $NT \times 1$ disturbance vector, X_{mk} is the $NT \times 1$ vector of observations on the k-th explanatory variable of the m-th equation and αs, βs are parameters to be estimated. The symbols, $\circ$ and $\coprod$, denote component multiplication of matrices.

The first term of (6.12) is called mean output function, which determines the mean level of output; and the second part output-variance function, which determines the variance of output

Assuming $i = 1, 2, \cdots, N$ and $t = 1, 2, \cdots, T$, let

$$h_{mit} = \prod_{k=1}^{K} X_{mkit}^{\alpha_{mk}}, \tag{6.13}$$

$$H_m = diag(h_{m1}, h_{m2}, \cdots, h_{mNT}), \tag{6.14}$$

$$H = diag(H_1, H_2, \cdots, H_M), \tag{6.15}$$

$$\epsilon_m = Z_\mu \mu_m + Z_\lambda \lambda_m + \nu_m, \tag{6.16}$$

where

$$Z_\mu = I_N \otimes e_T, \tag{6.17}$$

$$Z_\lambda = e_N \otimes I_T, \tag{6.18}$$

and $\otimes$ denotes the Kronecker operation; I_N, I_T denote $N \times N$ and $T \times T$ unit matrices; and e_N, e_T are $N \times 1$ and $T \times 1$ vectors of ones. The model of (6.12) can then be written as

$$Y_m = \gamma_m \prod_{k=1}^{K} X_{mk}^{\beta_{mk}} + u_m, \tag{6.19}$$

$$u_m = H_m \left(Z_\mu \mu_m + Z_\lambda \lambda_m + \nu_m \right), \tag{6.20}$$

where the *i-th* element of the vector $\mu_m = [\mu_{m1}, \mu_{m2}, \cdots, \mu_{mN}]'$ and the *t-th* element of the vector $\lambda_m = [\lambda_{m1}, \lambda_{m2}, \cdots, \lambda_{mT}]'$ represent the error components specific to the *i-th* section and *t-th* period in the *m-th* equation, respectively; the $NT \times 1$ vector $\nu_m = [\nu_{m1}, \nu_{m2}, \cdots, \nu_{mNT}]'$ contains the error component which is random over time and section for the *m-th* equation. Further, defining

$$Y = \begin{pmatrix} Y_1 \\ Y_2 \\ \vdots \\ Y_M \end{pmatrix}, \quad u = \begin{pmatrix} u_1 \\ u_2 \\ \vdots \\ u_M \end{pmatrix}, \quad \gamma = \begin{pmatrix} \gamma_1 \\ \gamma_2 \\ \vdots \\ \gamma_M \end{pmatrix} \tag{6.21}$$

and

$$X_c = diag\left(\prod_{k=1}^{K} X_{1k}^{\beta_{1k}}, \prod_{k=1}^{K} X_{2k}^{\beta_{2k}}, \cdots, \prod_{k=1}^{K} X_{Mk}^{\beta_{Mk}}\right), \tag{6.22}$$

the SUR models can be written as

$$Y = X_c\gamma + u. \tag{6.23}$$

Following Avery (1977) and Baltagi (1980), the three components of u (i.e., μ, λ and ν) are, as seems reasonable, assumed to be stochastically independent from each other and

$$E(\mu_{mi}) = E(\lambda_{mt}) = E(\nu_{mit}) = 0. \tag{6.24}$$

Under these assumptions, it can be shown that

$$\begin{aligned} E(\mu_{mi}\,\mu_{lj}) &= \sigma_{\mu ml} \quad i = j, \\ &= 0 \quad\quad i \neq j; \end{aligned} \tag{6.25}$$

$$\begin{aligned} E(\lambda_{mt}\,\lambda_{ls}) &= \sigma_{\lambda ml} \quad t = s, \\ &= 0 \quad\quad t \neq s; \end{aligned} \tag{6.26}$$

$$\begin{aligned} E(\nu_{mit}\,\nu_{ljs}) &= \sigma_{\nu ml} \quad i = j \;\&\; t = s, \\ &= 0 \quad\quad i \neq j \; or \; t \neq s; \end{aligned} \tag{6.27}$$

or in matrix notation,

$$E\begin{pmatrix} \mu_m \\ \lambda_m \\ \nu_m \end{pmatrix} (\mu_l' \, \lambda_l' \, \nu_l') = \begin{bmatrix} \sigma_{\mu ml} I_N & 0 & 0 \\ 0 & \sigma_{\lambda ml} I_T & 0 \\ 0 & 0 & \sigma_{\nu ml} I_{NT} \end{bmatrix} \tag{6.28}$$

for m and $l = 1, 2, \cdots, M$, where i, j are section subscripts, m, l equation subscripts and t, s time subscripts.

By defining

$$\epsilon = \begin{pmatrix} \epsilon_1 \\ \epsilon_2 \\ \vdots \\ \epsilon_M \end{pmatrix},$$

the covariance matrix for (6.23) can be expressed as

$$\begin{aligned}\Phi &= E(uu') = HE(\epsilon\epsilon')H \\ &= H\Omega H, \end{aligned} \tag{6.29}$$

where

$$\Omega = \begin{bmatrix} \Omega_{11} & \Omega_{12} & \cdots & \Omega_{1M} \\ \vdots & \vdots & \ddots & \vdots \\ \Omega_{M1} & \Omega_{M2} & \cdots & \Omega_{MM} \end{bmatrix}. \tag{6.30}$$

The typical element of Ω denoted by Ω_{ml} has the form

$$\begin{aligned}\Omega_{ml} &= E(\epsilon_m \epsilon_l') \\ &= \sigma_{\mu ml}A + \sigma_{\lambda ml}B + \sigma_{\nu ml}I_{NT}, \end{aligned} \tag{6.31}$$

where $A = I_N \otimes e_T e_T'$ and $B = e_N e_N' \otimes I_T$. Let

$$Q = I_{NT} - \frac{A}{T} - \frac{B}{N} + \frac{J_{NT}}{NT}, \tag{6.32}$$

$$J_{NT} = e_{NT} e_{NT}', \tag{6.33}$$

then equation (6.31) can be alternatively put as (Baltagi 1980)

$$\begin{aligned}\Omega_{ml} &= \sigma_{3ml}\frac{J_{NT}}{NT} + \sigma_{1ml}\left(\frac{A}{T} - \frac{J_{NT}}{NT}\right) \\ &\quad + \sigma_{2ml}\left(\frac{B}{N} - \frac{J_{NT}}{NT}\right) + \sigma_{\nu ml}Q, \end{aligned} \tag{6.34}$$

where

$$\sigma_{1ml} = \sigma_{\nu ml} + T\sigma_{\mu ml}, \tag{6.35}$$

$$\sigma_{2ml} = \sigma_{\nu ml} + N\sigma_{\lambda ml}, \tag{6.36}$$

$$\sigma_{3ml} = \sigma_{\nu ml} + N\sigma_{\lambda ml} + T\sigma_{\mu ml}, \tag{6.37}$$

and $\sigma_{\nu ml}$ are the distinct characteristic roots of Ω_{ml} of multiplicity 1, $N-1$, $T-1$ and $(N-1)(T-1)$, respectively. These eigenvalues of Ω_{ml} can be computed according to Nerlove (1971), if necessary.

After obtaining the values of σ_{1ml}, σ_{2ml}, σ_{3ml} and $\sigma_{\nu ml}$ by equations (6.35) to (6.37) for $m,\ l = 1, 2, \cdots, M$, Baltagi (1980) shows that

$$\begin{aligned}\Omega &= \Omega_3 \otimes \frac{J_{NT}}{NT} + \Omega_1 \otimes \left(\frac{A}{T} - \frac{J_{NT}}{NT}\right) \\ &+\Omega_2 \otimes \left(\frac{B}{N} - \frac{J_{NT}}{NT}\right) + \Omega_\nu \otimes Q, \end{aligned} \tag{6.38}$$

where

$$\Omega_3 = [\sigma_{3ml}], \tag{6.39}$$

$$\Omega_2 = [\sigma_{2ml}], \tag{6.40}$$

$$\Omega_1 = [\sigma_{1ml}], \tag{6.41}$$

$$\Omega_\nu = [\sigma_{\nu ml}], \tag{6.42}$$

all of dimension $M \times M$. As shown later, this expression will be useful for computing Ω^{-1}.

