single variable HYP. When we add to this a second term for gall-bladder disease (line 2, part C), the model then specifies that the relative risks associated with these two variables are multiplicative, and moreover that their joint effect is multiplicative with those of the matching variables. The relative risk for GALL, adjusted for the multiplicative effects of hypertension, is estimated as $\hat{\psi} = \exp(0.970) = 2.65$, scarcely different from the unadjusted value. Likewise the null hypothesis that $\psi = 1$ is tested by $\chi^2 = 3.61$ (uncorrected), which is also rather close to the unadjusted value. By way of contrast, the adjusted estimate of RR for GALL obtained in § 5.2, where we restricted attention to the eight case-control pairs which were homogeneous for HYP and heterogeneous for GALL, gives the relatively unstable value of $\hat{\psi} = 7/1$. The difference is explained by the fact that the model uses all the case-control pairs which are discordant for at least one of GALL and HYP (see Table 7.4) to estimate the main effects of both variables. The five pairs which are discordant for both variables, not used in the elementary analysis, now contribute to the estimate of the coefficient of GALL.

In case the reader is left with the impression that something has been gained for nothing by this procedure, we hasten to point out that the elementary estimate is strictly valid under a weaker set of assumptions than that based on the model. In Chapter 5 we effectively assumed only that the relative risk of GALL was constant with respect to HYP and the matching variables. The modelling procedure supposes in addition that HYP combines multiplicatively with the matching variables; it could lead to biased estimates of the coefficient of GALL if interactions were present. Of course, in some situations, such interactions involving the matching and other confounding variables might also be modelled and added to the equation as a means of further adjustment. For example, if we suspected that not only the main effects of HYP but also the interaction between HYP and AGE were confounding the estimate of the GALL coefficient, we would fit the equation with terms for GALL, HYP and HYP × AGE. Fortunately, the higher order interactions which might necessitate such a procedure are rarely present in epidemiological studies (Miettinen, 1974).

Further insight into the assumptions which underlie the model is given by consideration of line 3 of Part C, Table 7.3. Here the addition of the interaction term GALL × HYP allows us to estimate the relative risk of each possible combination of exposures to these two risk factors, relative to those who are exposed to neither. Thus $\hat{\psi}_{10} = \exp(1.517) = 4.56$ is the estimated RR for those with gall-bladder disease only, $\hat{\psi}_{01} = \exp(0.627) = 1.87$ for those with hypertension only, and $\hat{\psi}_{11} = \exp(1.517 + 0.627 - 1.548) = 1.81$ for those having a positive history of both diseases. In summary, the relative risks are given by this bizarre-looking table:

		Gall-bladder disease	
		−	+
Hypertension	−	1.00	4.56
	+	1.87	1.81

However the interaction effect is not significant, as indicated by the score statistic comparing lines 2 and 3 of Table 7.3, Part C.

In effect what we have now done is to create out of GALL and HYP a joint risk variable with four exposure categories: (−, −), (−, +), (+, −), and (+, +). The estimation problem is as described in § 5.5 for matched-pair studies with a polytomous risk variable. Table 7.4 presents the distribution of the 63 matched pairs according to the joint response of case and control, following the format of Table 5.5. We readily verify that the maximum likelihood equations (5.30) for data of this type, namely

$$14 + 1 + 0 = 20\,\frac{\psi_{01}}{1+\psi_{01}} + 5\,\frac{\psi_{01}}{\psi_{01}+\psi_{10}} + 1\,\frac{\psi_{01}}{\psi_{01}+\psi_{11}}$$

$$6 + 4 + 0 = 7\,\frac{\psi_{10}}{1+\psi_{10}} + 5\,\frac{\psi_{10}}{\psi_{01}+\psi_{10}} + 1\,\frac{\psi_{10}}{\psi_{10}+\psi_{11}}$$

$$2 + 1 + 1 = 5\,\frac{\psi_{11}}{1+\psi_{11}} + 1\,\frac{\psi_{11}}{\psi_{01}+\psi_{11}} + 1\,\frac{\psi_{11}}{\psi_{10}+\psi_{11}},$$

are solved by the estimates just derived using the general computer programme.

The analysis shown in Part D of Table 7.3 is identical with that in Part C except for the order of entry of the variables into the equation. If our interest is in the effects of GALL after adjustment for HYP, we would follow the sequence shown in Part D. In this example, the estimated coefficients and standard errors are not much affected by the presence of the other variable in the equation, which means that they are not confounded to any appreciable degree.

