

## Jackknifed Cochran-Mantel-Haenszel Test for Conditional Independence in Sparse $2 \times 2 \times K$ Tables

Kwang Mo Jeong<sup>1)</sup>

### Abstract

We are interested in the conditional independence in sparse  $2 \times 2 \times K$  tables with very rare cell counts. The most popular test is Cochran-Mantel-Haenszel statistic when sample sizes are moderately large enough to guarantee the chi-square approximation. We will consider jackknifing the CMH test and also suggest an approximate normal distribution for the standardized jackknifed CMH statistic. The main focus of this paper is to improve the chi-squared approximation to the CMH test by using the asymptotic normality of the jackknifed CMH test when sample sizes are very sparse but  $K$  and  $N \rightarrow \infty$ . The performance of the proposed jackknifed test, in the sense of significance level control and power, will be compared with that of the CMH test through a Monte Carlo study.

*Keywords* : Conditional Independence, Sparse  $2 \times 2 \times K$  Table, Jackknifing, Cochran-Mantel-Haenszel Statistic

### 1. Introduction

We are concerned with testing for conditional independence in sparse  $2 \times 2 \times K$  tables with very rare cell counts. The most popular test is Cochran-Mantel-Haenszel (CMH) statistic when sample sizes are moderately large enough to guarantee the chi-square approximation. The CMH statistic is known to have an asymptotic chi-square distribution with 1 degree of freedom(df) under conditional independence of row and column variables given marginal totals.

Simonoff(1986) suggested jackknifing and bootstrapping goodness-of-fit statistics in sparse multinomials. Two well-known goodness-of-fit tests are the Pearson statistic  $X^2$  and the likelihood ratio statistic (LRT)  $G^2$  for testing null hypothesis of specific multinomial probabilities. Simonoff(1986) used nonparametric techniques of jackknifing and bootstrapping to

---

1) Professor, Research Institute of Information and Communication, Department of Statistics, Pusan National University, 609-735, Pusan, Korea,  
E-mail : kmjung@hyowon.pusan.ac.kr

obtain the variance estimates of  $X^2$  and  $G^2$ . The bootstrap, the parametric bootstrap, the jackknife and a "categorical jackknife" methods were compared via a Monte Carlo simulation to choose the best one. The jackknife estimate of variance was good in parametric models for multinomial data. Koehler(1986) also discussed the asymptotic normality of the goodness-of-fit statistics for loglinear models in sparse tables. Through a Monte Carlo study the traditional chi-square approximation was shown to be reasonably accurate for the  $X^2$  for many sparse tables with some exceptional cases. The normal approximation appeared to be much more accurate than the chi-square approximation for the LRT  $G^2$  but the bias of estimate was remained as a nuisance problem in sparse tables.

We are confronted with sparse tables when matched case-control studies are designed. For example one person in case group is matched with one control, in which sample sizes in each  $2 \times 2$  table are very sparse. If  $K$  pairs of case-control are used in the experiment then the table structure is  $2 \times 2 \times K$ . In this way a fixed small number of cases can be matched to another fixed number of controls and hence it forms  $n:m$  matched case-control study. In this paper we will consider jackknifing the CMH test and also suggest an approximate normal distribution for the standardized jackknifed CMH statistic. That is, the critical points of the proposed test will be approximated using the standard normal distribution. The performance of the proposed jackknifed test, in the sense of significance level control and power, will be compared with that of the CMH test through a Monte Carlo study. The main focus of this paper is to improve the chi-squared approximation to the CMH test by using the asymptotic normality of the jackknifed CMH test when sample sizes are very sparse but  $K$  and  $N \rightarrow \infty$ .