Under the above model specification, βs represent production elasticities and αs "risk elasticities" or risk effects of inputs, where risk is defined as the variance of Y. Since αs can be of any sign, the proposed SUR are distinguished from more conventional ones in that they allow risks of output to change in any direction in response to input changes. Also, the three error components in the model are all heteroscedastic in the sense that variances of $H_m Z_\mu \mu_m$, $H_m Z_\lambda \lambda_m$ and $H_m \nu_m$ depend on the input levels. This implies that the magnitude of both section and time effects will be influenced by the measured input levels, which may be more realistic than otherwise.

The assumed dependence between the error components and explanatory variables normally leads to biased estimates of the αs (Kmenta, 1986, p. 634), but the estimates are consistent under appropriate conditions (Griffiths and Anderson, 1982, p. 531). However, the bias is inevitable here even without such an assumption since the model is nonlinear in parameters, and coefficient estimates of a nonlinear equation are generally biased (Box, 1971).

Given the covariance matrix of (6.23) in (6.29), it can be seen that to estimate $\gamma = (\gamma_1, \gamma_2, \cdots, \gamma_M)'$ and $\beta = (\beta_1, \beta_2, \cdots, \beta_M)'$, where $\beta_m = (\beta_{m1}, \beta_{m2}, \cdots, \beta_{mK})'$, the objective function to be minimised is

$$\begin{aligned}\Psi &= u'\Phi^{-1}u \\ &= u'H^{-1}\Omega^{-1}H^{-1}u \\ &= \dot{u}'\Omega^{-1}\dot{u}, \end{aligned} \tag{6.43}$$

where $\dot{u}' = u'H^{-1}$.

However, H cannot be computed without the estimates of $\alpha = (\alpha_1, \alpha_2, \cdots, \alpha_M)'$, which, in turn, requires the estimation of u. To proceed in this direction, the first step is to minimise

$$u'u = \sum_{m=1}^{M}\sum_{i=1}^{N}\sum_{t=1}^{T}\left(Y_{mit} - \gamma_m \prod_k^K X_{mkit}^{\beta_{mk}}\right)^2 \tag{6.44}$$

and obtain $\hat{\gamma}$ and $\hat{\beta}$. Since cross-equation error is not considered here, the estimation can be undertaken for each m separately. However, due to the existence of heteroscedasticity and cross-equation error, the estimates will be asymptotically inefficient. But, they are generally consistent. Therefore, the estimated residual $\hat{u}_{mit} = Y_{mit} - \hat{\gamma}_m \prod_k^K X_{mkit}^{\hat{\beta}_{mk}}$ will converge in distribution to u_{mit} under appropriate assumptions.

The second step is to estimate α. To do so, rewrite equation (6.20) in a slightly different form as

$$u_{mit} = h_{mit}\left(\mu_{mi} + \lambda_{mt} + \nu_{mit}\right). \tag{6.45}$$

Squaring the above equation and taking logarithms yields

$$\ln u_{mit}^2 = \ln(\mu_{mi} + \lambda_{mt} + \nu_{mit})^2 + 2\sum_{k=1}^{K}\alpha_{mk}\ln X_{mkit}. \tag{6.46}$$

Let

$$\begin{aligned}\alpha_{m0} &= E\left[\ln(\mu_{mi} + \lambda_{mt} + \nu_{mit})^2\right], && (6.47)\\ \xi_{mit} &= \ln(u_{mit}^2) - E[\ln u_{mit}^2], && (6.48)\end{aligned}$$

then

$$\begin{aligned}E(\ln u_{mit}^2) &= \alpha_{m0} + 2\sum_{k=1}^{K}\alpha_{mk}\ln X_{mkit}, && (6.49)\\ \xi_{mit} &= \ln(\mu_{mi} + \lambda_{mt} + \nu_{mit})^2 - \alpha_{m0}. && (6.50)\end{aligned}$$

Thus

$$\ln(\mu_{mi} + \lambda_{mt} + \nu_{mit})^2 = \alpha_{m0} + \xi_{mit}. \tag{6.51}$$

Substituting equation (6.51) into equation (6.46), it can be shown that

$$\ln u_{mit}^2 = \alpha_{m0} + 2\sum_{k=1}^{K} \alpha_{mk} \ln X_{mkit} + \xi_{mit}. \tag{6.52}$$

Combining the set of M equations,

$$\dot{Y} = \dot{X}\alpha + \xi \tag{6.53}$$

is obtained, where $\alpha = (\alpha_1, \alpha_2, \cdots, \alpha_M)'$, $\alpha_m = (\alpha_{m0}, 2\alpha_{m1}, \cdots, 2\alpha_{mK})'$, $\xi = (\xi_1, \xi_2, \cdots, \xi_{MNT})'$, $\dot{X} = diag(\dot{X}_1, \dot{X}_2, \cdots, \dot{X}_M)$, $\dot{X}_m$ is a $NT \times (K+1)$ matrix with ones in the first column and lnX_{mk} in the other columns. $\dot{Y}$ is defined similarly to $\dot{X}$ with $\dot{Y}_m = (\ln u_{m1}^2, \ln u_{m2}^2, \cdots, \ln u_{mNT}^2)'$.

When u_{mit} is replaced by its consistent estimator $\hat{u}_{mit}$, equation (6.52) can be used for estimation of α_m. However, properties of ξ_{mit} have to be investigated in order to discover the properties of the estimates and to employ an appropriate estimation technique.

If μ_{mi}, λ_{mt} and ν_{mit} are assumed to be normally distributed, the random variables defined as

$$\begin{aligned} q_{mit} &= (\mu_{mi} + \lambda_{mt} + \nu_{mit}) \div \sigma_m, & (6.54) \\ q_{lit} &= (\mu_{li} + \lambda_{lt} + \nu_{lit}) \div \sigma_l, & (6.55) \end{aligned}$$

where

$$\begin{aligned} \sigma_m &= \sqrt{\sigma_{\mu mm} + \sigma_{\lambda mm} + \sigma_{\nu mm}} \\ &= \sqrt{\sigma_{mm}}, \end{aligned}$$

will become standard normal variables with zero mean and unit variance. Moreover, q_{mit}^2, $m = 1, 2, \cdots, M$ are each χ^2 random variables with one degree of freedom. Taking the logarithm of the square of equation (6.54) produces

$$\begin{aligned} \ln q_{mit}^2 &= \ln(\mu_{mi} + \lambda_{mt} + \nu_{mit})^2 - \ln \sigma_m^2 \\ &= \alpha_{m0} + \xi_{mit} - \ln \sigma_m^2, & (6.56) \end{aligned}$$

where the second equality is obtained by use of equation (6.51). This variable is thus distributed as the logarithm of a χ^2 distribution with one degree of freedom. Since both α_{m0} and $\ln \sigma_m^2$ are constant and ξ_{mit} is defined by equation (6.50), it can be shown (Harvey 1976) that

$$\begin{aligned} Var(\ln q_{mit}^2) &= Var(\xi_{mit}) = 4.9348, & (6.57) \\ E(\ln q_{mit}^2) &= -1.2704 \\ &= \alpha_{m0} - \ln \sigma_m^2. & (6.58) \end{aligned}$$

According to equations (6.48) and (6.57), ξ_{mit} has zero mean and a constant variance. Therefore, α_m can be estimated by applying OLS to equation (6.52) for $m = 1, 2, \cdots, M$ separately and this produces no bias or inconsistency. But, it does result in inefficiency since the M sets of equations are related and each of them has a composite error structure similar to that of (6.20) as shown below.

When $i = j$ and/or $t = s$, q_{mit} and q_{ljs} will be correlated. This implies that $\ln q_{mit}^2$ and $\ln q_{ljs}^2$ will be also correlated when $i = j$ and/or $t = s$. It can be shown that

$$E\left[\ln q_{mit}^2 \ln q_{ljs}^2\right] = E(\xi_{mit}\,\xi_{ljs}) + 1.2704^2, \tag{6.59}$$

i.e.,

$$E(\xi_{mit}\,\xi_{ljs}) = E\left[\ln q_{mit}^2 \ln q_{ljs}^2\right] - 1.2704^2. \tag{6.60}$$

