ESSAYS ON NONNESTED HYPOTHESIS TESTING, OPTIMAL PRICE SLIDES IN FEEDER CATTLE CONTRACTS, AND GENERIC MEAT ADVERTISING

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PREFACE

This thesis consists of three papers. In the first paper, alternative approaches of using Monte Carlo methods to implement a Cox-type test for nonnested hypotheses are considered. These approaches are due to Pesaran and Pesaran and Lee and Brorsen. Pesaran and Pesaran's test is an asymptotic test. Lee and Brorsen's test is a Monte Carlo test, but it is not based on a pivotal statistic. An alternative Cox-type test based on an asymptotically pivotal statistic is proposed. This test is a Monte Carlo test. The finite sample performances of the three are compared. In the second paper, principal-agent models are developed to determine optimal price slides for feeder cattle sold through video auctions. The third paper aimed to determine why past studies on the effectiveness of generic meat advertising have reached conflicting conclusions.

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ABSTRACT

Alternative ways of using Monte Carlo methods to implement a Cox-type test for nonnested hypotheses are considered. Monte Carlo experiments are designed to compare the finite sample performances of a new Monte Carlo test based on an asymptotically pivotal statistic with Pesaran and Pesaran's test and a Monte Carlo test previously proposed by Lee and Brorsen. The Monte Carlo results provide strong evidence that the size of the Pesaran and Pesaran test is generally incorrect, except for very large sample sizes. All the tests have excellent power. The two Monte Carlo tests perform equally well for all sample sizes and are both clearly preferred to the Pesaran and Pesaran test, even in large samples.

Key Words and Phrases: Cox test; Monte Carlo test; nonnested hypotheses

A MONTE CARLO SAMPLING APPROACH TO TESTING NONNESTED HYPOTHESES: MONTE CARLO RESULTS

1. Introduction

The Cox statistic for testing nonnested hypotheses is the difference between the log likelihood ratio and its expected value under the null. While the log likelihood ratio is straightforward to obtain, the computation of its expected value is often intractable (Cox, 1962; Pesaran and Pesaran, 1993). Thus, a number of Cox-type tests that are easier to compute have been proposed in the econometric literature (e.g., Pesaran, 1974; Pesaran and Deaton, 1978; Aneuryn-Evans and Deaton, 1980). These tests, however, were developed for specific problems.

Simulation approaches to conducting Cox's test that are applicable to many problems have also been proposed. One approach, due to Pesaran and Pesaran (1993; 1995), uses stochastic simulation to calculate the numerator of the Cox test statistic. A second approach to conducting Cox's test is to use Monte Carlo hypothesis testing procedures based on the log-likelihood ratio statistic. Cox-type tests using this approach have been developed by Williams (1970) and Lee and Brorsen (1994). Of these two Monte Carlo tests, only Lee and Brorsen test is based on the Monte Carlo hypothesis testing procedures suggested by Noreen (1989) and Hall and Titterington (1989). These procedures allow directly computing the significance level (p-value) of the test statistic being used. In Noreen, the parameters under the null are assumed known. Noreen (1989) proves that in this case, Monte Carlo tests are valid in small samples. Hall and Titterington (1989) discuss the case where the parameters under the null are unknown and must be replaced by consistent estimates. They show that Monte Carlo tests under these circumstances are asymptotically valid, but still have excellent power and size properties.

Since introduced by Barnard (1963), Monte Carlo tests have received considerable attention. To conduct a Monte Carlo test, one must start by specifying an appropriate test statistic for the hypothesis of interest (Barnard, 1963; Hope, 1968). The value of the test statistic is calculated for the actual data under the null hypothesis. The test procedure then consists of generating random samples under the null hypothesis and comparing the value of the test statistic for each simulated sample to its value for the actual data. A p-value can be obtained directly by calculating the percentage (with a slight adjustment) of the simulated test statistics which are greater or smaller (depending on the rejection criterion) than the value of the test statistic computed with the actual data (Noreen, 1989; Hope, 1968).

Monte Carlo tests are very useful when the distribution of the test statistic is unknown or difficult to obtain analytically (Hope, 1968; Noreen, 1989). Monte Carlo tests have excellent size and power properties (Hall and Titterington, 1989; Hope, 1968). In particular, a Monte Carlo test that is based on an asymptotically pivotal statistic has better size properties than the corresponding asymptotic test (Hall and Titterington, 1989). Hope (1968) showed that Monte Carlo tests have powers that are very close to those of most uniformly powerful tests provided that sufficient random samples are used and there are no nuisance parameters. Hall and Titterington proved that the excellent power properties of Monte Carlo tests hold even if the test statistic used is not asymptotically pivotal, but the same is not true for the size properties.

The log-likelihood ratio statistic used in previous Monte Carlo tests is not asymptotically pivotal. Indeed, its distribution under the null depends on unknown parameters. An alternative Cox-type test is proposed here. This test uses Monte Carlo hypothesis testing procedures based on an asymptotically pivotal statistic. As mentioned above, pivotalness guarantees that Monte Carlo tests have better size properties than asymptotic tests. Pesaran and Pesaran (1993) also argued that a Monte Carlo test based on the log-likelihood ratio "may not have satisfactory asymptotic properties in the case of nonnested models where the log-likelihood ratio is not centered even in large samples" (p. 378). Past research using the log-likelihood ratio statistic in a Monte Carlo test has not addressed this issue. Monte Carlo experiments are used here to compare the finite sample performances of the Monte Carlo test proposed here with the one suggested by Lee and Brorsen (1994) and the asymptotic test developed by Pesaran and Pesaran (1993; 1995).

2. Cox's Test

Consider the following two nonnested hypotheses:

$$H_0: \quad f(y, \theta_0 | x) \tag{1}$$

$$H_1: \quad g(y, \theta_1 | z), \tag{2}$$

where y is a T x 1 vector of dependent variables, x and z are T x (K_0 + 1) and T x (K_1 + 1) matrices of independent variables, θ_0 and θ_1 are unknown vectors of parameters, f and g are density functions, K_0 and K_1 are the number of independent variables under H_0 and H_1, respectively, and T is the number of observations. For the test of the null hypothesis H_0 against H_1, Cox (1961; 1962) proposed the following test statistic:

$$T_0 = L_{01} - E_0(L_{01}), \tag{3}$$

where $L_{01} = L_0(\hat{\theta}_0) - L_1(\hat{\theta}_1)$. $L_0(\hat{\theta}_0)$ and $L_1(\hat{\theta}_1)$ are the maximized log-likelihoods under H_0 and$_1$ H, respectively, $E_0(L_{01})$ is the expected value of $E_0(L_{01})$ under H_0, and $\hat{\theta}_0$ and $\hat{\theta}_1$ are the maximum likelihood parameter estimates of the null and the alternative model, respectively. T_0 is asymptotically distributed with mean zero and variance v_0^2 under H_0 (Cox, 1962). For the test of H_1 against H_0, the test statistic would be $T_1 = L_{10} - E(L_{10})$. The notation used here corresponds to the test of H_0 against H_1.

3. Pesaran and Pesaran and Lee and Brorsen Test Procedures

Pesaran and Pesaran's test (PP)

The Cox test statistic in equation (3) is difficult to apply in practice because a closed form cannot always be found for the expected value of the log-likelihood ratio. Pesaran and Pesaran (1993; 1995) proposed computing the expected value of the log-likelihood ratio using simulation procedures. In this approach, the expected value of the log-likelihood ratio is approximated by the Kullback-Leibler measure of closeness of H_0 with respect to H_1 defined as:

$$C(\theta_0, \theta_1^*) = \int \log[f(y, \theta_0)/g(y, \theta_1^*)]f(y,$$

where $C(\theta_0, \theta_1^*)$ is the closeness measure of H_0 with respect to H_1, θ_1^* is the probability limit of $\hat{\theta}_1$ under H_0 and θ_1^* is a function of θ_0. Then, letting $C(\hat{\theta}_0, \hat{\theta}_1^*)$ be an estimator of $C(\theta_0, \theta_1^*)$ under H_0, the standardized Cox statistic for testing H_0 against H_1 is obtained as (Pesaran and Pesaran, 1993; 1995):

$$S_0(\hat{\theta}_0, \hat{\theta}_1) = \frac{\sqrt{n}[L_{01} - C(\hat{\theta}_0, \hat{\theta}_1^*)]}{\sqrt{\hat{v}_0^2(\hat{\theta}_0, \hat{\theta}_1^*)}}, \tag{5}$$

where $\hat{v}_0^2(\hat{\theta}_0, \hat{\theta}_1^*)$ is a consistent estimate of the asymptotic variance of $\sqrt{n}[L_{01} - C(\hat{\theta}_0, \hat{\theta}_1^*)]$, and $\hat{\theta}_1^*$ is a consistent estimator of θ_1^* under H_0.

Analytical derivation of $C(\hat{\theta}_0, \hat{\theta}_1^*)$ is generally not possible (Pesaran and Pesaran, 1993). It can, however, be computed using Monte Carlo integration as follows. Generate R random samples using the estimator $\hat{\theta}_0$ under H_0. Denoting $\hat{\theta}_{1j}$ as the parameter estimates of the alternative model obtained from the j[th] Monte Carlo sample, a consistent estimator of $\hat{\theta}_1^*$ is given by:

$$\hat{\theta}_1^*(R) = \frac{1}{R}\sum_{j=1}^{R} \hat{\theta}_{1j}. \tag{6}$$

This estimator depends on the number of random samples R. It approaches θ_1^* (which is a function of θ_0) as R increases (see Pesaran and Pesaran, 1995). The simulation estimator of the closeness measure, $C_R(\hat{\theta}_0, \hat{\theta}_1^*(R))$, is then obtained as:

$$C_R(\hat{\theta}_0,\ \hat{\theta}_1^*(R)) = \frac{1}{R}\sum_{j=1}^{R}(L_0(\hat{\theta}_0,\ y_j)\ -\ L_1(\hat{\theta}_1^*(R),\ y_j)), \tag{7}$$

where $L_0(\hat{\theta}_0,\ y_j)$ and $L_1(\hat{\theta}_1^*(R),\ y_j)$ are the log-likelihoods evaluated with the j[th] random sample under H_0 and H_1, respectively, and $\hat{\theta}_0$ and $\hat{\theta}_1^*(R)$ are treated as fixed (Pesaran and Pesaran, 1993). Note that y_j is the j[th] vector of the T artificially generated observations on the dependent variable y.

Pesaran and Pesaran (1995) discussed three asymptotically equivalent methods for computing v_0^2. The first method uses the "inner-product" expression for the information matrix (see Pesaran and Pesaran, 1993). In this case, the variance can be obtained by regressing $d_t = L_0(\hat{\theta}_0,\ y_t) - L_1(\hat{\theta}_1,\ y_t)$, the log-likelihood ratio for the t[th] observation (here, y_t is the t[th] observation on y, i.e., y_t is a scalar), on a constant and the first derivatives of $L_{0t}(\hat{\theta}_0,\ y_t)$ with respect to $\hat{\theta}_0$ (Cox, 1962; Pesaran and Pesaran, 1993; 1995). The sum of squared error of this regression is the estimate of the asymptotic variance of Cox test. Pesaran and Pesaran (1995) suggested using the simulation estimator $\hat{\theta}_1^*(R)$ to compute d_t rather than $\hat{\theta}_1$. The variance obtained using the inner product expression of the information matrix and the simulation estimator $\hat{\theta}_1^*(R)$ will be referred to as $\hat{v}_{n0}^2$. The second method uses the "outer-product" expression for the information matrix. Unlike the first method, the second method often yields negative values for the variance (Pesaran and Pesaran, 1993; 1995). Thus, the second method will not be used here. In the third method, the variance is simply computed as (Pesaran and Pesaran, 1995):

$$\hat{v}_{d0}^2 = \frac{\sum_{t=1}^{T} (d_t - \bar{d})^2}{T - 1}, \tag{8}$$

where, as before, d_t is computed using the estimators $(\hat{\theta}_0, \hat{\theta}_1^*(R))$, $\bar{d}$ is the mean of d_t, and T is the number of observations.