## 2. Jackknifing CMH Statistic

Let  $\psi_i$  be an odds ratio of the  $i$ th stratum in  $2 \times 2 \times K$  table. When the odds ratios  $\psi_i$ ,  $i=1,2,\dots,K$ , are the same with a common value  $\psi$  over all strata the table denotes homogeneous association. If the common odds ratio  $\psi$  equals 1 we say that the row and column variables are conditionally independent given the marginal totals in each table. So we are interested in testing the hypothesis of conditional independence such as

$$H_0: \psi_1 = \psi_2 = \dots = \psi_K = 1 \quad (2.1)$$

in sparse  $2 \times 2 \times K$  tables. The count  $n_{11k}$  has a hyper-geometric distribution given the marginal totals in  $k$ th partial table. Hence under  $H_0$  the mean  $E(n_{11k})$  is given by

$$E(n_{11k}) = n_{+1k}n_{1+k}/n_{++k} \quad (2.2)$$

and also the variance  $Var(n_{11k})$  is given by

$$\text{Var}(n_{11k}) = n_{+1k}n_{+2k}n_{1+k}n_{2+k}/n_{++k}^2(n_{++k} - 1), \quad (2.3)$$

where  $n_{1+k}$  means that  $n_{1+k} = n_{11k} + n_{12k}$  and the others are defined in similar ways.

The CMH statistic is defined to be

$$M = \frac{[\sum_{k=1}^K \{n_{11k} - E(n_{11k})\}]^2}{\sum_{k=1}^K \text{Var}(n_{11k})}, \quad (2.4)$$

where  $E(n_{11k})$  and  $\text{Var}(n_{11k})$  are given in (2.2) and (2.3), respectively. We note that the statistic  $M$  is asymptotically chi-square distributed with 1 df under  $H_0$ .

We here suggest jackknifing the CMH statistic  $M$  by omitting every  $2 \times 2$  partial table one by one in ordinary ways. Define  $M_{(-i)}$  as the CMH statistic with the  $i$ th table omitted in  $2 \times 2 \times K$  table, that is,

$$M_{(-i)} = \frac{[\sum_{k \neq i} \{n_{11k} - E(n_{11k})\}]^2}{\sum_{k \neq i} \text{Var}(n_{11k})}. \quad (2.5)$$

The pseudo-values are defined as

$$M^{(i)} = KM - (K-1)M_{(-i)}, \quad i = 1, 2, \dots, K.$$

Finally we define the jackknifed CMH statistic  $M_J$  to be

$$\begin{aligned} M_J &= \frac{1}{K} \sum_{i=1}^K M^{(i)} \\ &= KM - \frac{K-1}{K} \sum_{i=1}^K M_{(-i)} \end{aligned} \quad (2.6)$$

The estimate of variance of  $M_J$  in (2.6) is of the form

$$V_J = \frac{1}{K(K-1)} \sum_{i=1}^K (M_J - M^{(i)})^2. \quad (2.7)$$

We normalize the jackknifed statistic  $M_J$  using the variance estimate  $V_J$  of (2.7) as follows

$$Z_J = \frac{M_J - E(M_J)}{\sqrt{V_J}}$$

where  $E(M_J)$  is the expectation of  $M_J$  under conditional independence of (2.1). We can compute  $E(M_J)=1$  in a routine method under conditional independence. The test statistic  $M$  would be compared with the jackknifed statistic  $M_J$  in (2.6) in the respects of level control and powers via a Monte Carlo simulation for sparse  $2 \times 2 \times K$  tables. The significance levels of  $M_J$  can be determined by comparing the standardized  $Z_J$  with quantiles of standard normal distribution. We first illustrate the proposed jackknifing method through the following two practical examples.

**Example 2.1** Table 2.1, originally taken from Mantel(1963), refers to the effectiveness of immediately injected or  $1\frac{1}{2}$ -hour-delayed penicillin in protecting rabbits against lethal injection with  $\beta$ -hemolytic streptococci. The data was reanalyzed in Agresti(1990) to explain the CMH test versus model based goodness-of-fit tests such as the LRT and the Pearson chi-squared test.

Table 2.1 Effect of penicillin injection

penicillin level	response	delay	
		none	$1\frac{1}{2}$ h
1/8	cured	0	0
	died	6	5
1/4	cured	3	0
	died	3	6
1/2	cured	6	2
	died	0	4
1	cured	5	6
	died	1	0
4	cured	2	5
	died	0	0

The value of CMH statistic  $M$  is 5.657 with significance of 0.017. This means that the delay of injection time is a little strongly associated with the response of cured or died. On the other hand the normal approximation of jackknifed CMH statistic does not reject the conditional independence hypothesis with significance of 0.074 which is slightly greater than the level  $\alpha=0.05$ . As pointed out in Agresti(1990) the exact test of conditional independence has the significance of 0.040. Hence we note that the chi-square approximation of CMH test is liberal but a normal approximation to the jackknifed CMH statistic is a little more conservative compared to the exact test in the sense of Type I error rate.