Since

$$\begin{aligned} E(q_{mit}\,q_{ljs}) &= \tfrac{\sigma_{\mu ml}}{\sigma_m \sigma_l}, \quad i = j \\ &= 0, \qquad i \neq j, & (6.61) \\ E(q_{mit} q_{ljs}) &= \tfrac{\sigma_{\lambda ml}}{\sigma_m \sigma_l}, \quad t = s \\ &= 0, \qquad t \neq s, & (6.62) \\ E(q_{mit}\,q_{ljs}) &= \tfrac{\sigma_{ml}}{\sigma_m \sigma_l}, \quad t = s \ \&\ i = j \\ &= 0, \qquad t \neq s \text{ or } i \neq j, & (6.63) \end{aligned}$$

where $\sigma_{ml} = \sigma_{\mu ml} + \sigma_{\lambda ml} + \sigma_{\nu ml}$, the following can be derived (Griffiths and Anderson 1982, Johnson and Kotz 1972):

$$\begin{aligned}
\delta_{\mu ml} &= E\left[\xi_{mit}\xi_{lis}\right] \\
&= \sum_{h=1}^{\infty}\left(\frac{\sigma_{\mu ml}}{\sigma_m\sigma_l}\right)^{2h}\frac{h!\Gamma(\frac{1}{2})}{h^2\Gamma(h+\frac{1}{2})}, \qquad (6.64)\\
\delta_{\lambda ml} &= E\left[\xi_{mit}\xi_{ljt}\right] \\
&= \sum_{h=1}^{\infty}\left(\frac{\sigma_{\lambda ml}}{\sigma_m\sigma_l}\right)^{2h}\frac{h!\Gamma(\frac{1}{2})}{h^2\Gamma(h+\frac{1}{2})}, \qquad (6.65)\\
\delta_{ml} &= E\left[\xi_{mit}\xi_{lit}\right] \\
&= \sum_{h=1}^{\infty}\left(\frac{\sigma_{ml}}{\sigma_m\sigma_l}\right)^{2h}\frac{h!\Gamma(\frac{1}{2})}{h^2\Gamma(h+\frac{1}{2})}, \qquad (6.66)\\
\delta_{\nu ml} &= \delta_{ml} - \delta_{\mu ml} - \delta_{\lambda ml}, \qquad (6.67)\\
E[\xi_{mit}\xi_{ljs}] &= 0 \quad \text{if } t \neq s \text{ or } i \neq j.
\end{aligned}$$

Thus, ξ_{mit} can be viewed as having an error components structure similar to that of ϵ_{mit} and (6.52) can be estimated by the technique known as least squares with dummy variables (LSDV) (Maddala 1971). If μ_m^*, λ_m^* and ν_m^* are used to denote vectors containing these components, then

$$E\begin{pmatrix}\mu_m^* \\ \lambda_m^* \\ \nu_m^*\end{pmatrix}\left(\mu_l^{*\prime}\,\lambda_l^{*\prime}\,\nu_l^{*\prime}\right) = \begin{bmatrix}\delta_{\mu ml}I_N & 0 & 0 \\ 0 & \delta_{\lambda ml}I_T & 0 \\ 0 & 0 & \delta_{\nu ml}I_{NT}\end{bmatrix}. \qquad (6.68)$$

Because the system of equations represented by (6.43) is of composite error structure, α can be more efficiently estimated by modifying the procedure and formulae in Baltagi (1980). This eventually produces generalised least squares(GLS) estimates of α, namely $\hat{\alpha}$, where

$$\begin{aligned}
\hat{\alpha} &= \left[\dot{X}'\left(\Lambda_1^{-1}\otimes\left(\frac{A}{T}-\frac{J_{NT}}{NT}\right)\right)\dot{X} + \dot{X}'\left(\Lambda_2^{-1}\otimes\left(\frac{B}{N}-\frac{J_{NT}}{NT}\right)\right)\dot{X}\right.\\
&+ \left.\dot{X}'\left(\Lambda_3^{-1}\otimes\frac{J_{NT}}{NT}\right)\dot{X} + \dot{X}'\left(\Lambda_\nu^{-1}\otimes Q\right)\dot{X}\right]^{-1}\\
&\times \left[\dot{X}'\left(\Lambda_1^{-1}\otimes\left(\frac{A}{T}-\frac{J_{NT}}{NT}\right)\right)\dot{Y} + \dot{X}'\left(\Lambda_2^{-1}\otimes\left(\frac{B}{N}-\frac{J_{NT}}{NT}\right)\right)\dot{Y}\right.\\
&+ \left.\dot{X}'\left(\Lambda_3^{-1}\otimes\frac{J_{NT}}{NT}\right)\dot{Y} + \dot{X}'\left(\Lambda_\nu^{-1}\otimes Q\right)\dot{Y}\right] \qquad (6.69)
\end{aligned}$$

The Λs in the above expression are similar to Ωs defined by (6.35) to (6.42) with σs replaced by δs. The Λs can be estimated after calculating δs according to (6.64) to (6.67). However, such a calculation requires the estimation of the σs, as is discussed below in relation to equations (6.80) to (6.84). Alternatively, one can obtain the best unbiased estimates of Λs directly (Baltagi 1980) by

$$\begin{aligned} \hat{\Lambda}_\nu &= \frac{1}{(N-1)(T-1)}\zeta' Q \zeta, & (6.70)\\ \hat{\Lambda}_1 &= \frac{1}{(N-1)}\zeta' \left[\frac{A}{T} - \frac{J_{NT}}{NT}\right]\zeta, & (6.71)\\ \hat{\Lambda}_2 &= \frac{1}{(T-1)}\zeta' \left[\frac{B}{N} - \frac{J_{NT}}{NT}\right]\zeta, & (6.72)\\ \hat{\Lambda}_3 &= \hat{\Lambda}_1 + \hat{\Lambda}_2 - \hat{\Lambda}_\nu, & (6.73) \end{aligned}$$

where $\zeta = (\zeta_1, \zeta_2, \cdots, \zeta_M)$ is the $NT \times M$ matrix of disturbances, which can be estimated in two ways: (a) applying OLS to equation (6.52) for $m = 1, 2, \cdots, M$ separately and calculating the corresponding residuals; or (b) performing LSDV on (6.52) for $m = 1, 2, \cdots, M$ separately and computing the corresponding residuals (Amemiya 1971). It is noted that both sets of residuals can be used to replace ζ for estimating the Λs and the resulting α has the same asymptotic efficiency in each case. However, Λs estimated from the LSDV residuals are asymptotically more efficient than those from OLS residuals (Prucha 1984). Thus, LSDV is used in this study to obtain ζ.

Referring to both Baltagi (1980) and Prucha (1984), it can be shown that

$$\begin{aligned} \hat{\Lambda}_\mu &= \left[\hat{\delta}_{\mu ml}\right] = \frac{1}{T}\left(\hat{\Lambda}_1 - \hat{\Lambda}_\nu\right), \\ \hat{\Lambda}_\lambda &= \left[\hat{\delta}_{\lambda ml}\right] = \frac{1}{N}\left(\hat{\Lambda}_2 - \hat{\Lambda}_\nu\right), \\ \hat{\Lambda}_\nu &= \left[\hat{\delta}_{\nu ml}\right]. \end{aligned}$$

Once $\hat{\alpha}$ is obtained, ξ_{mit} can be estimated as

$$\hat{\xi}_{mit} = \ln \hat{u}^2_{mit} - \hat{\alpha}_{m0} - 2\sum_{k=1}^{K} \hat{\alpha}_{mk} \ln X_{mkit}. \qquad (6.74)$$

It is now possible to find the efficient estimates of β, which correct for heteroscedasticity, error components and correlation across equations. This is the task of the third step.

According to equations (6.56) and (6.58),

$$\begin{aligned}\ln \hat{q}^2_{mit} &= \hat{\alpha}_{m0} + \hat{\xi}_{mit} - \ln \hat{\sigma}^2_m \\ &= \hat{\xi}_{mit} - 1.2704, \end{aligned} \tag{6.75}$$

i.e.,

$$\hat{q}_{mit} = \sqrt{exp(\hat{\xi}_{mit} - 1.2704)}. \tag{6.76}$$

It can be shown that

$$\begin{aligned}E(q_{mit}\, q_{lit}) &= \frac{\sigma_{\mu ml} + \sigma_{\lambda ml} + \sigma_{\nu ml}}{\sigma_m \sigma_l} \\ &= \frac{\sigma_{ml}}{\sigma_m \sigma_l} \\ &= \rho_{ml}, \end{aligned} \tag{6.77}$$

where $\sigma_{ml} = \sigma_{\mu ml} + \sigma_{\lambda ml} + \sigma_{\nu ml}$ and ρ_{ml} is the correlation coefficient between ϵ_m and ϵ_l which can be estimated by

$$\hat{\rho}_{ml} = \frac{1}{NT} \sum_{i=1}^{N} \sum_{t=1}^{T} \hat{q}_{mit} \hat{q}_{lit}. \tag{6.78}$$

From equation (6.58),

$$\hat{\sigma}^2_m = exp(\hat{\alpha}_{m0} + 1.2704). \tag{6.79}$$

These give

$$\hat{\sigma}_{ml} = \hat{\rho}_{ml} \hat{\sigma}_m \hat{\sigma}_l. \tag{6.80}$$