The simulation estimator of the Cox statistic, $S_0(\hat{\theta}_0, \hat{\theta}_1)$, is:

$$S_0(R) = \frac{\sqrt{n}T_0(R)}{\sqrt{\hat{v}_{n0}^{2}}}, \tag{9}$$

where $T_0(R) = L_{01} - C_R(\hat{\theta}_0, \hat{\theta}_1^*(R))$ under H_0. $\hat{v}_{d0}^2$ could also be used in the denominator of $S_0(R)$. $S_0(R)$ is asymptotically distributed as N(0, 1) under H_0 (Pesaran and Pesaran, 1993).

The measure of closeness used by Pesaran and Pesaran has proved very useful in statistical inferences (Gourieroux and Monfort, 1995; White, 1994). Its use in Pesaran and Pesaran's test procedure greatly simplifies computing T_0. However, it may not well approximate the true expected value of the log-likelihood ratio since $\hat{\theta}_0$ and $\hat{\theta}_1^*(R)$ are considered as given when computing $C_R(\hat{\theta}_0, \hat{\theta}_1^*(R))$.

Lee and Brorsen's Test

As in Williams (1970), the Monte Carlo test proposed by Lee and Brorsen (1994) to discriminate among separate families of hypotheses uses the log-likelihood ratio as the test statistic. With the Lee and Brorsen's test (MC(LB)), the null hypothesis would be rejected if the actual value of L_{01} is less than its corresponding simulated value an unexpectedly small number of times. Thus, using Noreen's approach, the significance level of the test is calculated as (see Noreen, 1989; Hall and Titterington, 1989):

$$p\text{-}value = \frac{(numb[(L_{0j} - L_{1j}) \leq L_{01}] + 1)}{R + 1}, \quad \textbf{(10)}$$

where numb[] means the number of elements of the set for which the specified relationship is true. The test is appealing because it is simple to calculate.

4. An Alternative Test Procedure

An alternative Cox-type test is proposed in this section. The test is implemented using the Monte Carlo hypothesis testing procedures suggested by Noreen (1989) and Hall and Titterington (1989). With MC(LB), the log-likelihood ratio is used as the test statistic, but here we use a test statistic similar to that of Pesaran and Pesaran (1993; 1995). The test statistic is obtained as the ratio of $\sqrt{n}T_0$ to the square root of its variance v_0^2. Unlike MC(LB), this test statistic is asymptotically pivotal. The variance can be computed using any of the methods discussed above. However, the expected value of the log-likelihood ratio is computed differently from Pesaran and Pesaran (1993; 1995).

The expected value of L_{01} under H_0 is calculated by simulation as follows:

$$\hat{E}_0(L_{01}) = \frac{1}{R}\sum_{j=1}^{R} L_{01j}, \quad \textbf{(11)}$$

where $L_{01j} = L_0(\hat{\theta}_{0j}, y_j) - L_1(\hat{\theta}_{1j}, y_j)$, $\hat{\theta}_{0j}$ is the maximum likelihood estimator of θ_0 for the j[th] random sample, and all other parameters and variables are defined as previously. Note that, contrary to Pesaran and Pesaran, the parameter estimates used here to calculate the expected value of the log-likelihood ratio are not treated as fixed. The simulation estimator, $R^{-1}\sum_{j=1}^{R} L_{01j}$, converges to $E_0(L_{01})$ at $\theta_{0j} = \hat{\theta}_{0j}$ as the number of random samples R and the number of observation T increase. Under H_0, the standardized Cox test statistic (ST) for the actual data can be consistently estimated as:

$$ST_0 = \frac{\sqrt{n}[L_{01} - \hat{E}_0(L_{01})]}{\sqrt{\hat{v}_{n0}^2}}. \quad (12)$$

ST_0 can be computed using $\hat{v}_{d0}^2$ as well.

Once the value of the test statistic for the actual data is computed (i.e., ST_0), to implement the Monte Carlo test, the corresponding values of the test statistic for the simulated data are needed. Consider the j[th] random sample generated using $\hat{\theta}_0$ under H_0 and let ST_{0j} represents the standardized Cox test statistic for that sample. The computation of ST_{0j} requires the log-likelihood ratio for the jth sample, L_{01j}, its expected value, $E(L_{01j})$, and a simulation estimator of the variance v_0^2. The value of L_{01j} is already known and the variance can be easily computed without further simulations. However, further simulations must be carried out in order to compute the expected value of L_{01j}. We proceed as follows. Under H_0, R random samples are generated using the estimator $\hat{\theta}_{0j}$. Let y_{ji} be the i[th] random sample thus generated. For this sample, the log-likelihood ratio is $L_{01ji} = L_0(\hat{\theta}_{0i}, y_{ji}) - L_1(\hat{\theta}_{1i}, y_{ji})$, where $\hat{\theta}_{0i}$ and $\hat{\theta}_{1i}$ are the maximum likelihood parameter estimates under H_0 and H_1, respectively. After repeating this process R times, the expected value of L_{01j} can be estimated as:

$$\hat{E}_0(L_{01j}) = \frac{1}{R}\sum_{i=1}^{R} L_{01ji}, \ \forall j. \qquad (13)$$

Then, ST_{0j} is given by:

$$ST_{0j} = \frac{\sqrt{n}[L_{01j} - \hat{E}_0(L_{01j})]}{\sqrt{\hat{v}^2_{n0j}}}. \qquad (14)$$

R values of ST_{0j} are computed and the p-value of the Cox test is obtained as (Noreen, 1989; Hall and Titterington, 1989):

$$p\text{-}value = \frac{numb[ST_{0j} \le ST_0] + 1}{R + 1}. \qquad (15)$$

Note that both the PP and ST tests use Monte Carlo simulations to compute the expected values of the log-likelihood ratios for each test. However, there is a fundamental difference between these two versions of the Cox test. ST uses Monte Carlo hypothesis testing procedures while PP relies on asymptotic test procedures. Thus, ST should have better finite sample properties than PP. Moreover, since ST does not treat the parameter estimates as fixed when computing the expected value of the loglikelihood ratio, it should be closer to the actual Cox's test statistic than PP.

5. Monte Carlo Experiments

The Monte Carlo experiments are conducted using data from a real world problem.

The design matrix contains weekly data on hamburger prices and advertising expenditures. These data are taken from Griffiths, Hill, and Judge (pp. 295). The following two nonnested models are considered:

$$H_0: \quad tr_t = \alpha_0 + \alpha_1 \log(a_t) + \alpha_2 \log(p_t) + e_{0t} \tag{16}$$

$$H_1: \quad \log(tr_t) = \beta_0 + \beta_1 \log(a_t) + \beta_2 \log(p_t) + e_{1t}, \tag{17}$$

where tr_t is weekly hamburger chain's total receipts, p_t is price, a_t is advertising expenditures, and the e_t's are normally distributed with zero means and constant variances. These two functional forms closely approximate each other. All the tests have such excellent power that we purposely selected a case where it would be difficult to discriminate among the two hypotheses.

When the semi-logarithmic model is the true model (H_0), the dependent variable is generated according to:

$$tr_t = 82.514 + 24.841 \log(a_t) - 21.509 \log(p_t) + \hat{e}_0. \tag{18}$$

When the log-linear model is true (H_1), $\log(tr_t)$ is generated as:

$$\log(tr_t) = 4.466 + 0.206 \log(a_t) - 0.177 \log(P_t) + \hat{e}_1. \tag{19}$$

The parameter estimates of these data generating processes are obtained using 78 observations on tr_t, a_t, and p_t. Both $\hat{e}_0$ and $\hat{e}_1$ are generated using the RNDN command of GAUSS and standard deviations $\sigma_0 = (2.327, 6.984)$ and $\sigma_1 = (0.020, 0.055)$, respectively.

Note that 6.984 and 0.055 are the actual estimates of the standard deviations of the error terms under H_0 and H_1, respectively. The standard deviations are varied to determine the effects of the variances on the Monte Carlo results. A different seed is used only when σ_0 and σ_1 are varied.

The experiments are conducted using samples of 20, 50, 100, and 200 observations. The design matrix is duplicated when the samples of 100 and 200 observations are used. The number of replications is 1000 for samples sizes 20 and 50, and 500 for samples sizes 100 and 200. For Pesaran and Pesaran test procedure, the measure of closeness is calculated using 100 random samples. The number of random samples (R) used in the Monte Carlo tests is 99. Conducting the experiments with larger numbers of random samples did not substantially change the conclusions.

Both the inner product and the simplified versions of the variance are used for the Pesaran and Pesaran and the ST tests. The maximum likelihood parameter estimates θ_{0j} and θ_{1j} are used to calculate the variances of the test statistics for the simulated data. The variances of the test statistics for the actual data are calculated like in Pesaran and Pesaran. The log-likelihood functions of the log-linear model include the Jacobian terms.

6. Monte Carlo Results

The sizes and powers of the Pesaran and Pesaran (PP) test, MC(LB), and ST are reported in Tables 1 and 2 along with their standard errors in parentheses. The standard errors were obtained as the square root of $N^{-1}\alpha(1 - \alpha)$, where N is the number of replications and α is the estimated size or power. The nominal significance level selected is 0.05.

All of the tests have high power, which make them good candidates for discriminating among nonnested regression models. There is, however, a clear difference between the sizes of the Monte Carlo tests and the PP test. Consider the case where the inner product for the information matrix is used to calculate the variance of the Cox test. The size of the PP test is too high, except for samples of sizes 100 and 200 in table 2. Pesaran and Pesaran (1995) found similar results. Similarly, when the simplified version of the variance is used, the PP test over-rejects for all sample sizes but sample size 200 in table 1. In table 2, the size of the PP test is also incorrect in small samples, but sometimes the PP test under-rejects.

As expected, ST has correct size for all samples, irrespective of which version of the variance is used. Interestingly, the MC(LB) test also has correct size for all samples. The excellent size properties of the MC(LB) test could not be guaranteed a priori (even though it is a Monte Carlo test) since the log-likelihood ratio is not an asymptotically pivotal statistic. Contrary to Pesaran and Pesaran's argument, the Monte Carlo results reported here show that the MC(LB) test also has good asymptotic properties.

The ST and MC(LB) tests have very similar powers for all sample sizes. Since the PP test tends to reject too often, it is not surprising that it often has the largest power. In the few cases that the size of the PP test is correct, its power is roughly equal to the powers of the ST and MC(LB) tests.

7. Conclusions

This paper has determined the finite sample performances of three simulated Cox-type tests. The first test is not a true Monte Carlo test and is due to Pesaran and Pesaran. It uses stochastic simulation to compute the numerator of the Cox test statistic and tests are conducted based on asymptotic normality. The second test uses Monte Carlo hypothesis testing procedures to discriminate between two separate families of hypotheses. In this approach, the log-likelihood ratio is considered as the test statistic. The third Cox-type test is a new Monte Carlo test. Unlike the second test, however, the test statistic used in the third approach is asymptotically pivotal. Pivotalness assures that the excellent size properties of Monte Carlo tests hold.

The results of the Monte Carlo experiments show that, in general, the Pesaran and Pesaran test has incorrect size. As expected, the test proposed here has excellent size properties for all sample sizes, irrespective of which version of the variance is being used. Interestingly, the Monte Carlo test based on the log-likelihood ratio also has excellent size and power properties for all sample sizes, even though the log-likelihood ratio statistic is not asymptotically pivotal.

On the basis of their sizes, the Monte Carlo tests are clearly preferred to the Pesaran and Pesaran test. When the size of the Pesaran and Pesaran test is correct, its power is close or even equal to the powers of the Monte Carlo tests. Thus, we would recommend against using the Pesaran and Pesaran test. The Monte Carlo tests (ST and MC(LB)) have similar powers. The MC(LB) test is by far the simplest to compute and therefore we recommend that it be used in applied work.

Table 1. Monte Carlo Results. The Semi-logarithmic Model (H_0) is the True Model. The Log-Linear Model is the Alternative Model.