**Example 2.2** A data set consisting of 63 pairs of case-control groups is represented in the form of Table 2.2. A person of endometrial cancer was matched with 4 control subjects on the basis of residence, age, material status and date of entry into the community. The purpose of experiment was to find the effect of exogenous estrogens on the risk of endometrial cancer. The exposure denotes here the use of estrogens. Jewell (1984) also introduced this data to explain a common odds ratio estimator, which was originally reported by Mack, et al. (1976), can be represented as in Table 2.2.

Table 2.2. case-control data of 63 matched pairs

		number of controls exposed					total
		0	1	2	3	4	
cases	exposed	3	17	16	15	5	56
	non-exposed	0	4	1	1	1	7

Note: Mack, et al.(1976)

Each pair of case-control group can be expressed as a  $2 \times 2$  table of  $n=1$ ,  $m=4$  with the number of exposures denoting cell counts in each group, and hence 63 pairs form a  $2 \times 2 \times 63$  table. The value of CMH statistic is 31.16 with significance smaller than 0.0000, and the normalized jackknifed statistic has 7.84 with significance smaller than 0.0000 but a little stronger evidence if we represent more digits. We conclude that both tests support the strong association of estrogens with endometrial cancer. The Mantel-Haenszel common odds ratio estimator of  $\psi$  is 8.46 and this also indicates very strong association between two variables. In this example not only  $K=63$  is much larger than  $K=5$  of Example 2.1 but also more sparse because  $n=1$  over all strata.

### 3. Monte Carlo Simulation

#### 3.1. Design of the Experiment

To form the data of  $2 \times 2 \times K$  tables we do a Monte Carlo study according to sample sizes of case-control groups, exposure probabilities of case group, odds ratios and the number of strata. Sample sizes  $(n, m)$  were taken to be (1,1),(2,1),(4,1),(8,1),(2,2), and (5,5). When  $n=m$  the table is called balanced but for other cases it is unbalanced. We consider the odds ratios of 1.0, 1.5, 2.0, 2.5 and 3.0 so that the level controls and powers of tests are compared. The exposure probability  $\pi_1$  of case group varies from 0.1(0.2) to 0.3(0.4) according to the number of strata. On the other hand the exposure probability  $\pi_0$  of control group is computed by the relationship

$$\pi_0 = \frac{\pi_1}{\pi_1 + (1 - \pi_1)\psi}$$

where  $\psi$  denotes a common odds ratio defined before. The cell count  $n_{11k}$  is generated from the binomial distribution with success probability  $\pi_1$  among  $n$  trials. Similarly  $n_{12k}$  is generated from the binomial distribution with success probability  $\pi_0$  among  $m$  trials. We note that the generated cell counts  $n_{11k}$  and  $n_{12k}$  are assumed to be independent binomial random variables. The significance level considered are  $\alpha=0.10, 0.05$  and  $0.01$ . The common odds ratio of  $\psi=1.0$  denotes the conditional independence in  $2 \times 2 \times K$  table. The other values of odds ratios not equal to 1.0 denote the alternatives to conditional independence.