Now, $\sigma_{\mu ml}$, $\sigma_{\lambda ml}$ and $\sigma_{\nu ml}$ can be estimated by

$$\hat{\sigma}_{\mu ml} = \frac{2}{NT(T-1)} \sum_{i=1}^{N} \sum_{s=1}^{T-1} \sum_{t=s+1}^{T} \frac{\hat{u}_{mit}}{\hat{h}_{mit}} \frac{\hat{u}_{lis}}{\hat{h}_{lis}}, \tag{6.81}$$

$$\hat{\sigma}_{\lambda ml} = \frac{2}{NT(N-1)} \sum_{t=1}^{T} \sum_{i=1}^{N-1} \sum_{j=i+1}^{N} \frac{\hat{u}_{mit}}{\hat{h}_{mit}} \frac{\hat{u}_{ljt}}{\hat{h}_{ljt}}, \tag{6.82}$$

$$\hat{\sigma}_{\nu ml} = \hat{\sigma}_{ml} - \hat{\sigma}_{\mu ml} - \hat{\sigma}_{\lambda ml}, \tag{6.83}$$

where

$$\hat{h}_{mit} = \prod_{k=1}^{K} X_{mkit}^{\hat{\alpha}_{mk}}. \tag{6.84}$$

If these computations are being made with a view towards using (6.64) to (6.67), then the estimate for $\hat{\alpha}_{mk}$ would be from OLS or LSDV, rather than GLS, because (6.64) to (6.67) are required before GLS estimation is employed. Substituting $\hat{\sigma}_{\nu ml}$, $\hat{\sigma}_{\mu ml}$, and $\hat{\sigma}_{\lambda ml}$ into equations (6.35) to (6.37) enables the computation of $\hat{\Omega}$ via equations (6.38) to (6.42). According to equation (6.29),

$$\hat{\Phi} = \hat{H}\hat{\Omega}\hat{H}, \tag{6.85}$$

where $\hat{H}$ can be obtained through equations (6.13) to (6.15) with h_{mit} replaced by $\hat{h}_{mit}$. Thus, to obtain the efficient estimates of β represented by $\tilde{\beta}$, it is a matter of minimising

$$\begin{aligned} \hat{\Psi} &= u'\hat{\Phi}^{-1}u \\ &= u'\hat{H}^{-1}\hat{\Omega}^{-1}\hat{H}^{-1}u \\ &= \dot{u}'\hat{\Omega}^{-1}\dot{u}, \end{aligned} \tag{6.86}$$

where $\dot{u} = \hat{H}^{-1}u$.

For the purpose of computer programming, it is necessary to find a transformation of the error term, say $p\dot{u}$, such that $\dot{u}'p'p\dot{u} = \dot{u}'\hat{\Omega}^{-1}\dot{u}$. When $\hat{\Omega}$ is of small dimension, one of the methods is to find c and $\wedge$ such that $p = \wedge^{-\frac{1}{2}}c'$, where c is an orthogonal matrix consisting of the characteristic vectors of $\hat{\Omega}$ and $\wedge$ is a diagonal matrix consisting of eigenvalues of $\hat{\Omega}$. However, Ω is of order $(MNT \times MNT)$, which could well be in excess of dimension 200. In this case, solving $\hat{\Omega}$ for c and $\wedge$ requires solving a polynomial equation of degree over 200. This is a difficult task and unreliable results may be obtained. To tackle this problem, a two-step procedure is developed: (a) decomposing Ω^{-1} according to the suggestion of Baltagi (1980), which gives

$$\begin{aligned} \hat{\Omega}^{-1} &= \hat{\Omega}_3^{-1} \otimes \frac{J_{NT}}{NT} + \hat{\Omega}_1^{-1} \otimes \left(\frac{A}{T} - \frac{J_{NT}}{NT}\right) \\ &+ \hat{\Omega}_2^{-1} \otimes \left(\frac{B}{N} - \frac{J_{NT}}{NT}\right) + \hat{\Omega}_\nu^{-1} \otimes Q, \end{aligned} \tag{6.87}$$

where $\hat{\Omega}_1$, $\hat{\Omega}_2$, $\hat{\Omega}_3$ and $\hat{\Omega}_\nu$ can be calculated according to equations (6.35) to (6.37) and (6.39) to (6.42) with σs replaced by their estimated counterparts. It is noted that these matrices only have dimensions of $M \times M$; (b) let $\Omega_\nu^{-1} = P_4 P_4'$ and defining

$$\hat{\Omega}_i^{-1} = P_i P_i' \tag{6.88}$$

for $i = 1, 2, 3, 4$. Further defining

$$D_1 = \frac{A}{T} - \frac{J_{NT}}{NT}, \tag{6.89}$$

$$D_2 = \frac{B}{N} - \frac{J_{NT}}{NT}, \tag{6.90}$$

$$D_3 = \frac{J_{NT}}{NT}, \tag{6.91}$$

$$D_4 = Q, \tag{6.92}$$

then, since the $D_i s$ are all idempotent and $D_i D_j = 0$ for $i \neq j$, equation (6.88) can be written as

$$\begin{aligned}\hat{\Omega}^{-1} &= \sum_{i=1}^{4} (P_i P_i' \otimes D_i D_i) \\ &= \left(\sum_{i=1}^{4} P_i \otimes D_i\right)\left(\sum_{i=1}^{4} P_i' \otimes D_i\right).\end{aligned} \tag{6.93}$$

Therefore, an equivalent operation of minimising $\hat{\Psi}$ is to minimise $\ddot{u}'\ddot{u}$, where

$$\ddot{u} = \left(\sum_{i=1}^{4} P_i' \otimes D_i\right)\dot{u}. \tag{6.94}$$

To summarise, the estimation of seemingly unrelated regression models which carry risk implications and incorporate composite errors will normally involve the following steps:

(1) Find $\hat{\beta}$ and $\hat{\gamma}$ by using nonlinear least squares either to minimise $u_m' u_m$ for $m = 1, 2, \cdots, M$, respectively, or to minimise $u'u$; denote the corresponding residuals by $\hat{u}$.

(2) Obtain $\hat{\alpha}$ by applying the GLS technique on the SUR models with error components, where $\ln \hat{u}_{mit}^2$ is regressed linearly on the $\ln X_{mkit}s$; denote the corresponding residuals by ξ.

(3) Use ξ to estimate q via (6.76) and then ρ_{ml}, σ_{mm} via (6.78), (6.79). This enables the estimation of σ_{ml} via (6.80).

(4) Use $\hat{\sigma}_{ml}$ and $\hat{\alpha}$ to find $\hat{h}_{mit}$ from (6.84) and subsequently $\hat{\sigma}_{\mu ml}, \hat{\sigma}_{\lambda ml}$ and $\hat{\sigma}_{\nu ml}$ from (6.81) to (6.83). H can be estimated via (6.14) to (6.15).

(5) Construct $\hat{\Omega}_1, \hat{\Omega}_2, \hat{\Omega}_3$ and $\hat{\Omega}_\nu$ by replacing σs in (6.39) to (6.42) by their estimated counterparts computed in step (4).

(6) Find P_i of $\hat{\Omega}_i$ for $i = 1, 2, 3, 4$ and then obtain $\hat{\Omega}^{-1}$ from (6.93).

(7) Use $\hat{H}$ from step (4) and $\hat{\Omega}^{-1}$ from step (6) to find $\tilde{\gamma}$ and $\tilde{\beta}$ by employing nonlinear least squares to minimise $u'\hat{H}^{-1}\hat{\Omega}^{-1}\hat{H}^{-1}u$.

6.3 Estimation, Results and Interpretation

Iterative optimization techniques known as Gauss-type methods are often used to search for approximate least square estimates (β) of a nonlinear model(Judge et al. 1985, p. 969). Denoting residuals of the NL model by $\mathbf{e}(\beta)$ and the sum of squared errors by $R(\beta)$,

$$\begin{aligned} R(\beta) &= [Y - f(X,\beta)]'[Y - f(X,\beta)] \\ &= \mathbf{e}(\beta)'\mathbf{e}(\beta), \end{aligned} \tag{6.95}$$

then the general form of an interation of the Gauss method is (Judge et al. 1985, p. 960)

$$\hat{\beta}_{j+1} = \hat{\beta}_j - (2Z(\beta)'Z(\beta))^{-1}G_j, \tag{6.96}$$

where

$$\begin{aligned} Z(\beta) &= \frac{\partial f(X,\beta)}{\partial \beta} \\ &= \begin{bmatrix} \frac{\partial f(x_1,\beta)}{\partial \beta_1}|_{\beta_j} & \cdots & \frac{\partial f(x_1,\beta)}{\partial \beta_K}|_{\beta_j} \\ \vdots & \ddots & \vdots \\ \frac{\partial f(x_n,\beta)}{\partial \beta_1}|_{\beta_j} & \cdots & \frac{\partial f(x_n,\beta)}{\partial \beta_K}|_{\beta_j} \end{bmatrix} \\ &= -\frac{\partial \mathbf{e}(\beta)}{\partial \beta} \end{aligned} \tag{6.97}$$

$$G_j = \frac{\partial R(\beta)}{\partial \beta}|_{\beta_j} = 2\left[\frac{\partial \mathbf{e}(\beta)}{\partial \beta}|_{\beta_j}\right]' \mathbf{e}(\beta_j), \tag{6.98}$$

where n is the sample size, G_j is the gradient of the objective function and β_j is the estimate of the parameter vector from the previous iteration. The term $(2Z(\beta)'Z(\beta))^{-1}$ is called the direction matrix.