Sample Size	Test	$\sigma_0 = 2.327$ Size		Power		$\sigma_0 = 6.984$ Size		Power	
20	PP_1	0.121*	(0.010)	0.657	(0.015)	0.172*	(0.012)	0.375	(0.015)
	PP_2	0.144*	(0.011)	0.738	(0.014)	0.203*	(0.012)	0.421	(0.016)
	ST_1	0.042	(0.006)	0.487	(0.016)	0.039	(0.006)	0.181	(0.012)
	ST_2	0.057	(0.007)	0.569	(0.016)	0.043	(0.012)	0.246	(0.015)
	MC(LB)	0.059	(0.007)	0.529	(0.016)	0.056	(0.007)	0.239	(0.013)
50	PP_1	0.098*	(0.009)	0.935	(0.008)	0.138*	(0.011)	0.537	(0.016)
	PP_2	0.140*	(0.011)	0.953	(0.007)	0.161*	(0.012)	0.615	(0.015)
	ST_1	0.052	(0.007)	0.892	(0.010)	0.042	(0.006)	0.404	(0.016)
	ST_2	0.073	(0.008)	0.936	(0.008)	0.053	(0.007)	0.474	(0.016)
	MC(LB)	0.047	(0.007)	0.946	(0.007)	0.054	(0.007)	0.519	(0.016)
100	PP_1	0.080*	(0.012)	0.998	(0.002)	0.116*	(0.014)	0.726	(0.020)
	PP_2	0.104*	(0.014)	1.000	(0.000)	0.142*	(0.017)	0.790	(0.018)
	ST_1	0.052	(0.010)	0.998	(0.002)	0.046	(0.009)	0.708	(0.020)
	ST_2	0.058	(0.010)	0.998	(0.002)	0.052	(0.010)	0.782	(0.018)
	MC(LB)	0.050	(0.010)	0.996	(0.003)	0.062	(0.011)	0.774	(0.019)
200	PP_1	0.070	(0.011)	1.000	(0.000)	0.084*	(0.012)	0.946	(0.010)
	PP_2	0.082*	(0.012)	1.000	(0.000)	0.102*	(0.014)	0.960	(0.009)
	ST_1	0.052	(0.010)	1.000	(0.000)	0.056	(0.010)	0.928	(0.012)
	ST_2	0.062	(0.011)	1.000	(0.000)	0.068	(0.011)	0.944	(0.010)
	MC(LB)	0.054	(0.010)	1.000	(0.000)	0.064	(0.011)	0.946	(0.010)

Note: An asterisk means the estimated size is significantly different from 0.05. Subscripts 1 and 2 refer to the inner product and simplified versions of the variance, respectively.

Table 2. Monte Carlo Results. The Log-linear Model (H_1) is the True Model. The Semi-Logarithmic Model is the Alternative Model.

Sample Size	Test	$\sigma_1 = 0.020$ Size		Power		$\sigma_1 = 0.055$ Size		Power	
20	PP_1	0.108*	(0.010)	0.608	(0.015)	0.117*	(0.010)	0.441	(0.016)
	PP_2	0.137*	(0.011)	0.674	(0.015)	0.152*	(0.011)	0.503	(0.016)
	ST_1	0.044	(0.006)	0.372	(0.015)	0.040	(0.006)	0.161	(0.012)
	ST_2	0.053	(0.007)	0.442	(0.016)	0.050	(0.007)	0.201	(0.013)
	MC(LB)	0.059	(0.007)	0.439	(0.016)	0.058	(0.007)	0.180	(0.012)
50	PP_1	0.053	(0.007)	0.936	(0.008)	0.075*	(0.008)	0.630	(0.015)
	PP_2	0.082*	(0.009)	0.958	(0.006)	0.095*	(0.010)	0.698	(0.015)
	ST_1	0.051	(0.007)	0.853	(0.011)	0.049	(0.007)	0.353	(0.015)
	ST_2	0.062	(0.007)	0.893	(0.010)	0.057	(0.007)	0.425	(0.016)
	MC(LB)	0.044	(0.006)	0.897	(0.010)	0.047	(0.007)	0.445	(0.016)
100	PP_1	0.036	(0.008)	0.996	(0.003)	0.056	(0.010)	0.858	(0.016)
	PP_2	0.052	(0.010)	0.998	(0.002)	0.074	(0.012)	0.886	(0.014)
	ST_1	0.056	(0.010)	0.994	(0.003)	0.062	(0.011)	0.648	(0.021)
	ST_2	0.062	(0.011)	0.996	(0.003)	0.072	(0.012)	0.696	(0.021)
	MC(LB)	0.058	(0.010)	0.996	(0.003)	0.056	(0.010)	0.722	(0.020)
200	PP_1	0.034*	(0.008)	1.000	(0.000)	0.058	(0.010)	0.974	(0.007)
	PP_2	0.042	(0.009)	1.000	(0.000)	0.064	(0.011)	0.976	(0.007)
	ST_1	0.058	(0.010)	1.000	(0.000)	0.060	(0.011)	0.932	(0.011)
	ST_2	0.062	(0.011)	1.000	(0.000)	0.058	(0.010)	0.958	(0.009)
	MC(LB)	0.054	(0.010)	1.000	(0.000)	0.040	(0.009)	0.936	(0.011)

Note: An asterisk means the estimated size is significantly different from 0.05. Subscripts 1 and 2 refer to the inner product and simplified versions of the variance, respectively.

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Paper II

OPTIMAL CONTRACTS FOR FEEDER CATTLE UNDER ASYMMETRIC INFORMATION

OPTIMAL CONTRACTS FOR FEEDER CATTLE UNDER ASYMMETRIC INFORMATION

ABSTRACT

Two models are developed to explain the process of determining optimal contracts for feeder cattle sold through video auctions or by private treaties. The two models are based on principal-agent theory. The first model is a risk-sharing model which is consistent with the current practice of arbitrarily selecting the price slide and the base weight. The predictions of this model are consistent with actual behavior. However, the optimal risk-sharing contract is shown to be inefficient in solving the incentive problem inherent in the feeder cattle contractual arrangement. Feeder cattle sellers' estimates of contract weights are biased. The second model is a risk-sharing and incentives model. This model is used to determine the optimal values of the price slide, the base weight, and the contract price. Time to delivery has a positive effect on the price slide and the contract price. Bailey and Holmgren's hypothesis that buyers may receive higher contract prices if they are confident in their estimates of average delivery weights does not hold. Sellers should set the price slides at least greater than the market discounts.

Key Words: asymmetric information, feeder cattle, moral hazard, price slide, principal/agent theory

OPTIMAL CONTRACTS FOR FEEDER CATTLE UNDER ASYMMETRIC INFORMATION

The number of cattle sold through Superior Livestock Auction has rapidly increased over the last few years. In 1987, over 270,000 cattle were sold by the Superior Livestock Auction. This number more than doubles in 1990; over 760,000 cattle were sold (Bailey and Peterson; Bailey et al., 1991). Superior Livestock Auction currently sells more cattle than any other cattle auction in the U.S. (Bailey et al.).

Feeder cattle sold through video auctions and by private treaty are often for future delivery. Because delivery weights are not known at the time of contractual arrangements, sellers must estimate them. Since sellers and buyers have asymmetric information about weight risk, contracts need to be structured to provide sellers with an incentive to estimate and report weights honestly. The contract must also provide an incentive for sellers to not excessively feed cattle.

The usual approach to dealing with weight risk is to adjust the original contract price by a "price slide." The price slide is used to discount the original contract price if the actual average delivered weight is greater than a limit specified in advance by the seller. No adjustment is made to the original contract price if delivered cattle weigh less than the specified limit. Suppose, for example, that a producer's estimate of average delivered weight is 500 lbs. The producer could sell his cattle at $70/cwt. with a price slide of 10¢/cwt. for each pound of actual average weight over 520 lbs. If at delivery cattle average weight is 530 lbs, then $1/cwt (10¢ times 10 lbs.) is deducted from the original contract price, i.e., from the

$70/cwt. If, however, actual average weight is 515 lbs., no adjustment is made from the original contract price.

The optimal way of determining the contract price and the price slide is poorly understood. Very often, video auction representatives select a price slide based on their personal assessment of weight risk. Buyers may also select a price slide based on their experience. In either case, the price slide used may not be optimal. Bailey, Brorsen, and Fawson found the surprising result that time to delivery has a positive effect on prices at Superior Livestock Auction (SLA). Other empirical studies on cash forward contracting have consistently found that forward contract prices decrease as time to delivery increases (e.g., Brorsen, Coombs, and Anderson; Elam). We argue that the positive relationship between time to delivery and the contract price is due to the implicit option created by the price slide. Bailey and Holmgren argued that sellers may obtain higher contract price offers if they select small allowable weight differences and large price slides.[1] Although plausible, this hypothesis has yet to be tested.

The objective of this paper is to explain the process of determining optimal contracts for feeder cattle. Two models are developed using principal-agent theory. In the first model, the price slide and the estimated cattle delivery weight (or base weight) are held fixed. The buyer chooses the contract price to maximize expected utility subject to the seller accepting the contract (i.e., subject to a participation constraint). Thus, this model is consistent with the current practice where the seller selects the price slide and the base weight based on

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[1]In the above example, the allowable weight difference is 20 lbs. (520 lbs.- 500 lbs.).

experience and accepts the contract with the highest bid price. Note that the seller is not constrained to reveal the true value of the estimated cattle delivery weight. The price slide is used to share the weight risk between the seller and the buyer.

The second model uses a mechanism that allows risk-sharing and provides incentives for truthful revelation of the seller's estimate of average delivery weight. In this model, the seller chooses the price slide and the base weight to maximize expected utility. Similar to the first model, here the buyer also chooses the contract price to maximize expected utility. The buyer's choice, however, is subject to the rationality constraint and the seller's maximization problem. This model is used to determine optimal values of the base weight, price slide, and the contract price.

For each of these models, the characteristics of the optimal contract are determined using comparative statics. The effect of time to delivery on the optimal contract price is determined using the comparative statics results. Before drawing any conclusions from the risk-sharing model, its predictions are empirically tested using actual auction data. For the risk-sharing and incentive model, a numerical example is used to illustrate the sensitivity of the optimal contract to changes in time to delivery. Bailey and Holmgren's hypothesis is tested. Implications for optimally selecting contract prices and price slides are reported.

Theoretical Background

Principal-Agent Relationship

In a perfectly competitive market, perfect information about factor and product quality, prices, and effort exerted by agents is generally assumed (Sheldon). However, asymmetric information prevails in many real world situations. For example, the seller of a good may know more about production risk or product quality than the customers. Effort exerted by an agent may not be observable by others. In such cases, contractual arrangements may be used to optimally allocate resources. Principal-agent theory provides a framework for modeling such allocation problems (Varian; Rees). The principal-agent relationship relies upon a "contract that the parties either propose or accept and that more or less specifies what the principal expects from the agent and what the agent will receive in return" (McLean Parks and Conlon, p. 822).

Basic Principal-Agent Model

In general, the principal is viewed as employing the agent to perform a specific job whose monetary outcome is, say, x. The outcome x is observable by both parties, but it depends on the agent's action or effort which is not observable by the principal. The agent receives a payment in return for service. The basic principal-agent model can be built upon the following assumptions. Both the principal and the agent maximize expected utility. Effort reduces the agent's expected utility and so, if the agent accepts the contract, he will choose a level of effort that is best for himself (e.g., Rees; van Ackere; Varian). This results in an incentive problem which the principal must solve. The principal does so by designing the incentive payment, p(x), that will induce the agent to choose an effort level that is optimal for both parties. Formally, the model can be stated as (e.g., van Ackere):

$$(1) \quad \underset{p(x),e}{Max} \int_{x_{min}}^{x_{max}} U_P[(x - p(x))]\phi(x, e)dx$$

$$s.t. \int_{x_{min}}^{x_{max}} U_A[p(x)]\phi(x, e)dx - V(e) \geq \bar{U}_A, \qquad (individual\ rationality)$$

$$e \in Argmax_{\hat{e}} \int_{x_{min}}^{x_{max}} U_A[p(x)]\phi(x, e)dx - V(e), \qquad (incentive\ compatibility)$$

where e is the action or effort that the principal wants to induce, $\bar{U}_A$ is the reservation utility of the agent, $U_A(\ )$ is the agent's utility function ($U_A'(\ ) > 0$ and $U_A''(\ ) < 0$), $U_P(\ )$ is the principal's utility function ($U_P'(\ ) > 0$ and $U_P''(\ ) < 0$), V(e) is the agent's disutility of effort ($V'(e) \geq 0$ and $V''(e) \geq 0$), and $\phi(x, e)$ is the probability density function of x, conditional on effort. The first constraint is the rationality constraint. This constraint postulates that the agent will only accept the contract if he can reach at least some minimum expected utility level (called reservation utility), i.e., the contract does not make him worse off. It guarantees that the agent chooses the best possible effort level.