### 3.2. Simulation Results

The powers of two tests, the CMH test  $M$  and the jackknifed CMH test  $M_j$ , are listed in Table 3.1 (a) through (c) and also in Table 3.2 (a) through (c) according to different values of  $\pi_1$  and  $\alpha$ . In each table we considered various values of sample sizes  $n$  and  $m$ , number of strata  $K$ , and also values of odds ratio  $\psi$ . In Table 3.1 (a) we can find that  $M_j$  is a little conservative in the sense of controlling level  $\alpha=0.05$ , on the other hand  $M$  sometimes fail in controlling it even for large  $K$ . We note that  $M_j$  is more powerful than  $M$  when sample sizes are unbalanced but for the balanced case the phenomenon is conversed. In Table 3.1 (b) of  $\alpha=0.05$  the test  $M_j$  performs more nicely than  $M$  even if  $n=m=1$  compared to the case of  $\alpha=0.10$ . Both of the two tests don't control level  $\alpha=0.05$  when  $n=2$  and  $m=1$ . The powers of two tests, as expected, increase as level  $\alpha$  increases. As we see in Table 3.1 (c) of  $\alpha=0.01$  both  $M$  and  $M_j$  are not good in level control, and this fact is worse for the test  $M_j$  in general.

Simulation results for  $\pi_1=0.30$ , in this case not so sparse as in  $\pi_1=0.10$ , are given in Table 3.2 (a) through (c) in similar ways. In Table 3.2 (a) the test  $M$  sometimes doesn't control  $\alpha=0.05$  but its powers are greater than those of  $M_j$  for other cases. But when  $\alpha=0.05$ , which is listed in Table 3.2 (b), the jackknifed test  $M_j$  performs very well compared to  $M$  in the sense of level control and powers. Lastly we see many cases such that both  $M$  and  $M_j$  fail to control  $\alpha=0.01$  but  $M_j$  appears to perform at least as good as  $M$  when the level is controlled. We also note that the powers for both tests are increased when  $\pi_1=0.30$  compared to the case  $\pi_1=0.10$  which is the value of rare exposure probability.

From the simulation results we can summarize that  $M_j$  performs well for unbalanced sample sizes with moderate values of  $\alpha=0.05$  when  $\pi_1=0.10$ . Both of these tests are in general not good in level control when  $\alpha=0.01$ . We conclude that the jackknifed CMH test  $M_j$  can be a good alternative to the CMH test  $M$  for sparse  $2 \times 2 \times K$  tables.

Table 3.1 Powers of Two Test Statistics  
(a)  $\pi_1 = 0.10, \alpha = 0.10$

<i>n</i>	<i>m</i>	<i>K</i>	test	odds ratio				
				1.0	1.5	2.0	2.5	3.0
1	1	30	<i>M</i>	0.099	0.136	0.196	0.258	0.316
			<i>M<sub>J</sub></i>	0.075	0.128	0.196	0.271	0.328
		40	<i>M</i>	0.087	0.149	0.235	0.319	0.398
			<i>M<sub>J</sub></i>	0.058	0.115	0.190	0.268	0.351
		50	<i>M</i>	0.090	0.180	0.293	0.398	0.467
			<i>M<sub>J</sub></i>	0.061	0.135	0.235	0.323	0.396
2	1	30	<i>M</i>	0.102	0.135	0.207	0.291	0.366
			<i>M<sub>J</sub></i>	0.098	0.152	0.241	0.341	0.425
		40	<i>M</i>	0.127	0.154	0.249	0.345	0.435
			<i>M<sub>J</sub></i>	0.114	0.167	0.267	0.366	0.435
		50	<i>M</i>	0.112	0.151	0.293	0.418	0.536
			<i>M<sub>J</sub></i>	0.082	0.149	0.294	0.429	0.548
4	1	30	<i>M</i>	0.082	0.123	0.203	0.274	0.342
			<i>M<sub>J</sub></i>	0.070	0.152	0.267	0.353	0.437
		40	<i>M</i>	0.101	0.140	0.274	0.389	0.485
			<i>M<sub>J</sub></i>	0.082	0.166	0.316	0.432	0.531
		50	<i>M</i>	0.111	0.183	0.330	0.471	0.584
			<i>M<sub>J</sub></i>	0.083	0.196	0.354	0.501	0.614
8	1	30	<i>M</i>	0.096	0.147	0.240	0.330	0.415
			<i>M<sub>J</sub></i>	0.083	0.177	0.310	0.409	0.512
		40	<i>M</i>	0.086	0.161	0.293	0.423	0.515
			<i>M<sub>J</sub></i>	0.078	0.203	0.358	0.491	0.583
		50	<i>M</i>	0.097	0.183	0.357	0.520	0.623
			<i>M<sub>J</sub></i>	0.077	0.207	0.392	0.558	0.665
2	2	30	<i>M</i>	0.074	0.173	0.326	0.439	0.498
			<i>M<sub>J</sub></i>	0.065	0.156	0.282	0.405	0.456
		40	<i>M</i>	0.091	0.193	0.362	0.521	0.600
			<i>M<sub>J</sub></i>	0.066	0.163	0.319	0.471	0.554
		50	<i>M</i>	0.103	0.256	0.424	0.597	0.683
			<i>M<sub>J</sub></i>	0.077	0.215	0.379	0.541	0.638
5	5	30	<i>M</i>	0.094	0.324	0.613	0.764	0.878
			<i>M<sub>J</sub></i>	0.071	0.282	0.540	0.716	0.847
		40	<i>M</i>	0.085	0.376	0.705	0.873	0.945
			<i>M<sub>J</sub></i>	0.062	0.324	0.647	0.832	0.920
		50	<i>M</i>	0.122	0.426	0.773	0.927	0.972
			<i>M<sub>J</sub></i>	0.091	0.382	0.719	0.904	0.960