Another example of the analysis of matched-pair data with a polytomous exposure variable was presented at the end of § 5.5. There we estimated the relative risks of endometrial cancer for each of three increasing dose levels of conjugated oestrogens, using the no-dose category as baseline. In order to carry out an essentially identical analysis in the present framework, we first define the three indicator variables DOS1, DOS2 and DOS3, whose β coefficients represent the log odds ratios for each of the

Table 7.4 Histories of gall-bladder and hypertensive disease for cases and matched controls: Los Angeles study of endometrial cancer

Exposures of cases		Exposures of controls				Total
Gall bladder	Hypertension	− −	− +	+ −	+ +	
−	−	15	6	1	3	25
−	+	14	6	1	0	21
+	−	6	4	2	0	12
+	+	2	1	1	1	5
Total		37	17	5	4	63

dose levels shows in Table 7.2 relative to baseline. The conditional logistic regression model (7.3) in this case is merely a restatement of the model (5.29), in which the odds ratios corresponding to each category of exposure are assumed to be constant over the matching variables. By definition they satisfy the consistency relationship discussed earlier in § 5.5.

Part E of Table 7.3 presents the results. Regression coefficients for the three dose variables do indeed correspond to the odds ratios already estimated: $\exp(1.524) = 4.59$ for the 0.1–0.299 mg/day dose level; $\exp(1.266) = 3.55$ for 0.3–0.625 mg/day; and $\exp(2.120) = 8.33$ for over 0.625 mg/day. Likewise the score statistic for testing the null hypothesis is identical with the statistic (5.32) derived earlier, taking the value 16.96 for these data. The only important additional quantities available from the computer fit of the model are the standard errors of the parameter estimates, which enable us to put approximate confidence limits on the estimated relative risks. For example, $\exp(1.524 \pm 1.96 \times 0.618) = (1.37, 15.4)$ are the 95% limits for the 0.1–0.299 mg/day category.

In order to test for a trend in risk with increasing dose we use the single, coded dose variable DOS. Estimated relative risks for the three dose levels are then $\exp(0.690) = 1.99$, $\exp(2 \times 0.690) = 3.98$ and $\exp(3 \times 0.690) = 7.94$, respectively. Comparing the G statistics for the two dose-response models yields $65.50 - 62.98 = 2.52$, nominally a chi-square with two degrees of freedom, for testing the extent to which the linear trend adequately explains the variation in risk between dose levels. The observed departure from trend is not statistically significant ($p = 0.28$). On the other hand, the trend itself is highly significant ($p<0.0001$) as demonstrated by the value 14.71 for the score statistic. This too is identical to the trend statistic derived earlier (5.33), except that the continuity correction is not used by the computer programme. Note that there is not the slightest hint of interaction between dose and age (line 2, part F, Table 7.3).

In summary, analyses of matched-pair data *via* the conditional logistic model yield results identical to those of the "classical" procedures presented earlier for binary and polytomous risk factors. This is hardly surprising, as the previously discussed methods were themselves based on conditional likelihoods worked out in detail for each separate problem. Nevertheless it is an important fact since it shows that the very general methodology developed here is well integrated with the techniques used in the past. Even more important, of course, are extensions to problems involving multiple and/or continuous risk variables which we next consider in the more general context of 1:M matching.

7.4 1:M matching with single and multiple exposure variables: applications

While the regression variables defined in Table 7.2 have so far in this Chapter been used exclusively with the matched-pair data, their coefficients can in fact be better estimated by taking account of the full complement of controls selected for each case. Table 7.5 presents the results of several analyses, based on the conditional likelihood (7.2), which used all the available data. Since no information was available regarding the dose and/or duration of conjugated oestrogen use by certain of the women, their data records were excluded from the analysis when fitting equations containing these variables. While a missing value for the case leads to exclusion of the entire matched

Table 7.5 Results of fitting several conditional logistic regression models to the matched sets consisting of one case and four controls: Los Angeles study of endometrial cancer