Approaches to solving (1) have been widely discussed in the literature and will not be repeated here (see e.g., Jewitt; Rees; Rogerson; Mirrless). In general, the first order approach is used. With this method, the incentive compatibility constraint is replaced with:

$$(2) \quad \int_{x_{min}}^{x_{max}} U_A[p(x)]\phi'(x, e)dx - V'(e) = 0.$$

The first order approach will be used in this paper.

One variant of model (1) that is worth noting is the pure risk-sharing model. This model is relevant when effort is observable or can be fixed at some arbitrary level. In this case, model (1) becomes:

$$(3) \quad \underset{p(x)}{Max} \int_{x_{min}}^{x_{max}} U_P[(x - p(x))]\phi(x, e)dx$$

$$s.t. \int_{x_{min}}^{x_{max}} U_A[p(x)]\phi(x, e)dx - V(\bar{e}) \geq \bar{U}_A, \qquad \textit{(individual rationality)}$$

where $\bar{e}$ is a fixed level of effort. Contrary to (3), with model (1) there is a trade-off between sharing risk and providing incentives (Holmstrom; Rees, 1985a). The first analytical model developed in this paper uses equation (3) while the second uses equation (1).

Modifying the Basic Model

The principal-agent model has been used to determine optimal incentive contracts in many fields (see van Ackere for a survey). In most applications, model (1) is modified to suit the economic environment of interest. Contrary to (1), in many cases, effort or action is only implicit in the formulation of the model. Sobel, for example, used a model in which the agent is assumed to have exerted effort e_i when event I occurs. The model is formulated using the probability levels p_i rather than effort levels e_i.

Compensation schemes have also been used to solve the incentive problem inherent in principal-agent relationships when the action of the agent is unobservable or outcome is uncertain (e.g., Nalebuff and Stiglitz; Rees, 1985b; Harris and Raviv). A number of compensation schemes that do not explicitly involve effort have been used. Weitzman, for example, formulated a principal-agent model in which a compensation scheme is used to give firms an incentive to not misrepresent their output target. Although Weitzman recognized that effort affects the output distribution, he did not explicitly include effort in the model. Instead, in an extended version of the model, a bonus coefficient which is assumed to reflect the firm's willingness to exert more or less effort is used. Ross also used a compensation scheme to determine a firm manager's optimal choice of a financial structure. In Ross's model, effort is not used since the compensation scheme provides the agent with strong incentives to act in the interest of both parties. An incentive scheme which only implicitly refers to the agent's action is used in the models developed here.

Analytical Model

Feeder Cattle Contracting and The Incentive Problem

The incentive problem described above is inherent in any contractual arrangement where informational asymmetry is present (see e.g., Nicholson; Holmstrom). Hendricks and Porter define information on a common value auction as asymmetric when "the precisions of signals observed [concerning the value of the object to be sold] vary across participants" (p. 865). This definition fits well the case of feeder cattle auctions where sellers have better information about expected weights than buyers. Similar definitions of asymmetric information have been used in the principal-agent literature (see, e.g., Harris and Townsend; Haugen and Taylor; Holmstrom).

Consider a feeder cattle buyer who wants to contract with a seller for future delivery of cattle. The seller must deliver cattle with an acceptable weight and in return shall receive a payment from the buyer. The buyer's payment depends, of course, on delivered weight, Y, which is observable by both parties at delivery. At the time of contracting, the seller must provide an estimate of Y. The buyer, of course, would like an honest estimate of Y since his payment depends on it. However, the seller is better informed about expected weight than the buyer and so, an incentive problem (moral hazard) arises. Indeed, the seller may have incentive to misrepresent the estimate of Y and take advantage of the information asymmetry. This type of behavior prevails when there is asymmetric information because economics agents respond to the incentives they face (Nicholson).

Under asymmetric information, monitoring or a compensation scheme can be used to provide economics agents with an incentive to not misrepresent their target output, efforts, or abilities (see e.g., Nalebuff and Stiglitz; Weitzman). In the case of feeder cattle contracting, by offering a price slide, the seller guarantees to bear part of the weight risk. The larger the price slide, the more the weight risk shifted to the seller (Bailey and Holmgren). With the price slide, the payment per head (p(Y)) from the buyer to the seller has the following form:

$$(4) \quad p(Y) = \begin{cases} p_0 - \gamma(Y - Y_L) & \text{if } Y > Y_L \\ p_0 & \text{if } Y \leq Y_L \end{cases}$$

where p_0 is the contract price, γ is the price slide, and $Y_L = Y_0 + \delta$ is the weight limit specified in the contract. Y_0 is the seller's estimate of Y and δ is the allowable weight difference. The payment p(Y) is a compensation scheme which penalizes the agent if delivered weights are greater than Y_L. Compensation schemes of this type are used in many real world contractual relationships where asymmetric information exists (e.g., Phlips; Harris and Raviv).

Since the price slide is costly, the compensation scheme p(Y) should, theoretically, give the seller an incentive to reveal his estimate of Y honestly and feed cattle to an acceptable weight. But this may not be the case in practice since the price slide are 'arbitrarily' selected by the seller. When the price slide is selected in this way, weight risk may not be optimally shared between the seller and the buyer. In this case, the seller may still misrepresent the estimate of Y. The compensation scheme will therefore not be efficient and resources misallocation will result. If an optimal incentive contract is sought (a contract that will lead to optimal resources allocation under conditions of asymmetric information), the auction must design the contract in such a way that the seller not only provides an honest estimate of Y, but also select a price slide that is desirable for both parties.

A Principal-Agent Model for Feeder Cattle Contracting

Shavell indicated that "economic arrangements which involve problems of risk-sharing and incentives may be described in terms of the principal and agent relationship" (p. 55). The problem just described can be modeled using the principal-agent framework. Principal-agent theory can also be used to design optimal incentive feeder cattle contracts.

Consider the payment p(Y). The seller's (agent) payoff is:

$$(5) \quad r_A = \begin{cases} [p_0 - \gamma(Y - Y_0 - \delta)]Y & \text{if } Y > Y_L \\ p_0 Y & \text{if } Y \leq Y_L. \end{cases}$$

Let v(Y, V) represents a per unit value function for cattle, where V is a vector of other relevant variables and $v_Y(Y, V) < 0$. Note that feed prices are not directly used in v(Y, V). Corn prices are only implicitly included since changes in corn prices would change $v_Y(Y, V)$. The share of the cattle's value that goes to the buyer (principal) is:

$$(6) \quad r_P = \begin{cases} [v(Y, S) - (p_0 - \gamma(Y - Y_0 - \delta))]Y & \textit{if } Y > Y_L \\ [v(Y, S) - p_0]Y & \textit{if } Y \leq Y_L. \end{cases}$$

Note that $E(r_P)$ would be zero if markets were competitive and information is perfect, i.e., the principal would break-even. To simplify, assume that there is one agent and one principal.[2] Moreover, the agent and the principal are risk averse since they are both exposed to weight risk. The allowable weight difference, δ, is assumed to be set exogenously for simplicity. With these assumptions, the principal-agent model can be developed as follows. Consider first the case where the seller set the price slide and the base weight 'arbitrarily' (as is

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[2]Given our objective, there is no loss of generality with this assumption (see e.g., Nalebuff and Stiglitz).

currently done). The contractual arrangement occurs in two steps. The seller announces the values of the price slide and the base weight. Given these values, the buyer then chooses the contract price to maximize expected utility. In doing so, the buyer must ensure that the seller will accept the price.[3] The principal-agent model that corresponds to this case can be formulated as follows:

$$(7)\quad \underset{p_0}{Max} \int_{Y_{\min}}^{Y_L} U_P[r_P(Y, p_0)]f(Y, \theta^*)dY + \int_{Y_L}^{Y_{\max}} U_P[r_P(Y, p_0, \bar{Y}_0, \bar{\gamma})]f(Y, \theta^*)dY$$

$$s.t. \int_{Y_{\min}}^{Y_L} U_A[r_A(Y, p_0)]g(Y, \theta)dY + \int_{Y_L}^{Y_{\max}} U_A[r_A(Y, p_0, \bar{Y}_0, \bar{\gamma})]g(Y, \theta)dY \geq \bar{U}_A$$

where f( ) and g( ) are probability density functions and all other variables are defined as previously. Different density functions of Y are used for the agent and the principal since information about weight variability is asymmetrically distributed. θ is a set of information on which g( ) is conditional. θ includes variables such as time to delivery and season and $\theta^* \subset \theta$. The reservation utility $\bar{U}_A$ may be viewed as the utility level that the agent can achieve by selling the cattle on a different market for example. Note that the price slide and the base weight are fixed at $\bar{\gamma}$ and $\bar{Y}_0$. They represent the arbitrary levels of the price slide and the base weight selected by the agent.

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[3]This is consistent the bidding environment in which contracting occurs. Bidding can be viewed as an optimization process in itself. Bidding for contracts has been modeled in many studies using principal-agent theory (e.g., Samuelson; McAfee and McMillan (1986; 1987)).

The contract obtained by solving (7) does not guarantee an optimal solution to the incentive problem discussed above. This is because the agent can use the price slide to influence the principal's optimal choice of the contract price in his favor while misrepresenting his estimate of average delivery weight. This will be investigated using the comparative statics results.

Let aside the relationship between the price slide and the contract price, the agent can always misrepresent his estimate of average delivery weight since there is no "mechanism" in (7) that encourages honest revelation. A model that appropriately addresses the incentive problem inherent in the feeder cattle contractual arrangement can be formulated as follows:

$$(8) \quad \underset{Y_0,\, p_0,\, \gamma}{Max} \int_{Y_{\min}}^{Y_L} U_P[r_P(Y, p_0)]f(Y, \theta^*)dY + \int_{Y_L}^{Y_{\max}} U_P[r_P(Y, p_0, Y_0, \gamma)]f(Y, \theta^*)dY$$

$$s.t. \int_{Y_{\min}}^{Y_L} U_A[r_A(Y, p_0)]g(Y, \theta)dY + \int_{Y_L}^{Y_{\max}} U_A[r_A(Y, p_0, Y_0, \gamma)]g(Y, \theta)dY \geq \bar{U}_A$$

$$\int_{Y_L}^{Y_{\max}} U_A' \frac{\partial r_A(Y, p_0, Y_0, \gamma)}{\partial Y_0} g(Y, \theta)dY = 0$$

$$\int_{Y_L}^{Y_{\max}} U_A' \frac{\partial r_A(Y, p_0, Y_0, \gamma)}{\partial \gamma} g(Y, \theta)dY = 0$$

where all of the variables are defined as previously. As in the basic principal-agent model, the last two constraints of (8) are incentive compatibility constraints. Here, they insure that the agent will honestly reveal his estimate of average delivery weight as well as the price slide. Model (8) implies that the agent chooses the price slide and the base weight by solving a maximization problem rather than arbitrarily as in (7). The principal chooses the contract price by taking into account the rationality constraint and the agent maximization problem as well. Thus, the optimal values of Y_0 and γ are compatible with the principal's optimal choice of p_0 (see, e.g., Rees, 1985a, on this point).[4] Since the principal and the agent optimal choices are mutually compatible, the agent has no interest in misrepresenting his estimate of average delivery weight. As in (1) , model (8) allows risk-sharing and provides incentives for truthtelling. For the rest of this paper, model (8) will be referred to as the risk-sharing and incentives model. Model (7) will be referred to as the risk-sharing model.

Comparative Statics

A unique solution to optimization problems of the type considered here is not guaranteed. In such cases, one way to find a unique solution is to appropriately bracket the choice variable (see e.g., Rees, 1985; Holmstrom; Rogerson). This technique is adopted here.

[4]Recall that contracting occurs in two steps. Here, however, there are two expected utility maximization problems. The agent chooses the price slide and the base weight to maximize the expected utility of r_A given any contract price. The principal then chooses the contract price to maximize the expected utility of r_P given the agent expected utility maximization conditions and the participation constraint. This ensures compatible optimal values of the contract parameters.