The Gauss method is considered to be reliable provided that the direction matrix is nonsingular. Indeed, singularity of the direction matrix often proves to be the major cause of failure of the method. Also, convergence can be slow when the residuals are large (Judge et al. 1985, p. 961). One solution to these problems is to augment $2Z(\beta)'Z(\beta)$ by the matrix

$$\eta(M + \eta\vartheta), \tag{6.99}$$

where M is a diagonal matrix with the diagonal elements M_{ii} equivalent to the diagonal elements of $2Z(\beta)'Z(\beta)$. ϑ is a pre-determined constant and η is a constant changing its value in every iteration (Nash and Walker-Smith 1987, p. 206). This approach, called the Marquardt-Levenberg-Nash method, is adopted in this study. However, a larger value is assigned to η than those suggested by Marquardt (1963) and Nash and Walker-Smith (1987, p. 206). This is because a large residual sum of squares normally occurs with power functions and a larger η can help speed up convergence. The computer program can be found in Appendix C.

Noting the complexity of the SUR models, especially when a large number of parameters is involved, execution of the program can be costly. To reduce the number of iterations and obtain convergence in the right direction, choices of starting values are quite important. One possible choice is to estimate the βs without considering the cross-equation errors and heteroscedasticity. This can be done by setting $u_{it} = \epsilon_{it}$. The resulting estimates can be used as starting values for the SUR models with composite error and heteroscedasticity.

The survey data described in section 2.3.1 are used to estimate the SUR models. Those variables in value terms are deflated by a weighted index of agricultural prices in state and free markets. With M=3, NT = 112 and use of numerical derivatives, it takes 7 to 9 minutes to complete one iteration on the GOULD NP1 machine. About 10 different sets of starting values are used, five of them lead to the seemingly optimal point with the sum of squared residuals equals to 6.37×10^2. The solution corresponding to this point is considered to be at the global optimum. The estimates for the mean output function and the output variance function are, respectively, presented in Tables 6.1 and 6.2.

In Table 6.1, estimated coefficients of the SUR heteroscedastic models are reported in the third column. For comparison only, results from assuming $u_{it} = \nu_{it}$ are also presented.

From Table 6.1(a), it is seen that, among the eight variables included in the model for rice, four have coefficients with negative signs. That is, rice production elasticities with respect to labor, chemical fertiliser, animal cost and machinery cost are less than zero. Recalling that rice is mainly planted in Southern China, where substantial underemployment or over-supply of labor exists in the rural areas, it may be possible that negative returns with respect to labor began occurring, particularly after the resumption of double cropping (after triple cropping ceased) since the late 1970s. The negative elasticity with respect to chemical fertiliser is consistent with the findings of Wiens (1982). Large increases in the application of nitrogen without corresponding increase in potassium and phosphorus might be one of the most important reasons for this negative elasticity (Wiens 1978, Stone 1986). The negative elasticity associated with machinery cost is plausible as replacement of labor by machines "destroys" the traditional labor-intensive farming technique. This is particularly true with rice production since rice requires fine soil preparation and flat land, but machine operation cannot meet these requirments as well as skilled labor does. For animal cost, the negative sign is implausible. However, except for labor, all the negative coefficients have 95 per cent confidence intervals which include a positive range.

Among the remaining variables, all but irrigation are significant contributors to rice output. Examination of the magnitudes of the estimates indicates that change in sown area asserted the greatest positive impact on rice output, followed by organic fertiliser. The insignificance of irrigation may result from the fact that almost all the rice area sown is irrigated and thus irrigation is not a particularly limiting factor in rice production.

The estimates of the mean output function for maize are tabulated in Table 6.1 (b). Judging by the asymptotic t-ratios, all the positive estimates are statistically significant at the 0.05 level. On the other hand, all the three negative coefficients have 95 per cent confidence intervals which include a positive range. Furthermore, the three negative values

Table 6.1: Parameter Estimates for the Mean Output Function
(a) Rice

	Specifications of Error Structure	
	$u_{it} = \nu_{it}$	$u_{it} = (\mu_i + \lambda_t + \nu_{it})h_{it}$
$\hat{\gamma}$	6.836	269.663
	(3.29)	(3.37)
$\hat{\beta}_1$	−0.181	0.728
(Area)	(−2.47)	(8.78)
$\hat{\beta}_2$	0.347	−0.125
(Labor)	(10.52)	(−2.38)
$\hat{\beta}_3$	−0.007	−0.005
(Chemical Fertiliser)	(−0.18)	(−0.43)
$\hat{\beta}_4$	−0.031	−0.035
(Animal Cost)	(−1.61)	(−1.43)
$\hat{\beta}_5$	−0.010	0.017
(Irrigation)	(−0.75)	(0.73)
$\hat{\beta}_6$	−0.031	−0.033
(Machinery Cost)	(−2.59)	(−1.84)
$\hat{\beta}_7$	0.905	0.379
(Organic Fertiliser)	(11.98)	(5.46)
$\hat{\beta}_8$	0.120	0.098
(Other Costs)	(7.30)	(3.00)

Note: Figures in brackets are asymptotic t-ratios.

for labor, chemical fertiliser and animal cost are implausible. Unlike in the case of rice, machinery cost is positively related to maize production. A possible explanation is that, for maize production, machine operation is mainly involved with cultivation and planting. Thus, there is less post-harvest loss than if harvesting were done by machine. More importantly, timing of planting is more crucial for maize production than for rice and the requirement for seedbed preparation is not as great as for rice. Maize is mainly grown in the central and northern parts of China, where farming techniques are relatively poorer than in the south. In other words, replacement of labor by machines is likely to create a positive impact on maize output. Moreover, in the far north the excess labor problem is less severe if it exists at all. This may also help explain the positive sign of $\hat{\beta}_6$.

Area sown is the dominant source of change of maize output. The production elasticity with respect to sown area is 0.68, followed by 0.16 with respect to organic fertiliser and 0.15 with respect to other costs. The elasticity is only 0.02 for machinery cost and 0.016 for irrigation.

The wheat production function seems to be estimated most successfully (Table 6.1(c)). The only negative estimate is the elasticity of irrigation. Wheat is largely planted in the far north of China, where water supply relys heavily on rainfall. It is noted that the negative value has a small t-statistic. Thus, the true elasticity of wheat output with respect to irrigation might be very small and its estimate could well turn out to be nonpositive.

Contrary to both rice and maize, the coefficients of labor, chemical fertiliser and animal cost are all positive, although the estimate associated with animal cost is not significant at the 5 per cent level. Chemical fertiliser has the smallest positive elasticity and organic fertiliser has the largest elasticity. The elasticity with respect to labor is not only positive, but substantial relative to that for other inputs. This comes as no surprise since wheat is predominantly planted in the far north of China where labor is relative scarce. The above-mentioned reason could also explain the relatively large elasticity of machinery cost in wheat production.

Overall, Table 6.1 indicates that, where labor is relatively scarce, machinery generates a positive and significant impact on mean crop yield. For example, when labor input has

Table 6.1: Parameter Estimates for the Mean Output Function
(b) Maize

	Specifications of Error Structure	
	$u_{it} = \nu_{it}$	$u_{it} = (\mu_i + \lambda_t + \nu_{it})h_{it}$
$\hat{\gamma}$	325.277	415.365
	(4.02)	(6.42)
$\hat{\beta}_1$	0.584	0.676
(Area)	(15.10)	(13.24)
$\hat{\beta}_2$	0.012	−0.027
(Labor)	(0.32)	(−0.70)
$\hat{\beta}_3$	0.0002	−0.001
(Chemical Fertiliser)	(0.01)	(−0.13)
$\hat{\beta}_4$	−0.062	−0.017
(Animal Cost)	(−5.72)	(−0.81)
$\hat{\beta}_5$	0.013	0.016
(Irrigation)	(1.79)	(1.94)
$\hat{\beta}_6$	0.009	0.022
(Machinery Cost)	(0.88)	(2.13)
$\hat{\beta}_7$	0.106	0.161
(Organic Fertiliser)	(2.71)	(4.55)
$\hat{\beta}_8$	0.330	0.147
(Other Costs)	(8.61)	(5.36)

Note: Figures in brackets are asymptotic t-ratios.