Table 3.1 Powers of Test Statistics  
 (b)  $\pi_1 = 0.10$ ,  $\alpha = 0.05$

$n$	$m$	$K$	test	odds ratio				
				1.0	1.5	2.0	2.5	3.0
1	1	30	$M$	0.044	0.073	0.111	0.165	0.192
			$M_J$	0.067	0.121	0.186	0.259	0.317
	40	$M$	0.037	0.068	0.116	0.181	0.247	
		$M_J$	0.044	0.087	0.156	0.228	0.307	
	50	$M$	0.034	0.081	0.168	0.248	0.314	
		$M_J$	0.037	0.084	0.180	0.271	0.340	
2	1	30	$M$	0.054	0.064	0.096	0.150	0.195
			$M_J$	0.060	0.112	0.186	0.275	0.356
	40	$M$	0.065	0.087	0.141	0.217	0.274	
		$M_J$	0.062	0.112	0.203	0.293	0.378	
	50	$M$	0.049	0.081	0.177	0.274	0.355	
		$M_J$	0.044	0.095	0.217	0.334	0.438	
4	1	30	$M$	0.040	0.048	0.089	0.136	0.193
			$M_J$	0.042	0.115	0.201	0.285	0.359
	40	$M$	0.050	0.058	0.151	0.244	0.319	
		$M_J$	0.046	0.106	0.248	0.361	0.466	
	50	$M$	0.043	0.095	0.202	0.318	0.432	
		$M_J$	0.044	0.136	0.276	0.418	0.540	
8	1	30	$M$	0.042	0.057	0.109	0.179	0.230
			$M_J$	0.054	0.149	0.267	0.360	0.453
	40	$M$	0.042	0.080	0.170	0.261	0.338	
		$M_J$	0.045	0.149	0.280	0.410	0.499	
	50	$M$	0.044	0.095	0.218	0.339	0.465	
		$M_J$	0.036	0.140	0.317	0.469	0.583	
2	2	30	$M$	0.040	0.104	0.215	0.319	0.373
			$M_J$	0.036	0.101	0.210	0.314	0.373
	40	$M$	0.046	0.118	0.250	0.394	0.477	
		$M_J$	0.052	0.108	0.237	0.386	0.472	
	50	$M$	0.048	0.157	0.305	0.473	0.573	
		$M_J$	0.042	0.131	0.287	0.446	0.551	
5	5	30	$M$	0.052	0.220	0.466	0.659	0.801
			$M_J$	0.043	0.194	0.435	0.627	0.784
	40	$M$	0.038	0.269	0.590	0.795	0.886	
		$M_J$	0.033	0.244	0.559	0.753	0.864	
	50	$M$	0.065	0.317	0.662	0.869	0.945	
		$M_J$	0.051	0.272	0.633	0.838	0.925	