It is assumed that there exists an interval $[p_{0L}, p_{0U}]$ over which problem (7) has a unique solution. p_{0L} and p_{0U} are lower and upper limits on p_0, respectively. p_{0L} can be considered as a reservation price and can be used to compute the reservation utility. The Kuhn-Tucker conditions are (see e.g., Rogerson):

$$(9) \quad \int_{Y_{min}}^{Y_{max}} [U_P' + \lambda U_A'] \frac{\partial r_P}{\partial p_0} f(Y, \theta^*) dY \begin{cases} \leq 0 & \text{if } p_0 = P_{0L} \\ = 0 & \text{if } p_0 \in (p_{0L}, p_{0U}) \\ \geq 0 & \text{if } p_0 = p_{0U}. \end{cases}$$

Note that the strict equality condition only hold if p_0 is neither equal to p_{0L} or p_{0U}.

The risk sharing model is difficult to solve analytically. To make tractable, one can be proceed as follows. First, consider the agent's maximization problem for any given contract price p_0. The optimal choice of the agent can be determined by solving the two incentive compatibility constraints for Y_0 and γ as a function of the contract price and the weight slide. Then, by substituting this solution into the principal's objective function, one can solve for the optimal value of the contract price p_0^*. To find the optimal values Y_0^* and γ^*, the optimal contract price is plugged in the formulas of Y_0 and γ obtained from the agent's maximization problem. A similar approach has been used by van Ackere. Using this approach, comparative statics are easily derived for both the agent and the principal's problems.

Comparative Statics Results

Characteristics of the Optimal Risk-Sharing Contract

The following comparative statics results are obtained after totally differentiating the strict equality first order condition in equation (9) (see appendix A). Each result is derived under the usual assumption that all other exogenous variables are held fixed.

PROPOSITION 1. *The optimal contract price increases as the agent increases the price slide:* $\frac{dp_0^*}{d\gamma} > 0$; *but, it decreases when the allowable weight difference is increased:* $\frac{dp_0^*}{d\delta} < 0$.

This implies that, with the current contracting practice, for small allowable weight differences, the agent will have strong incentives to select higher price slides (for any given Y_0 of course).

PROPOSITION 2. *The optimal contract price decreases when the agent's estimate of delivery weight is increased:* $\frac{dp_0^*}{dY_0} < 0$.

This result is as expected since heavier cattle are less valued as mentioned above. Results 1 and 2 imply that, although heavier cattle are less valued, the agent can fixed a very high value of Y_0 but still obtain a relatively high contract price. In fact, for fixed allowable weight difference and delivery weight, the agent can always obtain a higher contract price by simply increasing the price slide. The optimal value of the price slide is unknown and weight risk may be inefficiently shared. Moreover, the price slide will not give the agent strong incentives to feed cattle at a desirable weight. At delivery, either the principal or the agent may end up worse off. Thus, results 1 and 2 imply that the optimal contract obtained here is inefficient.

PROPOSITION 3. *The effect of time to delivery on the optimal contract price is negative if the weight distributions are decreasing in the cattle weight variances, and positive otherwise.*

As shown in appendix A the sign of $\frac{dp_0^*}{dt}$ depend on the signs of $\frac{\partial\sigma_P^2}{\partial t}$, $\frac{\partial\sigma_A^2}{\partial t}$, $\frac{\partial f(\,)}{\partial\sigma_P^2}$, $\frac{\partial g(\,)}{\partial\sigma_A^2}$, and $\frac{\partial v(\,)}{\partial t}$. At the time of contracting, $\frac{\partial v(\,)}{\partial t} = 0$. The following assumption are then made. $\frac{\partial\sigma_P^2}{\partial t}$ and $\frac{\partial\sigma_A^2}{\partial t}$ are positive. f( ) and g( ) are unimodal distributions. With these assumptions, if $\frac{\partial f(\,)}{\partial\sigma_P^2}$ and $\frac{\partial f(\,)}{\partial\sigma_P^2}$ are negative, then $\frac{dp_0^*}{dt}$ will be negative. $\frac{dp_0^*}{dt}$ will be positive otherwise.

Characteristics of The Optimal Risk-Sharing and Incentives Contract

The comparative statics results are obtained using the approach outlined in the preceding section. The derivations are shown in appendix B. Considering the agent's optimization problem we have the following results.

PROPOSITION 4. *The effect of the allowable weight difference on the optimal values of Y_0 and γ may be positive, negative, or zero:* $\frac{dY_0^*}{d\delta} \lesseqgtr 0$; $\frac{d\gamma^*}{d\delta} \lesseqgtr 0$.

The comparative statics in appendix B indicate that the effect of δ on the optimal value of γ depends on the sign of

$$E1 = \frac{\int_{\Omega_2} U_A^{//} \frac{\partial r_A}{\partial \delta} \frac{\partial r_A}{\partial \gamma} g(Y,\ \theta) dY}{\int_{\Omega_2} U_A^{//} \frac{\partial r_A}{\partial \delta} \frac{\partial r_A}{\partial Y_0} g(Y,\ \theta) dY} - \frac{\int_{\Omega_2} [U_A^{//} \frac{\partial r_A}{\partial Y_0} \frac{\partial r_A}{\partial \gamma} + U_A^{/} Y] g(Y,\ \theta) dY}{\int_{\Omega_2} U_A^{//} (\frac{\partial r_A}{\partial Y_0})^2 g(Y,\ \theta) dY},$$

while its effect on Y_0 depends on the sign of

$$E2 = \frac{\int_{\Omega_2} U_A^{//} \frac{\partial r_A}{\partial \delta} \frac{\partial r_A}{\partial \gamma} g(Y,\ \theta) dY}{\int_{\Omega_2} U_A^{//} \frac{\partial r_A}{\partial \delta} \frac{\partial r_A}{\partial Y_0} g(Y,\ \theta) dY} - \frac{\int_{\Omega_2} [U_A^{//} \frac{\partial r_A}{\partial Y_0} \frac{\partial r_A}{\partial \gamma} + U_A^{/} Y] g(Y,\ \theta) dY}{\int_{\Omega_2} U_A^{//} (\frac{\partial r_A}{\partial \gamma})^2 g(Y,\ \theta) dY},$$

where Ω_2 is the relevant support of Y. The signs of E1 and E2 cannot be determined a priori. Indeed, E1 and E2 may have the same sign or different signs; they may both be equal to zero or one may be positive or negative and the other equals to zero. Thus, the effects of the weight slide on the optimal values of the base weight and price slide cannot be signed.

PROPOSITION 5. *The optimal values of Y_0 and γ may decrease, increase, or remain the same if time to delivery is increased:* $\frac{dY_0^*}{dt} \lesseqgtr 0$; *and* $\frac{d\gamma^*}{dt} \lesseqgtr 0.$

As in (d), here, the impacts of time to delivery depend an expression that cannot be signed a priori.

For the principal's optimization problem, the effects of weight slide and time to delivery on the optimal contract can be determined by proceeding as in the case of the risk-sharing model after replacing Y_0 and γ by Y_0^* and γ^*. The results will be the same as in the case of the risk-sharing model.

Empirical Test of The Risk-Sharing Model

Test Procedures

If sellers' estimates of average delivered weights are unbiased, the mean of the differences between actual and estimated delivery weights should be zero. Let ϵ be the mean of the differences between the two weights. Then, the null hypothesis to be tested is H_0: $\epsilon = 0$. This hypothesis is tested using a t-test. A similar approach is used to test the null hypothesis that the difference in the number of head offered and the number of head delivered is zero.

The assumption that weight variability increases with time to delivery is tested using the following equation:

$$(11) \quad e = \alpha_0 + \alpha_1 D1 + \alpha_2 D3 + \alpha_3 D4 + \alpha_4 Y88 + \alpha_5 Y89 + \alpha_6 STEERS + \alpha_7 WEST + \alpha_8 SOUTH + \alpha_9 UPPER + \alpha_{10} WCOAST + v,$$

where $e = W_a - W_e$ and v is distributed with mean zero and variance

$$(12) \quad \sigma_v^2 = \exp(\beta_0 + \beta_1 WEIGHT + \beta_2 WEIGHT2 + \beta_3 STEERS + \beta_4 TIME + \beta_5 Y88 + \beta_6 Y8$$

$$+ \beta_7 D1 + \beta_8 D3 + \beta_9 D4 + \beta_{10} WEST + \beta_{11} SOUTH + \beta_{12} UPPER + \beta_{13} WCOAST$$

The variable WEIGHT represents the base weight, WEIGHT2 is the square of the base weight, STEERS is a dummy variable for steers, TIME denotes time to delivery, the Y_is are year dummy variables, the D_is are quarter dummy variables, and WEST, SOUTH, UPPER, and WCOAST are dummy variables representing the regions where the cattle are located. Equations (11) and (12) are estimated using the maximum likelihood estimation procedures in SHAZAM.

The effects of the contract weight, weight slide, price slide, and time to delivery on the contract price are derived from the following equation:

$$(13) \quad p_0 = \alpha_0 + \alpha_1 PSLIDE + \alpha_2 WSLIDE + \alpha_3 WEIGHT + \alpha_4 WEIGHT2 + \alpha_5 TIME + \alpha_6 TIME$$

$$+ \alpha_7 PSLIDE*\hat{e} + \alpha_8 WSLIDE*\hat{e} + \sum_{i=9}^{K1} \alpha_i OLC_i + \sum_{i=K1+1}^{K2} \alpha_i OMC_i + \epsilon,$$

where ϵ has mean zero and variance

$$(14) \quad \sigma_\epsilon^2 = \exp(\beta_0 + \beta_1 WEIGHT + \beta_2 WEIGHT2 + \beta_3 NUM + \beta_4 NUM2 + \beta_5 TIME + \beta_6 TIME2$$

$$+ \beta_7 FEEDER + \beta_8 FEEDER2 + \beta_9 D1 + \beta_{10} D3 + \beta_{11} D4 + \beta_{12} WEST + \beta_{13} SOUTH$$

$$+ \beta_{14} UPPER + \beta_{15} WCOAST + \beta_{16} D1 + \beta_{17} D3 + \beta_{18} D4 + \beta_{19} Y88 + \beta_{20} Y89).$$

The variable p_0 is the contract price, ê is the predicted value of the standard deviation of weight, WSLIDE is the weight slide, PSLIDE is the price slide, FEEDER and FEEDER2 are the nearby futures price and its square, respectively, OLC is other lot characteristics, OMC is other market conditions, NUM and NUM2 are the number of head and the square of the number of head, respectively, and all other variables are defined as previously. Note that contrary to Bailey et al.'s (1991; 1993) formulation where weight risk is defined as the ratio of the weight slide to the price slide, here weight risk is accounted for with the variables WLSIDE*ê and PSLIDE*ê. This formulation is less restrictive than the one used by Bailey et al.

The mean and variance equations of this regression model are estimated using maximum likelihood. The estimated mean equation is used to plot the contract price against base weight, weight slide, and time to delivery.

The data used to test for unbiasedness of the base weights and estimate the two regression models are actual Superior Livestock Auction data for the 1987-1989 period (Bailey). The data contain information on lot characteristics, contract prices, base weights, and other relevant variables needed to estimate the models.[5] Before discussing the regression results, the summary statistics and the histograms of selected variables are presented. The summary statistics are reported in table 1. Figures 1, 2, 3, and 4 represent the histograms of the differences in weight and number of head, price slide, and weight slide, respectively. Figures 1 and 2 indicate that the distribution of the difference in weights is more spread than that of the difference in the number of head. The histogram of the price slide indicates that most of the values of the price slide are clustered around 3, 4, and 5 cents per hundred weight. The histogram of the weight slide shows that most values of the weight slide are 10 or 25 pounds.

Empirical Test Results

Table 2 contains the t-ratios and p-values of the tests that the differences in weights and head are zero. The p-values indicate that the difference in weights is significantly different from zero at the 5 percent level while the difference in head is not. Sellers' estimates of average weights are biased upward but the number of head is generally not biased. This confirms the inference drawn from the comparative statics results that sellers' estimates of average delivery weights can be biased.