Table 6.1: Parameter Estimates for the Mean Output Function
(c) Wheat

	Specifications of Error Structure	
	$u_{it} = \nu_{it}$	$u_{it} = (\mu_i + \lambda_t + \nu_{it})h_{it}$
$\hat{\gamma}$	103.304	136.950
	(3.79)	(3.75)
$\hat{\beta}_1$	0.382	0.198
(Area)	(4.41)	(1.96)
$\hat{\beta}_2$	0.212	0.140
(Labor)	(4.95)	(2.14)
$\hat{\beta}_3$	−0.014	0.049
(Chemical Fertiliser)	(−0.82)	(1.98)
$\hat{\beta}_4$	−0.044	0.064
(Animal Cost)	(−2.37)	(1.79)
$\hat{\beta}_5$	0.011	−0.024
(Irrigation)	(0.80)	(−1.21)
$\hat{\beta}_6$	0.074	0.084
(Machinery Cost)	(2.90)	(3.29)
$\hat{\beta}_7$	0.230	0.261
(Organic Fertiliser)	(7.60)	(4.09)
$\hat{\beta}_8$	0.148	0.187
(Other Costs)	(2.78)	(3.13)

Note: Figures in brackets are asymptotic t-ratios.

negative returns in rice production, machinery creates a negative effect on production and the effect is significant at the 10 per cent level. In the case of maize production, labor had no significant impact and machinery generated a limited, though a significant effect on yield (the coefficient is only 0.02), whereas when the labor effect is significantly positive in wheat production, the machinery effect becomes positive, significant and substantial (the elasticity is 0.08).

The parameters determining the signs of marginal risks are presented in Table 6.2. Although attention will be focused on the estimates given by GLS, parameters estimated by other techniques are also shown in Table 6.2. The goodness of fit for the SUR system is calculated according to

$$R^2_{SUR} = 1 - \frac{\tilde{e}'(\Sigma^{-1} \otimes I_{NT})\tilde{e}}{Y'(\Sigma^{-1} \otimes D_{NT})Y} \tag{6.100}$$

where Σ^{-1} is the variance-covariance matrix of the SUR models, $\tilde{e}$ is a $MNT \times 1$ vector containing the GLS residuals, and $D_{NT} = I_{NT} - J_{NT}/NT$. The F_{SUR} statistic is obtained based on R^2_{SUR} (Judge et al. 1985, p. 478). The R^2_{SUR} and F_{SUR} are not reported in the tables. The calculation shows that R^2_{SUR} equals 0.55 and F_{SUR} equals 16.01. Noting that data used for estimation are basically cross-sectional (time span is relatively short), 0.55 indicates a reasonable goodness of fit. The F_{SUR} is statistically significant at any conventional level, which suggests the existence of heteroscedasticity. This may imply the inadequacy of conventional functions or the superiority of the heteroscedastic SUR models.

Machinery, organic fertiliser and other costs seem to have stabilizing effects on rice output (Table 6.2(a)). The coefficient for machinery is insignificant. It is reasonable to have a negative $\hat{\alpha}_8$ since the major component of other costs is expenditure on management. The significance of both positive $\hat{\beta}_7$ and negative $\hat{\alpha}_7$ imply the importance of organic fertiliser in achieving a high and stable yield in China's rice production. The variance of production is positively related to chemical fertiliser application, though there is a lack of statistical significance. This is in line with the expectation of Hazell (1984) who suspected that, as seed-fertiliser technology advances with the adoption of high-yielding varieties, increased use of chemical fertiliser may bring about higher production variability. As far as animal cost is concerned, the significantly positive sign is implausible and thus needs further investigation.

Table 6.2: Parameter Estimates for the Output-Variance Function
(a) Rice

	Estimation Technique		
	OLS	LSDV	GLS
$\hat{\alpha}_0$	22.432	-	18.813
	(14.90)	-	(7.66)
$2\hat{\alpha}_1$	3.443	1.339	2.072
(Area)	(8.02)	(0.67)	(2.56)
$2\hat{\alpha}_2$	−0.910	0.651	0.174
(Labor)	(−3.03)	(0.44)	(0.32)
$2\hat{\alpha}_3$	0.303	1.017	0.515
(Chemical Fertiliser)	(2.82)	(1.16)	(1.92)
$2\hat{\alpha}_4$	0.470	1.228	1.005
(Animal Cost)	(2.63)	(1.36)	(2.84)
$2\hat{\alpha}_5$	0.273	1.049	0.796
(Irrigation)	(1.69)	(1.27)	(2.40)
$2\hat{\alpha}_6$	0.101	−0.179	−0.005
(Machinery Cost)	(1.08)	(−0.33)	(−0.03)
$2\hat{\alpha}_7$	−2.003	−1.987	−1.850
(Organic Fertiliser)	(−5.59)	(−1.22)	(−2.84)
$2\hat{\alpha}_8$	−0.450	−1.894	−1.433
(Other Costs)	(−1.89)	(−1.66)	(−3.17)
R^2	0.637		
F-ratio	22.609		

Note: Figures in brackets are asymptotic t-ratios.

While irrigation is expected to help stabilise production, the empirical result here does not seem supportable. Noting that $\hat{\alpha}_5$ is significant and of considerable magnitude, better management of the irrigation system in China is implied to be urgently needed. This is because the positive $\hat{\alpha}_5$ and negative $\hat{\beta}_5$ could well be the result of malfunctioning of the irrigation system due to a collapsed management of water resource and irrigation facilities after the introduction of the APRS in 1978. The impact of area sown on production risks basically depends on the correlation coefficients among rice outputs of different seasons and on management skills. In general, a positive relationship is expected. Finally, labor does not produce a significant impact on production risk. This is primarily because the labor input in China was near "saturation" long before 1980. Thus its changes may not generate any effect on either mean output or output risk.

Contrary to the case of rice production, animal cost and irrigation were estimated to be stabilizing factors in maize production in China (Table 6.2(b)). This may be due to the relative insensitivity of maize to the timing, quantity and frequency of water supply. In other words, irrigation can help stabilise maize production and, while there are problems of irrigation in China, these may generate only very limited impact on maize yield variability. The variables other than animal cost and irrigation are all positively related to maize production variance. This is plausible for labor, area sown and chemical fertiliser for the reasons discussed earlier. The positive signs of machinery, organic fertiliser and other costs are implausible. However, all the positive estimates have 95 per cent confidence intervals which include negative values.

The relationship estimated between wheat output variance and inputs is presented in Table 6.2(c). All the slope parameters are insignificant at the 5 per cent level. The negative value for area sown is unexpected as is that for organic fertiliser. The estimates associated with labor and other costs are not only positive, but also quite large in magnitude. It should be stressed that all the slope coefficients could well be zeros in accordance with the asymptotic t-ratios.

It is difficult to generate findings from the estimates of the three equations because (a) most of the estimates are not encouraging in terms of statistical significance; and (b) the

Table 6.2: Parameter Estimates for the Output-Variance Function
(b) Maize

	Estimation Technique		
	OLS	LSDV	GLS
$\hat{\alpha}_0$	9.138	-	9.107
	(6.77)	-	(3.91)
$2\hat{\alpha}_1$	0.377	1.675	1.056
(Area)	(0.83)	(0.45)	(1.34)
$2\hat{\alpha}_2$	0.368	0.013	0.058
(Labor)	(1.03)	(0.004)	(0.11)
$2\hat{\alpha}_3$	0.040	0.054	0.099
(Chemical Fertiliser)	(0.35)	(0.08)	(0.56)
$2\hat{\alpha}_4$	−0.055	−0.785	−0.440
(Animal Cost)	(−0.39)	(−0.70)	(−1.77)
$2\hat{\alpha}_5$	−0.160	−0.436	−0.182
(Irrigation)	(−2.22)	(−0.79)	(−1.28)
$2\hat{\alpha}_6$	0.282	0.390	0.349
(Machinery Cost)	(2.87)	(0.51)	(1.86)
$2\hat{\alpha}_7$	0.340	0.338	0.437
(Organic Fertiliser)	(1.08)	(0.16)	(0.76)
$2\hat{\alpha}_8$	0.250	0.484	0.261
(Other Costs)	(0.82)	(0.29)	(0.49)
R^2	0.533		
F-ratio	14.684		

Note: Figures in brackets are asymptotic t-ratios.