No. of parameters	Goodness of fit G	Score test	Regression coefficients ± standard error for each variable in the equation		
			A. Oestrogen use and age level (based on all 63 matched sets, 315 observations)		
			EST	EST × AGE1	EST × AGE2
0	202.79	–			
1	167.44	31.16	2.074 ± 0.421		
3	166.76	0.76	1.431 ± 0.826	0.847 ± 1.034	0.780 ± 1.154
			B. Oestrogen use and coded age level (based on all 63 matched sets, 315 observations)		
			EST	EST × AGE3	
1	167.44	31.16	2.074 ± 0.421		
2	167.05	0.39	1.664 ± 0.750	0.385 ± 0.616	
			C. Conjugated oestrogen use and age (based on 59 matched sets, 291 observations)		
			CEST	CEST × AGE1	CEST × AGE2
0	188.13				
1	159.22	27.57	1.710 ± 0.354		
3	158.28	0.89	1.583 ± 0.815	–0.081 ± 0.930	0.764 ± 1.143

set, a missing value in a control record might simply mean that the number of controls in that set was reduced by one.

In order to estimate the overall relative risk associated with a history of exposure to any oestrogen, we employed the general purpose computer programme with the single binary variable EST (Part A, Table 7.5). This yields $\hat{\psi} = \exp(2.074) = 7.95$, which is of course the same value as found in § 5.3 by solving the equation (5.17) for conditional maximum likelihood estimation. The standard error $0.421 = \sqrt{0.177}$, given by formula (5.21), has already been used to place an approximate 95% confidence interval of $\exp(2.074 \pm 1.96 \times 0.421) = (3.5, 18.1)$ about the point estimate. Likewise the score test statistic is identical to the summary chi-square defined in (5.19), but calculated without the continuity correction so as to give $(110–13)^2/302 = 31.16$ in place of the corrected value 29.57 found earlier.

Continuing the lines of the analysis shown in Table 5.2, we investigated a possible difference in the relative risk for EST in the three age groups 55–64, 65–74 and 75+ by adding to the regression equation interaction terms involving EST and age. In order to account for the breakdown of age into three groups, two binary indicator variables were defined: AGE1 = 1 for 65–74 years, and 0 otherwise; and AGE2 = 1 for 75+ years, 0 otherwise. Thus, from line 2, Part A, Table 7.5, $\exp(1.431) = 4.18$ is the estimated relative risk for women aged 55–64 years, $\exp(1.431 + 0.847) = 9.76$ for those 65–74 years, and $\exp(1.431 + 0.780) = 9.12$ for the 75+ year olds, these results agreeing with those shown in Table 5.2. While there is an apparent increase in the relative risk for the women aged 65 or more years, the score test of 0.76 shows that

the differences are not statistically significant (p = 0.68). Note that this value agrees with that calculated earlier from the explicit formula (5.23) for the score test of interaction.

A single degree of freedom test for a trend in relative risk with increasing age is obtained by fitting a single interaction term as shown in Part B of Table 7.5. Coding AGE3 to be 0, 1 or 2 according to the subject's age group, the resulting score test for interaction is the uncorrected version of the statistic (5.24), taking the value 0.39. The corrected value calculated earlier was 0.09. Estimated relative risks for the three age categories are in this case $\exp(1.664) = 5.28$, $\exp(1.664 + 0.385) = 7.76$ and $\exp(1.664 + 2 \times 0.385) = 11.40$, respectively. However since there is no evidence that the apparent trend is real, such estimates would not normally be reported.

The flexibility of the regression approach is particularly evident when dealing with matched sets containing a variable number of controls. Part C of Table 7.5 presents

Table 7.6 Matched univariate analysis of Los Angeles study of endometrial cancer: all cases and controls used except as noted

Variable	Levels	RR	χ^2 [a]	DF	p
Gall-bladder disease	Yes	3.69	13.83	1	0.0002
	No	1.00			
Hypertension	Yes	1.51	1.85	1	0.18
	No	1.00			
Obesity	Yes	1.76	5.70	2	0.06
	No	1.00			
	Unk	0.63			
Obesity	Yes	2.02	5.16	1	0.02
	No/Unk	1.00			
Other drugs (non-oestrogen)	Yes	3.90	10.38	1	0.001
	No	1.00			
Any oestrogens	Yes	7.96	31.16	1	<0.00001
	No	1.00			
Conjugated oestrogens[b]: dose in mg/day	None	1.00	33.22	3	<0.00001
	0.1–0.299	4.11			
	0.3–0.625	4.86			
	0.625+	10.97			
	Trend[c]	5.53	27.57	1	<0.00001
Conjugated oestrogens[d]: duration in months	None	1.00	34.93	4	<0.00001
	1–11	2.66			
	12–47	4.17			
	48–95	8.13			
	96+	10.41			
	Trend[e]	1.81	34.79	1	<0.00001