The parameter estimates of equations (11) and (13) are reported in tables 3 and 4, respectively. The parameter estimate of time to delivery in the cattle weight variance equation (table 3) is positive, indicating that time to delivery has a positive effect on the weight

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[5]Data after 1989 were available. They are not used here since they do not contain all the information needed.

variance. This conforms with the assumption made in the theoretical model. In the contract price equation (table 4), the parameter estimates of the price slide variables are all positive. This confirms the prediction in proposition 1 that the contract price increases with the price slide. The base weight was used in equation (13) in quadratic form. The parameter estimate of the base weight is negative while that of the square of the base weight is positive. Figure 5 shows the effect of the base weight on the contract price. As expected, the contract price decreases as base weight is increased. This validates proposition 2 of the theoretical model. The effect of time to delivery on the contract price is plotted in figure 6. The contract price is shown to increase with small values of time to delivery and to decrease otherwise. In the actual data set, most of the values of time to delivery are within the range where the contract price increases. This may explain why past studies found that time to delivery has a positive effect of the contract price. The effect of the weight slide on the contract price is shown in figure 7. The contract price decreases when the weight slide is increased. This result was expected since the base weight and the weight slide must have the same effects. It also conforms to proposition 1 in the theoretical model.

The effects of the weight and price slide on the base weight were also plotted. The plots were derived from the regression of the weight and price slides on the base weight and the base weight squared. Figure 8 indicates that the base weight decreased when the price slide was increased. In figure 9, the weight slide is shown to increase with increases in the base weights.

The empirical tests just discussed strongly support the predictions of the risk-sharing model. The estimates of average delivery weight are biased thus, verifying the argument that the risk-sharing contract is inefficient in solving the incentive problem mentioned earlier. The fixed price slide failed because it does not guarantee unbiased estimates of average weights.

Illustrative Example of The Risk-Sharing and Incentives Model

The Optimization Approach

This section describes a numerical example used to obtain more insight into the comparative statics of the risk-sharing and incentives model. The numerical example is also used to test the hypothesis that sellers offer higher price slides when they are confident in their estimates of average weights. The numerical example is also used to determine how sellers should set the price slides and what an efficient contract would be.

The principal and the agent are assumed to possess negative exponential utility functions. The functions f( ) and g( ) are assumed to be normal density functions. Gauss Legendre quadrature formulas with sixty-point gaussian quadrature weights and abssicas are used to approximate the expected utilities of the agent and the principal. The gaussian quadrature weights and abssicas are obtained from Stroud and Secrest. The complete derivation of the approximation is described in appendix C.

In the previous section it was shown that the agent estimate of weight is biased. This bias, however, was small. Here, the model is solved with weight unbiasedness imposed, but the weight slide is determined optimally rather than assuming it fixed. Weights unbiasedness is imposed by setting the actual and the estimated weights equal to 630 pounds (sample mean). The effects of time to delivery on the optimal values of the contract are determined by varying the weight variances of the agent and the principal's weight distributions. To test Bailey and Holmgren hypothesis, we proceed as follows. The weight variance of the principal is held fixed. The optimal contract is then solved for different weight variances of the agent distribution. Bailey and Holmgren's hypothesis would be rejected if the optimal price slides decrease as weight variances are decreased.

If estimated weights are truly unbiased and the price slides greater than the marginal true values of the cattle (i.e. $\gamma > -v_Y(\ )$), then the incentive problem would be effectively eliminated. In what follows, the optimal contract is solved assuming weights unbiasedness and letting the price and weight slides fixed at 5¢/cwt and 15 pounds, respectively. The optimal contract prices is solved for under two different values of $v(Y, V)$, the actual value and a 20 percent decrease in the actual value. The marginal market values of the cattle are then calculated and compared to the price slide (as indicated in parentheses above). These results will give important information about how sellers should set the price slides.

Results of The Numerical Example

The optimal contract prices, price slides, and weight slides are reported in table 5 for different weight variances. The weight slides decrease as time to delivery increases. As predicted by the theoretical model, the optimal contract prices increase when the weight slides are decreased. It was argued that buyers would require higher price slide if time to delivery is increased. This was shown to hold with the regression results reported in table 4. The results obtained here show that the price slide does increase when time to delivery increases.

These results did not change when the weight variance of the buyer was held fixed and the seller's weight variance varied. The price slides decrease when the seller's weight variance is decreased. This indicates that Bailey and Holmgren's hypothesis does not hold.

Table 6 reports the optimal values of the contract price when weight unbiasedness is imposed and the weight and price slides held fixed. As before, the optimal contract price increases when the weight variance increases. The third column of table 6 reports the optimal contract prices when the slope of the cattle true value function, v( ), is decreased by 20 percent. In this case, the values of the optimal contract price are lower than those in column two. This result reflects the fact that the seller's payoff depends on market discounts. The impacts of a 1 percent decrease are calculated by interpolation. They range from ¢1.8/cwt to ¢2/cwt decrease in the cattle true value. These values are less than the value of the price slide used (¢5/cwt).

Several conclusions can be drawn from this numerical example. First, Bailey and Holmgren's hypothesis does not hold. Second, sellers should offer higher price slides when time to delivery is increased. Indeed, for buyers, the price slide is like a warranty against bearing most of the weight risk. Also, since the price slide is costly, it imposes truthfulness on the part of the seller. The seller has interests to deliver cattle with an acceptable average weight. The benefit of higher price slides for the seller is to receive higher contract price offers from the buyer. Third, the seller must set the price slide greater than the market discount. In fact, there is no reason for the buyer to offer a high contract price if the contract discounts less heavier cattle than the market does. Note that this pricing method is only efficient if estimated weights are unbiased. If estimated weights are biased, a fixed price slide will fail in any case. Finally, note that since the price slide increases with time to delivery, the forward contract premium will also increase as time to delivery increases. Intuitively, higher contract premiums create the incentives to deliver cattle with acceptable average weights. As time to delivery increases, higher contract premiums are indication of the seller willingness to deliver cattle with acceptable weights. Cattle are valued more at higher contract premiums. Thus, the contract prices increase as time to delivery increases.

Conclusions

Two models are developed in this paper to explain the process of determining optimal contracts for feeder cattle sold through video auctions or by private treaties. The two models are based on principal-agent theory. In the first model, the price slide and the base weight are assumed fixed. This is consistent with the current contracting practice. The characteristics of the optimal contract obtained using this model are determined through comparative statics. An empirical test using actual auction data shows that the model's predictions are consistent with actual behavior. However, the optimal contract is shown to be inefficient in solving the incentive problem inherent in the feeder cattle contractual arrangement. Sellers' underestimate average delivery weights by 3.5 pounds, so the present system does lead to a small amount of bias.

An alternative model which uses a mechanism that allows risk-sharing and provides incentives for truthful revelation of the seller's estimate of average delivery weight is developed. The model is used determine the optimal contract assuming conditions of unbiased average delivery weights. The optimal contract is the contract for which the discount is at least greater than the market discount. If weights are truly unbiased, such a contract will eliminate the incentive problem.

Several implications were drawn from the models used in this paper. First, Bailey and Holmgren's hypothesis does not hold. Second, sellers should offer higher price slides when time to delivery is increased. Indeed, for buyers, the price slide is like a warranty against bearing most of the weight risk. Also, since the price slide is costly, it imposes truthfulness on the part of the seller. The seller has interests to deliver cattle with an acceptable average weight. The benefit of higher price slides for the seller is to receive higher contract price offers from the buyer. Third, the seller must set the price slide greater than the market discount. In fact, there is no reason for the buyer to offer a high contract price if the contract discounts less heavier cattle than the market does. Note that this pricing method is only efficient if estimated weights are unbiased. If estimated weights are biased, a fixed price slide will fail in any case. Finally, note that since the price slide increases with time to delivery, the forward contract premium will also increase as time to delivery increases. Intuitively, higher contract premiums create the incentives to deliver cattle with acceptable average weights. As time to delivery increases, higher contract premiums are indication of the seller willingness to deliver cattle with acceptable weights. Cattle are valued more at higher contract premiums. Thus, the contract prices increase as time to delivery increases.

Table 1. Summary Statistics of Selected Variables, Video Cattle Auction Data, 1987-1989

Variable	Units	Mean	Minimum	Maximum	Standard Deviation
Heads Offered		155.0	19.0	2250.0	132.2
Heads Delivered		153.1	14.0	1980.0	129.3
Base Weight	pounds	631.2	240.0	1200.0	140.8
Actual Weight		634.7	158.1	1244.6	143.4
Contract Price	$/cwt	82.4	51.5	130.0	10.6
Difference in Number of Head		-1.7	-1925.0	1435.0	77.6
Difference in Weight		3.5	-381.9	385.1	38.7
Price Slide	cents/cwt	5.3	0.0	80.0	3.7
Weight Slide	pounds	15.6	-25.0	40.0	7.4
Time to Delivery	days	37.7	1.0	290.0	36.5

Note: The number of observations is 3119.

Table 2. Tests for Significance Differences Between the Actual and the Estimated Weights and Number of Heads, Feeder Cattle Auction Data, 1987-1989

Variable	T-Ratio	P-Value
Difference in Weight	5.0070840	0.0001
Difference in Head	-1.2377666	0.2159

Table 3. Parameter Estimates of the Cattle Weight Variance Equation, Feeder Cattle Auction Data, 1987-1989

Variable	Parameter Estimate	Standard Error
Mean Equation		
Intercept	4.7861*	1.8190
Steers	7.5208*	1.3060
Y88	-1.5834	1.8610
Y89	-6.4764*	1.9240
D1	0.4099	1.9090
D3	-7.9019*	1.7550
D4	-3.4734**	2.0230
West	1.4832	2.0830
South	3.8760*	1.9600
Upper	-1.1749	5.7010
West Coast	4.1391	2.8100
Variance Equation		
Intercept	4.8502*	0.4648
Weight	0.0048*	0.0015
Weight Square	-0.0021*	0.0011
Date	0.0039*	0.0007
Y88	0.0179	0.0706
Y89	-0.1806*	0.0762
D1	0.1400*	0.0752
D3	0.3143*	0.0695
D4	0.0905	0.0894
West	0.2621*	0.0779
South	-0.2460*	0.0993
Upper	-0.4261**	0.2674
West Coast	-0.3396*	0.1452
Estimated Loglikelihood	-15684.5000	

Note: Asterisks denote significance at the 5 percent level

Table 4. Parameter Estimates of the Contract Price Equation, Video Cattle Auction Data, 1987-1989

Variable	Parameter Estimate	Standard Error
Mean Equation		
Intercept	10.3400	15.3800
Futures Price	2.4539*	0.4008
Futures Price Square	-0.0109*	0.0026
Steers	4.4599*	0.2879
Number	0.0012*	0.0005
Weight	-1.1471*	0.0047
Number Square	-0.0005**	0.0003
Weight Square	0.0764*	0.0035
English-Exotic-Cross	-0.7040*	0.3470
English-Cross	-0.6731*	0.3498
Exotic-Cross	-1.2781*	0.3773
Angus	0.9993	0.7197
Dairy	-10.1170*	0.5075
Medium Heavy	-1.6031*	0.4028
Medium Flesh	-1.5601*	0.3833
Light-Medium Flesh	-1.8281*	0.4177
Large Frame	4.5034*	1.5470
Medium-Large Frame	3.6222*	1.5480
Medium Frame	1.5903	1.5840
No Horn	0.2962	0.4784
Some Horn	-0.4757*	0.1163
D1	0.8801*	0.1650
D3	2.0416*	0.3159
D4	1.1826*	0.2501
West	0.0790	0.1998
South	-4.5778*	0.2901
Upper	2.2601*	0.4592
West Coast	-2.3772*	0.2928
LSW	-1.1652*	0.1245
Truck	-0.4893	0.4111
Unmixed	0.8959*	0.4669
Time	0.0229*	0.0029
Miles	-0.0127*	0.0002

Table 4. Continued

Price Slide	0.0634*	0.0175
Weight Slide	-0.0270*	0.0147
Y88	1.1773*	0.2239
Y89	2.7880*	0.3422
Time Square	-0.00009*	0.0000
*WSLIDE*e*	0.0047*	0.0015
*PSLIDE*e*	0.0282*	0.0037
Variance Equation		
Intercept	18.5030*	7.5400
Weight	-0.0250*	0.0015
Weight Square	0.0164*	0.0011
Number	-0.0011*	0.0003
Number Square	0.0002	0.0002
Time	-0.0053*	0.0017
Time Square	0.000006	0.0000
Futures Price	-0.1781	0.2002
Futures Price Square	0.0011	0.0013
West	-0.1408*	0.0781
South	0.1419	0.0995
Upper	-0.7824*	0.2690
West Coast	-0.4865*	0.1458
D1	0.0117	0.0944
D3	0.1506	0.0994
D4	0.1706	0.1131
Y88	-0.2471*	0.0958
Y89	-0.2976*	0.1168
Estimated Loglikelihood	-7775.6000	

Note: Asterisks denote significance at the 5 percent level

Table 5. Optimal Contract Price, Weight Slide, and Price Slide for Alternative Values of Cattle Weight Variance and Weight Slide, Risk-Sharing and Incentives Model

	Optimal Values of		
Standard Deviation of Weight	Contract Price ($/cwt)	Weight Slide (Pounds)	Price Slide (cents/lbs)
70	92.00	-21.263	4.675
60	90.80	-3.354	4.644
50	84.50	12.127	3.868

Table 6. Optimal Contract Price for Alternative Values of Cattle Weight Variance, Weight Unbiasedness Imposed

Standard Deviation of Weight	Contract Price for (in \$/cwt)	
	Actual Value of Cattle	20% Decrease in Actual Value
40	64.0	60.3
50	64.1	60.4
60	64.3	60.5
70	64.5	60.6
80	64.8	60.7
90	65.1	61.0

Note: The slope of the cattle per unit value function was decreased by 20 percent.