Table 6.2: Parameter Estimates for the Output-Variance Function
(c) Wheat

	Estimation Technique		
	OLS	LSDV	GLS
$\hat{\alpha}_0$	8.310	-	7.226
	(6.99)	-	(2.54)
$2\hat{\alpha}_1$	0.016	−0.709	−0.407
(Area)	(0.04)	(−0.37)	(−0.41)
$2\hat{\alpha}_2$	0.886	−0.207	0.700
(Labor)	(3.40)	(−0.17)	(1.26)
$2\hat{\alpha}_3$	−0.331	0.290	0.018
(Chemical Fertiliser)	(−3.01)	(0.96)	(0.09)
$2\hat{\alpha}_4$	−0.005	0.003	−0.073
(Animal Cost)	(−0.03)	(0.01)	(−0.24)
$2\hat{\alpha}_5$	−0.002	0.184	0.056
(Irrigation)	(−0.02)	(0.42)	(0.24)
$2\hat{\alpha}_6$	0.444	−0.011	0.247
(Machinery Cost)	(4.14)	(−0.03)	(1.13)
$2\hat{\alpha}_7$	−0.141	0.682	0.113
(Organic Fertiliser)	(−0.47)	(0.67)	(0.19)
$2\hat{\alpha}_8$	0.482	1.270	0.878
(Other Costs)	(1.64)	(1.58)	(1.65)
R^2	0.596		
F-ratio	19.010		

Note: Figures in brackets are asymptotic t-ratios.

magnitudes of and especially the signs of parameters are so inconsistent across equations. However, as far as the relationship between the 'green revolution' and production risks is concerned, the empirical results indicate that there is a positive link between seed-fertiliser technology and output variability. This may be due to the introduction of HYVs which have a narrower genetic base than their predecessors (Hazell 1984). The nature of irrigation in the context of output variability crucially depends on the reliability of the water supply. Taking into account the fact that the irrigation systems in many parts of China are generally in a state of poor repair and often severely damaged, the nonnegative effect of irrigation on output risk may be understandable. The machinery input possibly brought about higher risks, which could arise from the poor quality of both tools and operations.

The estimated covariance matrices $[\hat{\delta}_{\mu ml}]$, $[\hat{\delta}_{\nu ml}]$, $[\hat{\delta}_{\lambda ml}]$ and $[\hat{\delta}_{ml}]$ of the output-variance functions are given in Table 6.3. From comparison of the corresponding values of $[\hat{\delta}_{\lambda ml}]$ and $[\hat{\delta}_{\mu ml}]$, it is clear that the time effect may be negligible. The existence of cross-equation covariance is seen by the possibly significant off-diagonal values of $[\hat{\delta}_{ml}]$. If the assumption of a normal distribution for each of the three (time, section and random) errors holds, the

Table 6.3: Covariance Matrices of Output-Variance Functions

	-0.010	-0.043	-0.168
$[\hat{\delta}_{\lambda ml}]$	-0.043	0.058	-0.046
	-0.168	-0.046	0.148
	1.660	1.336	-0.697
$[\hat{\delta}_{\mu ml}]$	1.336	3.373	-0.402
	-0.697	-0.402	3.321
	5.293	-0.227	-0.088
$[\hat{\delta}_{\nu ml}]$	-0.227	2.803	0.122
	-0.088	0.122	2.009
	6.093	0.833	-0.576
$[\hat{\delta}_{ml}]$	0.833	5.035	-0.118
	-0.576	-0.118	3.981

Table 6.4: Covariance Matrices of Mean Output Functions

	15928.522	5809.082	840678.539
$[\hat{\sigma}_{\mu ml}]$	5809.082	4593.849	271162.822
	840678.539	271162.822	186857666.081
	1570.784	619.503	-131845.170
$[\hat{\sigma}_{\lambda ml}]$	619.503	246.119	-277397.578
	-131845.170	-277397.578	76840813.036
	14630.159	3448.611	1982192.815
$[\hat{\sigma}_{\nu ml}]$	3448.611	56.530	985374.936
	1982192.815	985374.936	263829703.787

diagonal elements of $[\hat{\delta}_{ml}]$ should be close to 4.9348 (Harvey 1976). Statistical tests (F statistics) indicate that all three values are not significantly different from 4.9348 at the 5 per cent level. In passing, it is noted that the negative values on the diagonals of these matrices are possible and they can be set to zero in practice if necessary (Fuller and Battese 1974, p. 72).

The variance-covariance matrices of the mean output functions are given in Table 6.4. The lack of time effects is again seen by the small ratios of $\hat{\sigma}_{\lambda ml}/\hat{\sigma}_{\mu ml}$. The contemporary covariances across equations are all positive and substantial.

6.4 Summary

In this chapter, SUR models which incorporate time-specific and section-specific error components and permit the marginal variances of outputs to be of either positive or negative sign are proposed. An estimation procedure is suggested and a corresponding computer program in FORTRAN is developed. This attempt is of empirical significance, particularly in agro-economic research, since outputs of various agricultural activities tend to be influenced by some common factors, notably weather and policy changes. Also, increases of different inputs can either enhance or reduce output risks. Conventional SUR models restrict the marginal risks to be positive.

Using combined time-series (4 years) and cross-sectional (28 regions) data on Chinese rice, maize and wheat production, heteroscedastic SUR production functions were estimated. The results suggest that, as chemical fertiliser, sown area and irrigation cost increase, output variances generally rise. In contrast, increase in the organic fertiliser, machinery and the other inputs may help stabilise Chinese foodgrain production. Labor input does not create significant impacts on either mean outputs or output variances.

It must be noted that most of the inputs considered in the models are not necessarily significantly related to production risks. This is not to suggest that these and other inputs are, in fact, unimportant or unnecessary in production and its riskiness. It may, however, imply the importance of weather and government intervention in agriculture in determining the variability of Chinese cereal production.

Chapter 7

EPILOGUE

7.1 Introduction

The objectives of the study, as set out in Chapter 1, have been basically fulfilled. There are, however, some further issues relevant to Chinese foodgrain production variability remaining to be discussed. These, together with various limitations of the study, provide topics for further research.

To conclude this thesis, the limitations of the study are presented in section 7.2, followed by discussion on alternatives towards handling production variability. Finally, in section 7.4, the major findings are summarised and some brief remarks are made on appropriate policy implications.

7.2 Limitations of the Study and Needed Further Research

As in many economic studies, there are problems with data, methodology and possibly interpretation of results in this study. Particularly in the case of China, some of these problems are inevitable. This is due, partly, to the shortage of literature on the Chinese agricultural economy. Furthermore, both quantity and quality of Chinese data are a major obstacle in attempting a satisfactory analysis of Chinese's economic issues (Walker 1982).

Although a special chapter was devoted to data problems, it is worth emphasising some of the negative effects of data problems on the empirical results presented in this thesis. In particular, missing data sets raised the need to artificially define a Residual region and a Residual crop for variance decomposition (cf. Chapter 4). This may have distorted some of the results. The data for other-grains and other-region were calculated from the available data, some of which were from different sources and/or somewhat arbitrarily estimated. This is probably one of the major reasons why variation in other-grains accounted for a surprisingly large percentage of overall variability for some regions and for China as a whole.

Similarly, the poor estimation results in Chapter 5 could also result from the poor quality of data due to errors incurred in the data-gathering process. Also, the shortage of regional observations over time possibly led to unreliable estimates of the region-effect and its associated variance-covariance matrix.

Further effort is required to look at the possible changes in the patterns and underlying causes of Chinese foodgrain production variability after the economic reform initiated in 1978. While the impact of these changes on foodgrain production variability is about to appear, this important issue is beyond the scope of this thesis.

As far as analytical techniques are concerned, halving of covariance terms in Chapter 4 may be inappropriate. When covariance terms outweigh the sum of variance terms, as in the Chinese case, the handling of covariance terms becomes particularly important. Some alternative methods, as suggested in Chapter 4, may be useful.

The power function employed in Chapter 6 is rather restrictive. A possible extension would be to generalise the model so as to allow for the specification of functions which are log-linear in the parameters. Such a generalisation might help to improve the empirical results presented in Chapter 6.

Institutional effects on Chinese foodgrain production were evaluated via a rather crude technique in Chapter 5. Efforts to separate the weather effects, 'green revolution' effects, policy effects and institutional effects would be worthwhile. In this regard, simulation may prove to be a more suitable and powerful tool.