[a] Uncorrected score test
[b] Based on 59 sets, 291 observations
[c] Regression on coded dose levels: 0 = none; 1 = 0.1–0.299 mg/day; 2 = 0.3–0.625 mg/day; 3 = 0.625+ mg/day
[d] Based on 57 sets, 277 observations
[e] Regression on coded duration: 0 = none; 1 = 1–11 months; ...; 4 = 96+ months

the regression analysis of the data considered in § 5.4 on use of conjugated oestrogens. Of 59 matched sets for whom the case history of conjugated oestrogen use was known, 55 had the full complement of 4 controls while for each of the 4 others, one control was lacking information. Running the computer programme with a single binary variable CEST representing the history of use of conjugated oestrogens, we easily replicate the results already obtained: $\hat{\psi} = \exp(1.710) = 5.53$ for the estimate of relative risk and $\chi^2 = 27.57$ for the uncorrected chi-square test of the null hypothesis. It is also easy to test for constancy of the relative risk over the three age groups by addition of the interaction variables CEST × AGE1 and CEST × AGE2 to the equation. The score test for this addition, which is the generalization of (5.24) discussed in § 5.4, yields the value $\chi^2_2 = 0.89$ (p = 0.64). We did not report this result earlier because of the labour involved in the hand calculation.

Thus far in this section we have used the general methods for matched data analysis primarily in order to replicate the results already reported in Chapter 5 for particular elementary problems. The emphasis has been on demonstrating the concordance between the quantities in the computerized regression analysis, and those calculated earlier from grouped data. In the remainder of the section we carry out a full-scale multivariate analysis of the Los Angeles data much as one would do in actual practice.

As an initial step in this process, Table 7.6, which summarizes and extends the results obtained so far, presents relative risk estimates and tests of their statistical significance for each risk variable individually. Comparing the entries there with those in Table 5.1 we see that there is little to choose between the matched and unmatched analyses for this particular example (see § 7.6, however). The rather large number of "unknown" responses for obesity indicated lack of information on this item in the medical record. Grouping these with the negatives led to only a slight decrease in the goodness of fit ($\chi^2_1 = 0.75$, p = 0.39) and to a slight increase in the relative risk associated with a positive history. We therefore decided to use the dichotomy positive *versus* negative/unknown in the subsequent multivariate analyses. This meant that the final analyses used the five binary variables GALL-bladder disease, HYPertension, OBesity, NON-oestrogen drugs and any oESTrogen, none of which had missing values. There were also two polytomous variables representing DOSe and DURation of conjugated oestrogen, both of which had missing values.

Table 7.7 presents the results for a series of multivariate analyses involving the five binary risk factors and several of their two-factor interactions. Model 2 contains just the main effects of each variable. Their β coefficients have been exponentiated for presentation so as to facilitate their interpretation in terms of relative risk. In fact the estimates of RR for gall-bladder disease and oestrogen use do not change much from the univariate analysis (Table 7.6), while those for the other three variables are all somewhat smaller. The coefficient for hypertension becomes slightly negative, while those for obesity and non-oestrogen drugs are reduced to non-significant levels. The reduction for non-oestrogen drugs is particularly striking, and inspection of the original data indicates this is due to a high degree of confounding with oestrogen use: for the controls, only 16 or 21.1% of 76 who did not take non-oestrogen drugs had a history of oestrogen use, *versus* 111 or 63.1% of 176 who did take non-oestrogen drugs (Table 7.8).

Models 3–5 explore the consequences of dropping from the equation those variables which do not have significant main effects. The confounding between other drugs and

Table 7.7 Matched multivariate analysis of five binary risk factors and their interactions: Los Angeles study of endometrial cancer