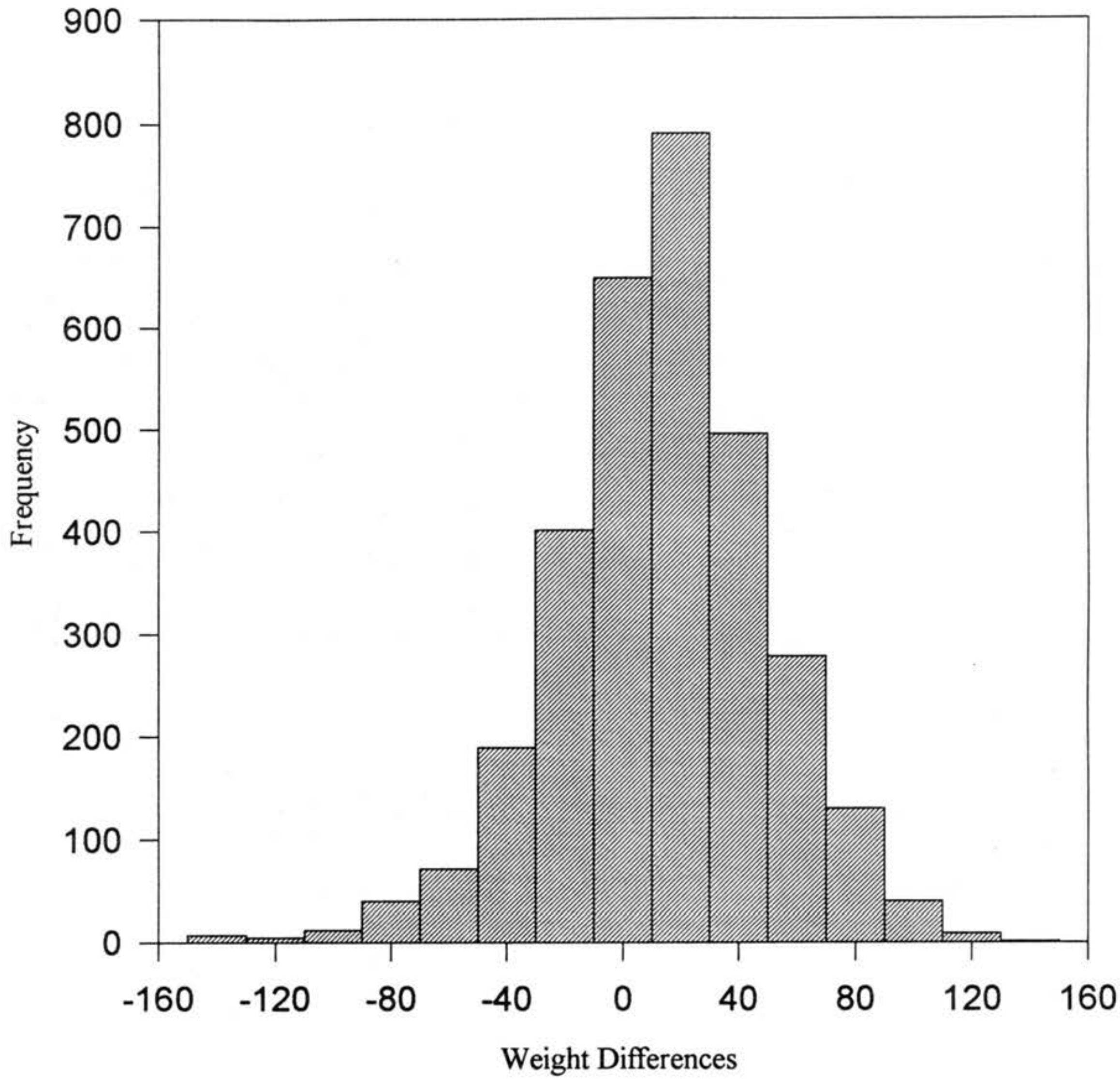

Figure 1. The histogram of the differences between actual and estimated feeder cattle weights, 1987-1989

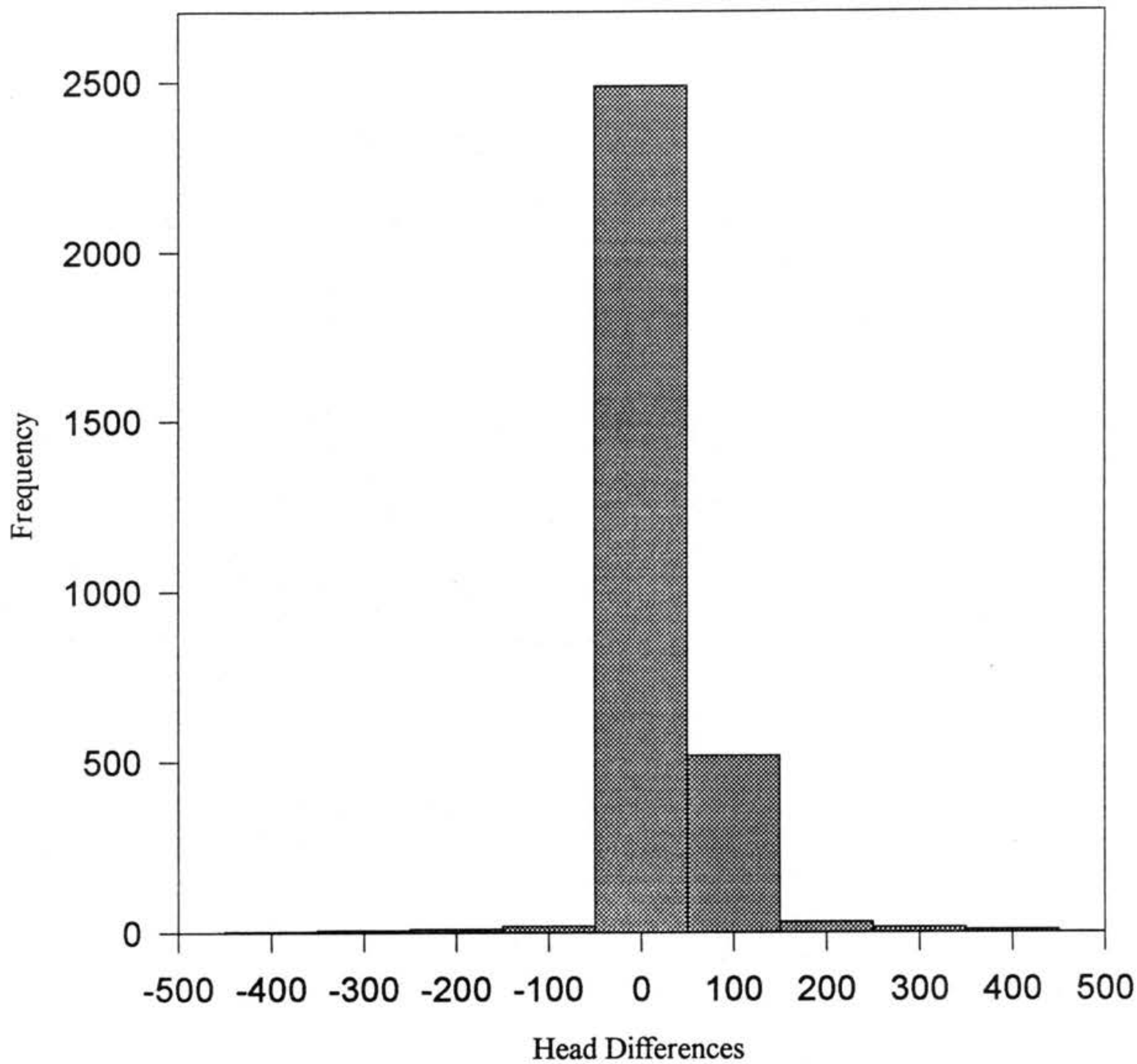

Figure 2. The histogram of the differences between the actual and the number of heads offered, 1987-1989

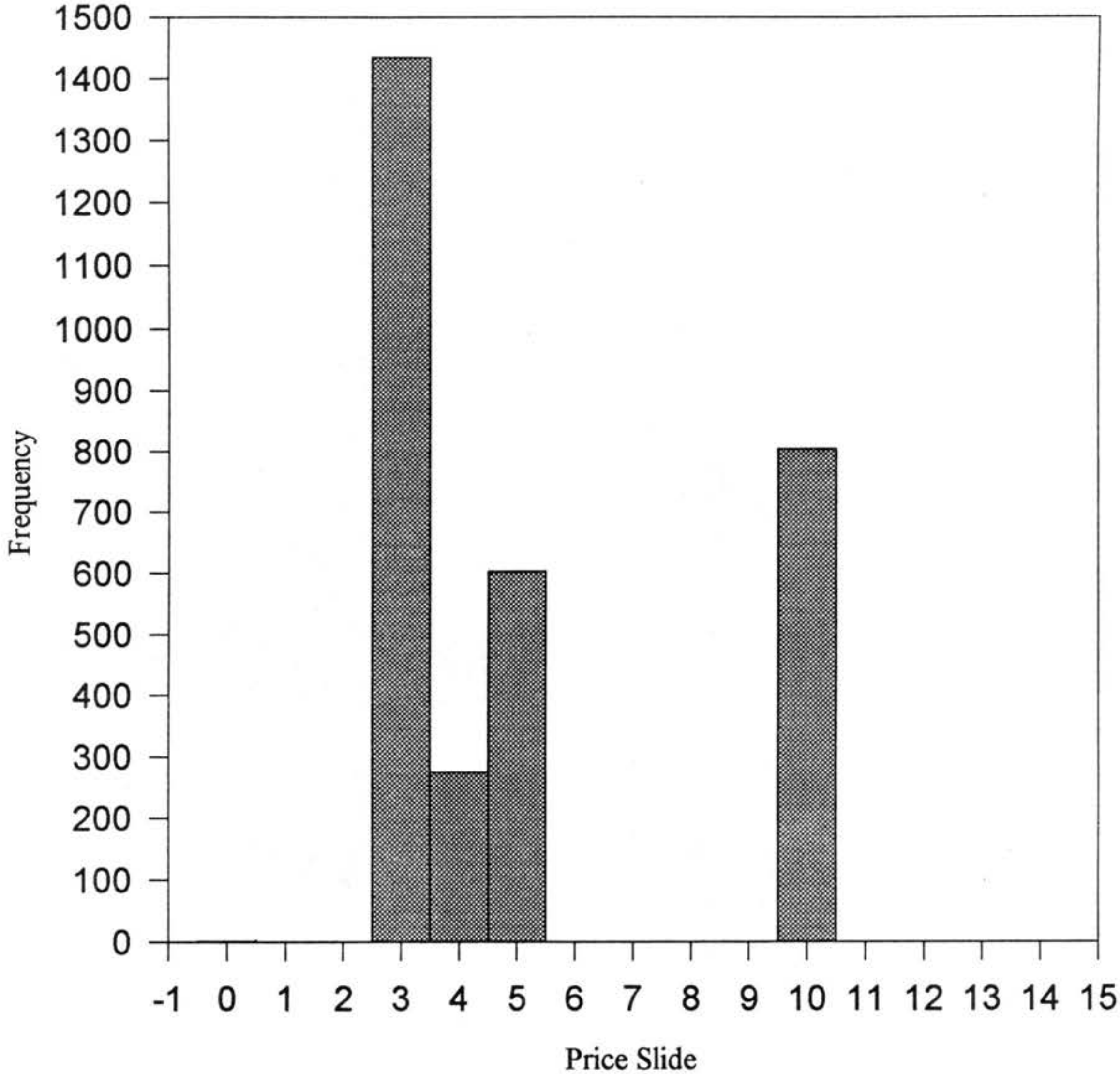

Figure 3. The histogram of the price slide of the video cattle auction data, 1987-1989