The conclusion drawn in Chapter 6 is subject to changes in weather patterns. Since efficient plans (Hazell 1982). These plans offer a framework under which the grain-purchase contract system could operate and be adjusted when necessary.

In the other direction, effort should be made to breed new crop varieties which are more resistant to pests, weeds, diseases and weather disturbances than existing cultivars. The trade-off between stability and high yield must be seriously considered before releasing a new cultivar. Also, given the diverse growing conditions throughout China and the importance of covariabilities in composing instability of China's foodgrain production, plant breeding may need to be more location-oriented than before.

Increases in capital construction are recommended as one possible measure to reduce weather or environment-related yield variability. This is generally accepted in China by both economists and government. Notable examples include the Hui River and the Yellow River projects which have almost eliminated large-scale flooding. Likewise, the north-plain irrigation scheme in Heilongjiang Province has the potential to help stabilise crop yield in that region if electricity and water supplies can be secured. Over the last few years, state investment in agricultural capital construction has been decreasing. While this decrease may have little impact on output volume in the short-run, its damaging effect on foodgrain production stability can never be overlooked.

Improvement of the agricultural extension system is also likely to have an impact on crop production stability. Farmers need to be well informed as to the effects of various agricultural technologies on production levels and production risk or variability. Without proper extension under any small-scale family farming system, the adoption of new technologies may bring about higher variability. This is particularly important in China, as the extension network is heavily damaged at present, and it has so far neglected variability issues.

7.3.2 Mitigating production variability or its effect

Given a particular level of production variability for individual crops, there exist some alternative procedures to mitigate crop output variability at the farm, regional or national level.

Perhaps the most traditional method is product diversification. However, effectiveness of any form of diversification depends crucially on the covariabilities among the outcomes of the chosen activities. Spatial diversification is of limited use in China since the amount of land operated by each family is too small to allow for feasible spatial diversification. Thus, staggered plantings and sequential diversification may be regarded as suitable techniques for stabilising total farm output. However, diversification often leads to stable total output at the cost of inefficient resource use. As such, the extent to which the diversification option should be encouraged is an open subject for further research. This is of national significance as China possesses a very low resource/person ratio and has struggled to obtain self-sufficiency in foodgrain supply.

Crop insurance could provide a formal mechanism to transfer production risk or variabilities. As previously argued, yield variability is the dominant source of production variability, so insurance might be the best solution (Hazell, Pomareda and Valdes 1985). It is noted that currently there is no crop insurance in China. The usual problems, such as adverse selection and moral hazard, would have to be seriously considered in designing such an insurance program. Evidence provided by Hazell, Pomareda and Valdes (1985) suggests that a national agricultural insurance scheme would need government backing. Such a scheme might also be used to transfer income to farmers in order to bridge the income gap between farmers and non-farmers. Raising farmers' income through other ways, e.g., lifting agricultural product prices, has proven difficult and often led to undesirable results. The failure of most comprehensive insurance programs may imply the necessity for crop insurance to be compulsory, risk-specific and partial.

7.4 Major Findings and Remarks on Policy Implications

Dramatic changes have occurred in China since the late 1970s. It is now apparent that these changes have been towards replacing the planned economy by a market-based economy. The changes are likely to alter the patterns and sources of foodgrain production variability in China. Future research is needed to identify the effect of the changes on Chinese foodgrain production once data become available. However, the present study may provide useful information for relevant policy evaluation and possibly for future policy design. It can also serve as a basis for further research on Chinese foodgrain production variability.

In Chapter 3, single-variable measures were applied to regional data to measure intra-crop and intra-region variability. An inverse relationship was found between the importance of a crop and its variability in terms of both sown-area and output. This finding reflects the positive effect of the procurement system on stabilising sown area as confirmed by the results in Chapter 5, where significant decreases in production variance were shown to be attributable to reductions in sown-area variations between 1949-58 and 1963-77, and between 1949-58 and 1978-85. Thus, abolition of the procurement system is called into question. If the substitute, namely, the grain-purchase contract system, does not work as desired, the re-introduction of the procurement system with some modifications may be a feasible option.

This finding also calls for greater attention to be paid to coarse grains, not only because they have been neglected by the government, but also because their volume will increase as the rapid development of animal husbandry leads to increased demand for coarse grains.

Policy-makers in China used to focus on raising and stabilising crop yields in the developed regions. It is only since the mid 1980s or so that attention has been diverted to less developed areas. This is partially responsible for the appearance of a trend of increasing variability from the South to the North and from the East to the West. The finding of such a trend appeals for special consideration in designing policy to raise yields in less developed regions. Efforts must be made to improve farmers' management skills and farming conditions. These are important for both raising and stabilising crop yields. The current strategy of simply allocating more inputs to the less developed regions has neglected variability issues. It is noted that increases in the application of some inputs, particularly chemical fertiliser, may lead to higher production variability, as shown in Chapter 6.

By single-variable measures, output of rice was shown to be most stable and wheat to be less stable among the crops considered in this study. The proposition by some Chinese economists to increase wheat production at the expense of rice production has to be revised if stability of China's foodgrain supply is taken into account.

When covariabilities were also considered together with intra-crop and intra-region variabilities in Chapter 4, it was found that, as far as sown-area is concerned, covariance among regions dominated the total variability. This is true for every individual crop. In the case of output, the among-region covariance shared nearly 30 per cent of total output variability. These findings once again imply the negative effect of rigid nation-wide policy on production variability. It is particularly recommended that balanced allocation of state investment, input and consumption rations, etc. be abolished because it could contribute significantly to the composition of covariabilities.

It was shown in Chapter 4 that yield variability played an dominant role in composing output variations for important crops and sown area variability for less important crops. This may indicate that for those regions mainly producing fine grains, emphasis should be put on stabilising yields, while emphasis should be focused on stabilising sown-area for the other regions.

One interesting point is the existence of positive production covariance among crops within regions. This casts some doubts on the usefulness of crop diversification in reducing regional production variability. Such a result suggests that encouraging regional specialisation will lead to an increase in national foodgrain production, while having little influence on production variability. Therefore, the practised self-sufficiency strategy of regional governments cannot be justified on the basis of either mean production or production security.

The results from Chapter 5 show that total variability of China's foodgrain production decreased from 1949-58 to 1978-85 and from 1963-77 to 1978-85. From 1949-58 to 1978-85, all crops experienced large decreases in sown-area variance. Meanwhile, yield variations enhanced the total variability. However, the stabilising effect of sown-area control via implementation of procurement policy outweighed the destabilising effect of yield variation. This is not surprising since the influence of yield variation on output instability is not as large nor as significant as that of sown-area (cf. Chapter 3). Thus, it seems questionable for the government to devote major efforts to stabilise crop yield while neglecting sown-area variability. If sown-area was not of serious concern prior to 1985, because it was controlled by the detailed national plan, then sown-area variability must now attract policy-makers' attention. Currently, there is no explicit or effective mechanism to control area sown in China.

It is known that introduction of the APRS has asserted positive effects on production volumes. The introduction also led to a decrease in production variance. The decrease was largely attributed to the farmers' improved initiatives and a flexible government control over sown-area. At present, the fixed low grain prices and high inflation have swept off farmers' initiatives. Conversely, land privatisation would seem inevitable in the medium term, which may well lead to high sown-area variability. Thus, there may be a large increase in the variability of Chinese foodgrain production in the near future unless (a) appropriate schemes to control sown-area are designed and implemented with the progress of land privatisation; (b) price structures, especially agricultural product price structures, are adjusted so that grain producers are not in a disadvantageous position, at least, relative to other producers in the agricultural sector; and (c) price stabilisation programs are introduced as the whole economy moves towards a free economy.

In Chapter 6, some inputs, e.g., chemical fertiliser and sown-area, were shown to be positively related to production variance, and other inputs, e.g., organic fertiliser and machinery cost, negatively related. The significant effect of input changes on production variability may well be relevant to inter-region and/or inter-crop covariabilities as well as to intra-crop or intra-region variabilities. These results imply the necessity for return to extensive application of organic fertiliser. This tradition was lost when the APRS was introduced and labor cost became high in the early 1980s. It might be useful to tie the allocation of chemical fertiliser with the application of organic fertiliser. This could be important for both sustaining gains in yield and in reducing production variability. However, most inputs considered in Chapter 6 did not significantly affect output variance. Thus, weather is still the major factor determining production variability. In view of this result, the central government's policy of decreasing agricultural investment needs to be reversed. Unless reversed, the present policy will destabilise foodgrain production, especially in the long run, because the state investment was largely devoted to reducing the effect of large-scale