Model	No. of parameters	Goodness of fit G	Score test[a]	Relative risks (exponentiated regression coefficients) for each variable in the equation Standardized regression coefficients in parentheses GALL	HYP	OB	NON	EST	GALL×EST	OB×EST	NON×EST	GALL×OB	GALL×NON
1	0	202.79											
2	5	153.74	42.75	3.63	0.82	1.61	1.95	6.78					
				(3.12)	(–0.55)	(1.31)	(1.31)	(4.21)					
3	4	154.04	42.63[b]	3.59		1.58	1.85	6.58					
				(3.10)		(1.27)	(1.23)	(4.17)					
4	3	155.64	41.74[b]	3.58		1.67		7.69					
				(3.10)		(1.43)		(4.62)					
5	3	155.68	41.42[b]	3.63			2.00	6.79					
				(3.12)			(1.39)	(4.22)					
6	2	157.74	39.92[b]	3.58				8.29					
				(3.10)				(4.81)					
7	3	153.46	4.66	18.07				14.88	0.128				
				(3.28)				(4.41)	(–2.06)				
8	4	151.58	4.39[c]	17.19		1.63		13.74	0.136				
				(3.23)		(1.35)		(4.27)	(–2.01)				
9	5	151.50	0.43	17.84		2.85		19.92	0.132	0.532			
				(3.26)		(1.13)		(3.43)	(–2.02)	(–0.65)			
10	6	151.00	0.17	14.78		2.46		18.98	0.127	0.576		1.39	
				(2.72)		(0.93)		(3.43)	(–2.05)	(–0.56)		(0.41)	
11	4	151.17	4.92[d]	19.45			2.14	12.28	0.120				
				(3.32)			(1.46)	(4.03)	(–2.12)				
12	5	148.75	2.23	22.51			8.63	54.60	0.103		0.156		
				(3.27)			(1.80)	(3.07)	(–2.14)		(–1.42)		
13	6	148.04	0.68	9.36			4.94	40.36	0.089		0.225		2.98
				(1.55)			(1.23)	(2.94)	(–2.22)		(–1.11)		(0.81)

[a] Score test with respect to preceding model, unless otherwise noted
[b] Score test for all variables in model (with respect to Model 1)
[c] Score test *versus* Model 4
[d] Score test *versus* Model 5

Table 7.8 Joint distribution of cases and controls according to selected risk factors: Los Angeles study of endometrial cancer

A. Gall-bladder disease and oestrogens

	Gall-bladder disease negative		Gall-bladder disease positive		Totals
	Oestrogen–	Oestrogen+	Oestrogen–	Oestrogen+	
Cases	3	43	4	13	63
Controls	117	111	8	16	252
Relative risks					
Unmatched	1.0	15.1	19.5	31.7	
Matched[a]	1.0	14.9	18.1	34.5	

B. Oestrogen and non-oestrogen drug use

	Other drugs negative		Other drugs positive		Totals
	Oestrogen–	Oestrogen+	Oestrogen–	Oestrogen+	
Cases	1	6	6	50	63
Controls	60	16	65	111	252
Relative risks					
Unmatched	1.0	22.5	5.5	27.0	
Matched[b]	1.0	54.6	8.6	73.5	

[a] From Model 7, Table 7.7.
[b] From Model 12, Table 7.7 (hence adjusted for gall-bladder disease)

oestrogen is evident from the fact that the coefficient for the latter depends most noticeably on whether or not the former is present. Subtracting the goodness-of-fit statistics between Models 6 and 2 yields $\chi^2_3 = 4.00$ ($p = 0.26$) for testing the joint contribution of hypertension, obesity and non-oestrogen drug use to the equation.

The contrast between Models 7 and 6 shows that there is a strong and statistically significant ($p = 0.03$) *negative* interaction between the two variables that have substantial main effects on risk, namely gall-bladder disease and oestrogens. The basic data contributing to this negative interaction are shown in Part A of Table 7.8, together with relative risks estimated *via* the model, e.g., $RR = 14.9 \times 18.1 \times 0.128 = 34.5$ for the double exposure category. The interaction effect itself is perhaps best illustrated by contrasting the RR of 14.9 for oestrogens among those who had no history of gall-bladder disease with the RR of $34.5/18.1 = 1.9$ among those with such a history.

Similar negative interactions are evident in Models 10 and 12 for obesity with oestrogens, and other drugs with oestrogens, respectively. From the unmatched data, shown in Part B of Table 7.8, we see that the instability in the regression coefficients for Model 12 stems from the fact that only a single case falls in the joint "non-exposed" category. While they are statistically significant only in the case of gall-bladder disease, the data suggest that there are negative interactions of oestrogen use with the other

factors which are possibly linked to endometrial cancer. Given that a woman is already at elevated risk from her history of gall-bladder disease, obesity, or non-oestrogen drug use, the further increase in risk from use of oestrogens is not nearly as important as when she is not exposed to other risk factors. This same observation, that oestrogen use interacts negatively with traditional risk factors for endometrial cancer, such as hypertension and obesity, has been made in other case-control studies (Smith et al., 1975). It suggests that the effects of oestrogen use are more likely to combine additively rather than multiplicatively with those of other factors. Another interesting feature of the relationship, which could not be investigated in the Los Angeles study, is that the excess risk is much smaller among ex-users compared with continuing users of oestrogen (Jick et al., 1979).