Table 3.1 Powers of Test Statistics  
(c)  $\pi_1 = 0.10, \alpha = 0.01$

$n$	$m$	$K$	test	odds ratio				
				1.0	1.5	2.0	2.5	3.0
1	1	30	$M$	0.009	0.014	0.022	0.037	0.040
			$M_J$	0.036	0.070	0.107	0.166	0.208
	40	$M$	0.004	0.013	0.027	0.039	0.059	
		$M_J$	0.014	0.040	0.086	0.132	0.198	
	50	$M$	0.005	0.017	0.040	0.073	0.106	
		$M_J$	0.016	0.039	0.098	0.165	0.225	
2	1	30	$M$	0.010	0.011	0.017	0.019	0.026
			$M_J$	0.028	0.072	0.138	0.205	0.263
	40	$M$	0.008	0.016	0.033	0.058	0.072	
		$M_J$	0.022	0.065	0.119	0.183	0.247	
	50	$M$	0.007	0.021	0.046	0.078	0.108	
		$M_J$	0.013	0.059	0.130	0.221	0.293	
4	1	30	$M$	0.005	0.002	0.006	0.007	0.010
			$M_J$	0.018	0.068	0.122	0.178	0.242
	40	$M$	0.007	0.007	0.013	0.038	0.054	
		$M_J$	0.015	0.047	0.143	0.236	0.318	
	50	$M$	0.005	0.008	0.037	0.077	0.121	
		$M_J$	0.012	0.068	0.176	0.287	0.400	
8	1	30	$M$	0.004	0.002	0.003	0.006	0.008
			$M_J$	0.020	0.078	0.148	0.230	0.301
	40	$M$	0.012	0.010	0.029	0.051	0.067	
		$M_J$	0.017	0.085	0.182	0.284	0.370	
	50	$M$	0.012	0.015	0.048	0.081	0.125	
		$M_J$	0.009	0.087	0.199	0.312	0.443	
2	2	30	$M$	0.009	0.025	0.063	0.113	0.161
			$M_J$	0.014	0.044	0.106	0.183	0.240
	40	$M$	0.011	0.039	0.091	0.171	0.244	
		$M_J$	0.014	0.059	0.134	0.217	0.310	
	50	$M$	0.017	0.039	0.130	0.222	0.300	
		$M_J$	0.015	0.047	0.154	0.253	0.356	
5	5	30	$M$	0.012	0.068	0.220	0.405	0.560
			$M_J$	0.021	0.081	0.252	0.433	0.587
	40	$M$	0.006	0.102	0.331	0.577	0.705	
		$M_J$	0.005	0.099	0.357	0.577	0.723	
	50	$M$	0.007	0.118	0.418	0.683	0.829	
		$M_J$	0.011	0.124	0.418	0.680	0.813	

Table 3.2 Powers of Test Statistics

(a)  $\pi_1 = 0.30$ ,  $\alpha = 0.10$ 

$n$	$m$	$K$	test	odds ratio				
				1.0	1.5	2.0	2.5	3.0
1	1	30	$M$	0.090	0.180	0.306	0.434	0.528
			$M_J$	0.065	0.145	0.250	0.368	0.466
	40	$M$	0.086	0.190	0.343	0.508	0.637	
		$M_J$	0.064	0.165	0.305	0.460	0.589	
	50	$M$	0.092	0.220	0.444	0.610	0.735	
		$M_J$	0.080	0.194	0.410	0.578	0.695	
2	1	30	$M$	0.108	0.208	0.389	0.537	0.640
			$M_J$	0.085	0.190	0.365	0.517	0.624
	40	$M$	0.101	0.226	0.448	0.628	0.755	
		$M_J$	0.078	0.185	0.409	0.595	0.721	
	50	$M$	0.102	0.290	0.544	0.730	0.856	
		$M_J$	0.075	0.256	0.507	0.691	0.818	
4	1	30	$M$	0.098	0.218	0.412	0.573	0.702
			$M_J$	0.079	0.198	0.391	0.557	0.677
	40	$M$	0.111	0.257	0.487	0.677	0.812	
		$M_J$	0.078	0.229	0.451	0.656	0.792	
	50	$M$	0.108	0.279	0.587	0.779	0.901	
		$M_J$	0.084	0.245	0.540	0.747	0.882	
8	1	30	$M$	0.090	0.230	0.443	0.625	0.740
			$M_J$	0.070	0.212	0.423	0.613	0.731
	40	$M$	0.106	0.272	0.534	0.730	0.857	
		$M_J$	0.074	0.260	0.507	0.702	0.846	
	50	$M$	0.107	0.323	0.634	0.817	0.910	
		$M_J$	0.077	0.286	0.595	0.793	0.893	
2	2	30	$M$	0.118	0.270	0.494	0.683	0.812
			$M_J$	0.085	0.233	0.440	0.634	0.774
	40	$M$	0.100	0.326	0.607	0.803	0.897	
		$M_J$	0.074	0.275	0.550	0.752	0.868	
	50	$M$	0.102	0.368	0.697	0.870	0.947	
		$M_J$	0.082	0.310	0.645	0.842	0.921	
5	5	30	$M$	0.098	0.492	0.844	0.966	0.993
			$M_J$	0.076	0.437	0.791	0.956	0.989
	40	$M$	0.094	0.568	0.929	0.991	1.000	
		$M_J$	0.063	0.507	0.901	0.986	0.999	
	50	$M$	0.100	0.668	0.960	0.995	1.000	
		$M_J$	0.071	0.610	0.941	0.993	0.999	