So far our analysis has accounted only for the fact of oestrogen use and not of dose or duration. Unfortunately, information about one or both of these items was lacking for nine cancer cases, leading to the exclusion of the corresponding matched sets from the analysis, and for one control in each of seven of the remaining 54 sets. Moreover, the drug tended to be administered at one of a few standard doses, which precluded analysis of this variable as a true continuous variable. Instead both dose and duration were treated as ordered categorical variables, and arbitrary scale values were assigned to the increasing levels for regression analysis of trends (see Tables 7.2 and 7.6).

A series of analyses which investigate the effect of dose and/or duration of conjugated oestrogen exposure on risk is presented in Table 7.9. In part A of the table we first fit the main effect for oestrogen exposure followed by a single variable DOS representing the trend in risk with coded dose level. Since women with EST = 1 but DOS = 0 use oestrogens but not the conjugated variety, the coefficient of EST determines the relative risk for women taking only non-conjugated oestrogens, exp(1.451) = 4.3. Estimated relative risks for the three dose levels of conjugated oestrogen are $\exp(1.451+0.402) = 6.4$, $\exp(1.451+2\times0.402) = 9.5$ and $\exp(1.451+3\times0.402) = 14.3$, respectively. The third model is a generalization of the second in that the effects of the individual dose levels are allowed to vary independently rather than being determined by the trend. While the estimated relative risks for dose levels 1 and 2 are rather similar, there is no strong evidence for a deviation from the fitted trend ($\chi^2_2 = 2.41$, p = 0.30). As shown in Model 4, there is a significant trend with duration, even after accounting for the dose effects.

Part B of the table considers in a similar way the effect of duration of exposure. Here there is a smooth progression in risk, and the fit of the linear trend in coded duration level seems quite adequate ($\chi^2_3 = 1.11$, p = 0.78). The trend in dose continues to be significant even after adjustment for duration (Model 3, Part B).

In Part C of the table we simultaneously fit separate effects for both dose and duration. Since the sums of both DOS1 + DOS2 + DOS3 and DUR1 + DUR2 + DUR3 + DUR4 equal the variable CEST defined above, it was necessary to drop one of these indicator variables from the equation in order to avoid linear dependence among the variables and to obtain unique estimates of all coefficients; this explains the absence of DOS1 from the list of variables. Comparing Model 2 with Model 1 shows that the effects of dose and duration are reasonably multiplicative; addition of the linear interaction term results in only a slight improvement in goodness of fit($\chi^2_1 = 0.59$, p = 0.44). In Models 3–6 we consider the effects of some of the other risk factors after

Table 7.9 Multivariate analysis of effects of dose and duration of conjugated oestrogens: Los Angeles study of endometrial cancer

Model	No. of parameters	Goodness of fit G	Score test[b]	Regression coefficients for each variable in the equation (standardized coefficients in parentheses)								
A. Effect of dose												
1	1	139.86	27.22	EST 2.088 (4.60)	DOS	DOS1	DOS2	DOS3	DUR			
2	2	135.63	4.19	1.451 (2.59)	0.402 (2.01)							
3	4	133.20	2.41	1.856 (2.74)		0.029 (0.05)	0.023 (0.04)	1.141 (1.80)				
4	5	128.32	4.82	1.987 (2.86)		−1.101 (−1.33)	−1.116 (−1.32)	−0.013 (−0.02)	0.420 (2.15)			
B. Effect of duration												
1	2	134.84	4.91[c]	EST 1.431 (2.58)	DUR 0.309 (2.17)	DUR1	DUR2	DUR3	DUR4	DOS		
2	5	133.76	1.11	1.868 (2.73)		−0.418 (−0.58)	0.122 (0.19)	0.596 (0.88)	0.899 (1.43)			
3	6	129.52	4.22	1.946 (2.83)		−1.655 (−1.70)	−0.876 (−1.08)	−0.586 (−0.65)	−0.296 (−0.34)	0.578 (2.01)		