Table 3.2 Powers of Test Statistics  
(b)  $\pi_1 = 0.30, \alpha = 0.05$

$n$	$m$	$K$	test	odds ratio				
				1.0	1.5	2.0	2.5	3.0
1	1	30	$M$	0.038	0.099	0.194	0.270	0.376
			$M_J$	0.039	0.102	0.198	0.273	0.383
		40	$M$	0.050	0.117	0.237	0.383	0.501
			$M_J$	0.043	0.108	0.232	0.376	0.494
		50	$M$	0.055	0.151	0.340	0.506	0.629
			$M_J$	0.048	0.130	0.310	0.480	0.605
2	1	30	$M$	0.057	0.123	0.264	0.404	0.518
			$M_J$	0.053	0.133	0.285	0.422	0.537
		40	$M$	0.051	0.142	0.310	0.491	0.625
			$M_J$	0.046	0.136	0.308	0.490	0.637
		50	$M$	0.048	0.206	0.423	0.606	0.737
			$M_J$	0.035	0.193	0.405	0.596	0.735
4	1	30	$M$	0.058	0.134	0.273	0.425	0.543
			$M_J$	0.045	0.140	0.294	0.448	0.583
		40	$M$	0.061	0.161	0.342	0.551	0.709
			$M_J$	0.051	0.158	0.357	0.573	0.730
		50	$M$	0.051	0.180	0.428	0.654	0.812
			$M_J$	0.039	0.181	0.423	0.654	0.817
8	1	30	$M$	0.044	0.145	0.300	0.483	0.612
			$M_J$	0.039	0.154	0.328	0.525	0.650
		40	$M$	0.044	0.179	0.410	0.595	0.749
			$M_J$	0.029	0.194	0.428	0.612	0.769
		50	$M$	0.055	0.207	0.485	0.724	0.851
			$M_J$	0.044	0.212	0.494	0.722	0.849
2	2	30	$M$	0.057	0.175	0.377	0.569	0.723
			$M_J$	0.044	0.154	0.349	0.526	0.689
		40	$M$	0.047	0.224	0.489	0.700	0.813
			$M_J$	0.033	0.193	0.443	0.667	0.787
		50	$M$	0.061	0.265	0.584	0.803	0.895
			$M_J$	0.050	0.229	0.525	0.759	0.875
5	5	30	$M$	0.047	0.367	0.748	0.929	0.984
			$M_J$	0.043	0.327	0.705	0.911	0.972
		40	$M$	0.040	0.442	0.873	0.978	0.999
			$M_J$	0.029	0.400	0.838	0.969	0.993
		50	$M$	0.051	0.560	0.929	0.988	0.999
			$M_J$	0.038	0.513	0.908	0.983	0.999

Table 3.2 Powers of Test Statistics  
(c)  $\pi_1 = 0.30$ ,  $\alpha = 0.01$

$n$	$m$	$K$	test	odds ratio				
				1.0	1.5	2.0	2.5	3.0
1	1	30	$M$	0.009	0.018	0.054	0.106	0.153
			$M_J$	0.016	0.036	0.097	0.159	0.235
	40	$M$	0.012	0.035	0.082	0.150	0.238	
		$M_J$	0.013	0.046	0.109	0.199	0.306	
	50	$M$	0.009	0.036	0.123	0.228	0.350	
		$M_J$	0.010	0.049	0.159	0.278	0.407	
2	1	30	$M$	0.008	0.036	0.094	0.151	0.239
			$M_J$	0.016	0.069	0.156	0.257	0.365
	40	$M$	0.009	0.049	0.128	0.219	0.328	
		$M_J$	0.010	0.068	0.169	0.288	0.433	
	50	$M$	0.011	0.058	0.186	0.336	0.480	
		$M_J$	0.011	0.076	0.231	0.404	0.558	
4	1	30	$M$	0.010	0.025	0.091	0.180	0.281
			$M_J$	0.009	0.069	0.177	0.300	0.419
	40	$M$	0.015	0.052	0.145	0.259	0.409	
		$M_J$	0.021	0.078	0.213	0.367	0.541	
	50	$M$	0.014	0.064	0.225	0.381	0.546	
		$M_J$	0.014	0.085	0.277	0.463	0.639	
8	1	30	$M$	0.010	0.040	0.109	0.210	0.314
			$M_J$	0.014	0.085	0.186	0.345	0.484
	40	$M$	0.008	0.052	0.170	0.326	0.467	
		$M_J$	0.008	0.087	0.277	0.446	0.596	
	50	$M$	0.104	0.069	0.228	0.453	0.624	
		$M_J$	0.017	0.099	0.317	0.554	0.720	
2	2	30	$M$	0.011	0.057	0.174	0.323	0.455
			$M_J$	0.012	0.070	0.187	0.343	0.494
	40	$M$	0.006	0.087	0.236	0.460	0.623	
		$M_J$	0.006	0.089	0.254	0.460	0.628	
	50	$M$	0.011	0.099	0.333	0.568	0.729	
		$M_J$	0.013	0.098	0.336	0.561	0.725	
5	5	30	$M$	0.010	0.171	0.527	0.804	0.933
			$M_J$	0.014	0.178	0.506	0.800	0.903
	40	$M$	0.005	0.251	0.685	0.923	0.975	
		$M_J$	0.007	0.227	0.658	0.905	0.971	
	50	$M$	0.011	0.314	0.802	0.958	0.995	
		$M_J$	0.009	0.296	0.775	0.955	0.994	

## References

- [1] Agresti, A. (1990), *Categorical Data Analysis*, John Wiley & Sons
- [2] Jewell, N. P. (1984), Small-Sample Bias of Point Estimators of the Odds Ratio from Matched Sets, *Biometrics*, 40, 421-435
- [3] Koehler, K. J.(1986), Goodness-of-Fit Tests for Log-Linear Models in Sparse Contingency Tables, *Journal of the American Statistical Association*, 81, 483-493
- [4] Mack, T. M., Pike, M. C., Henderson, B. E., Pfeffer, R. I., Gerkins, V. R., Arthur, B. S. and Brown, S. E. (1976), Estrogens and Endometrial Cancer in a Retirement Community, *New England Journal of Medicine*, 294, 1262-1267
- [5] Mantel, N. (1963), Chi-Square Tests with One Degree of Freedom: Extensions of the Mantel-Haenszel Test, *Journal of the American Statistical Association*, 58, 690-700
- [6] Morris, C. (1975) Central Limit Theorems for Multinomial Sums, *Annals of Statistics*, 3, 165-188
- [7] Parr, W. C. and Tolley, H. D.(1982), Jackknifing in Categorical Data Analysis, *Australian Journal of Statistics*, 24, 67-79
- [8] Simonoff, J. S. (1986), Jackknifing and Bootstrapping Goodness-of-Fit Statistics in Sparse Multinomials, *Journal of the American Statistical Association*, 81, 1005-1011