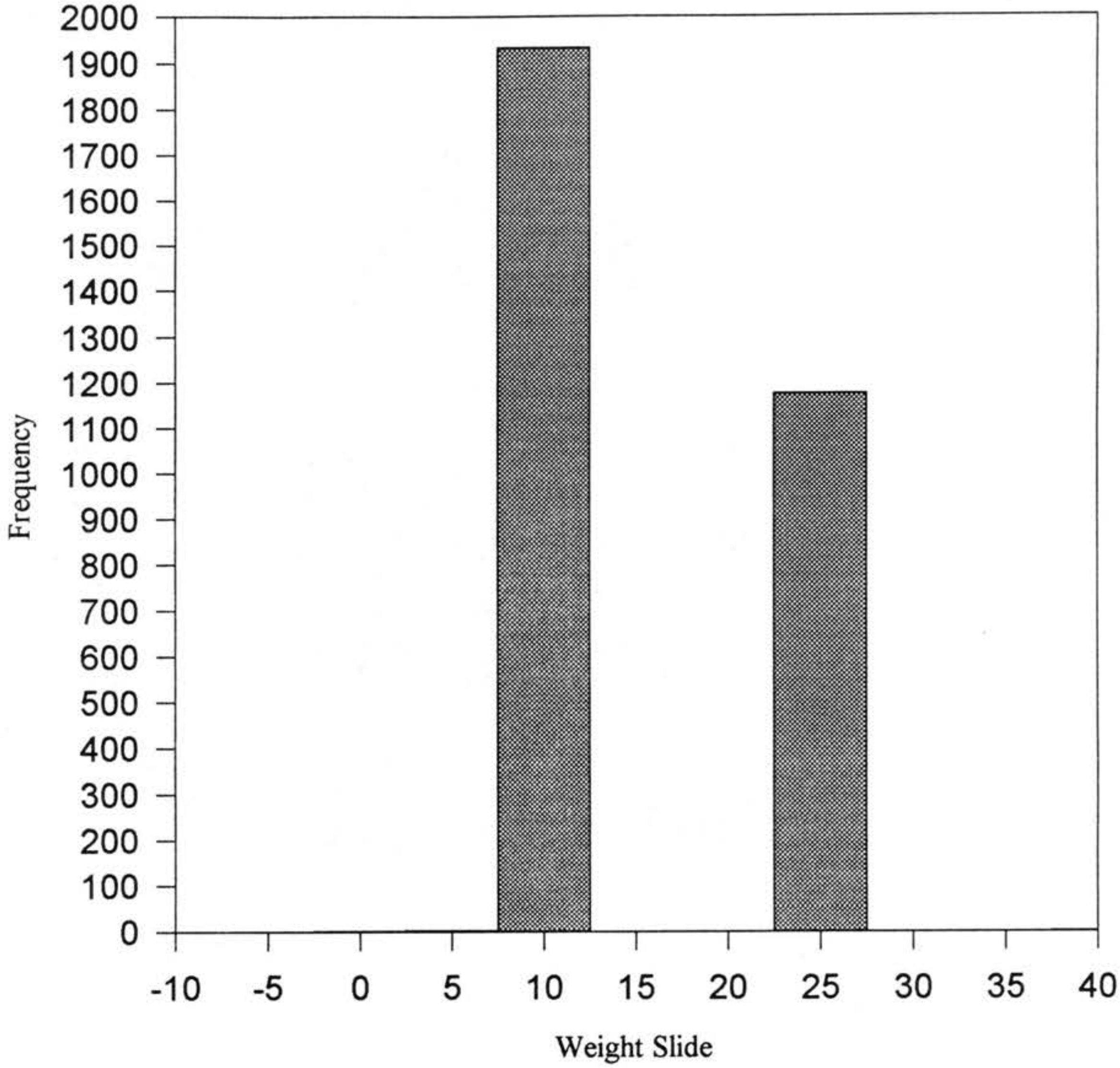

Figure 4. The histogram of the weight slide, feeder cattle auction data, 1987-1989

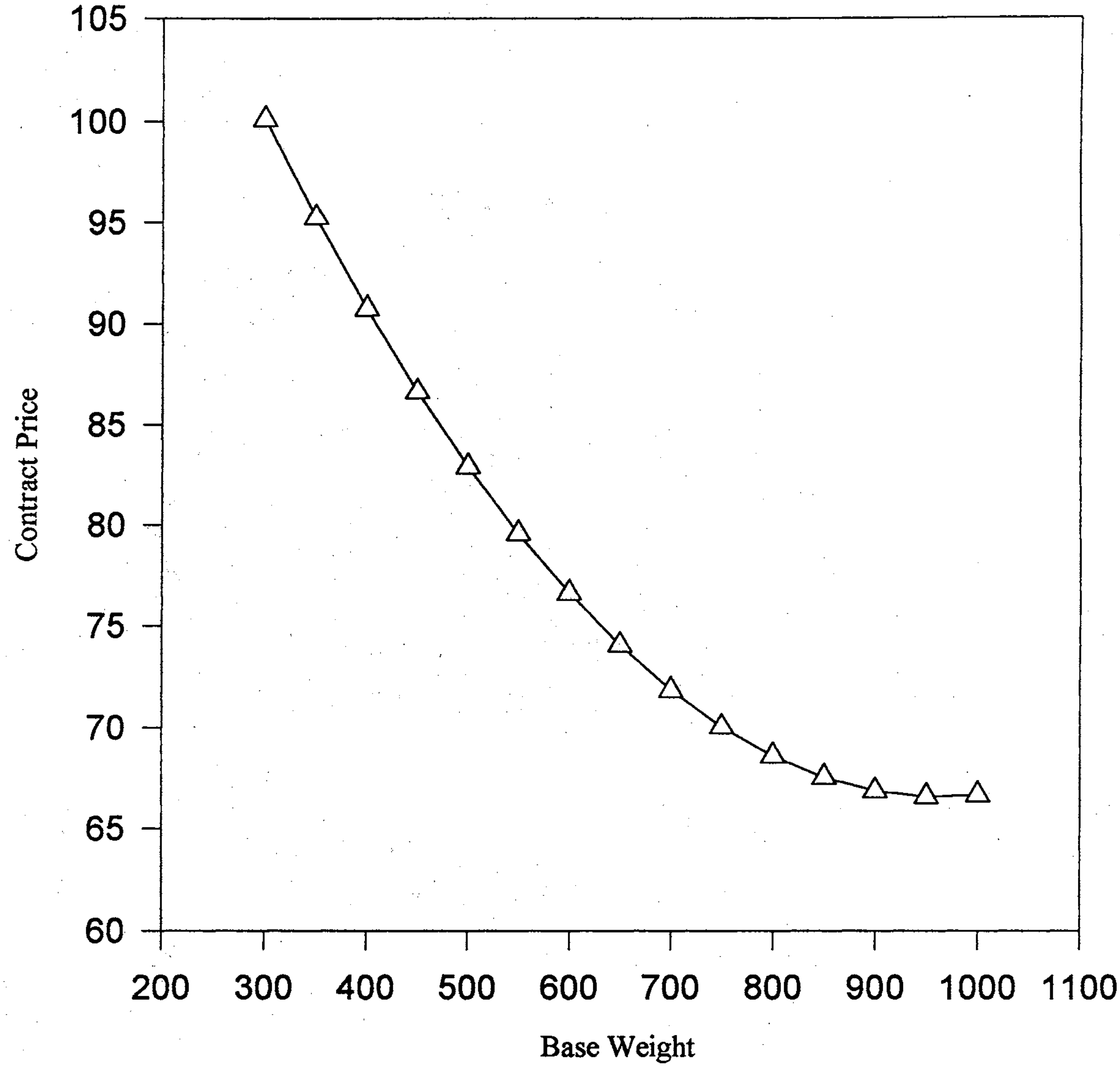

Figure 5. The effect of cattle weights on the contract price

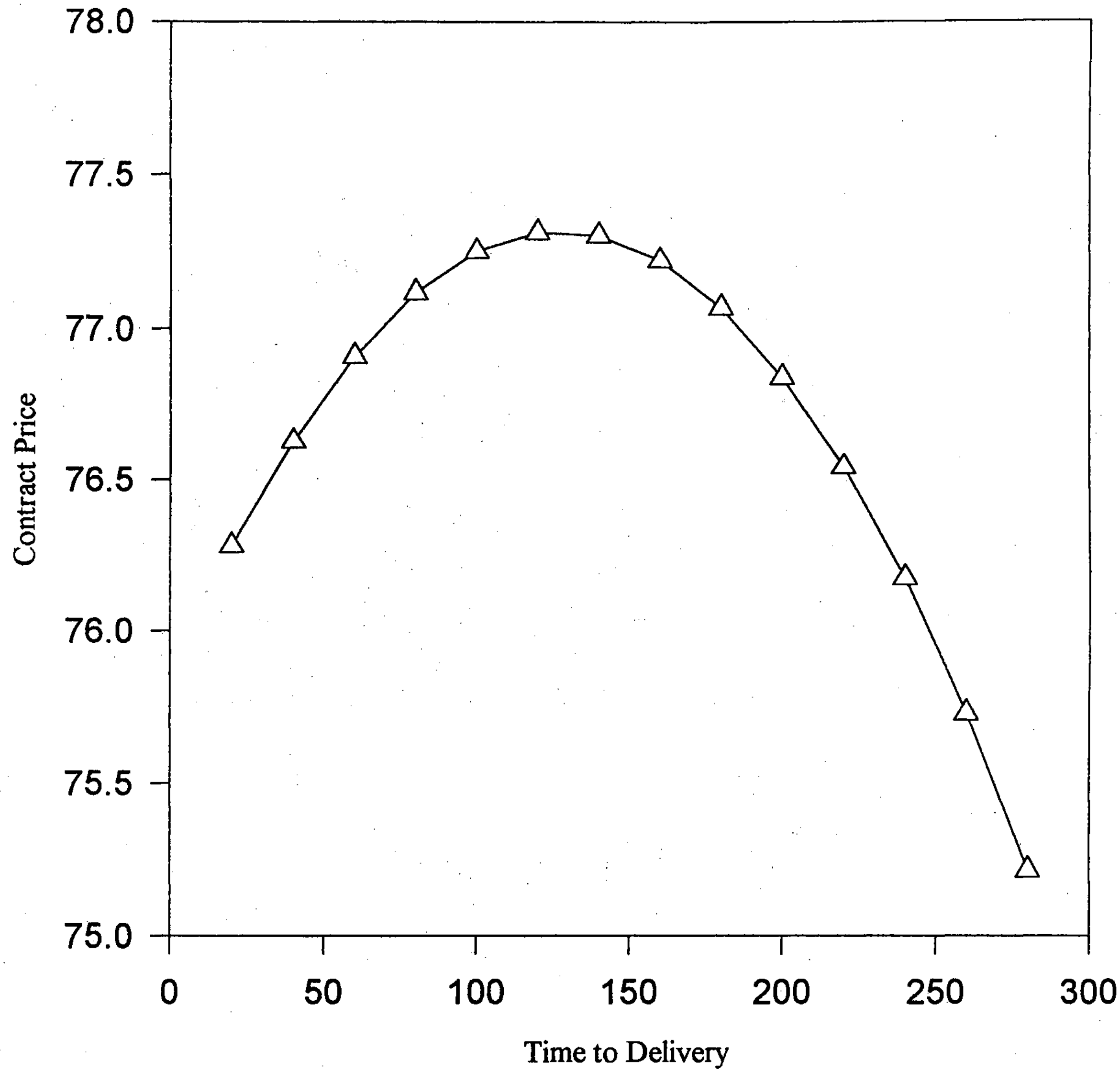

Figure 6. The effect of time to delivery on the contract price

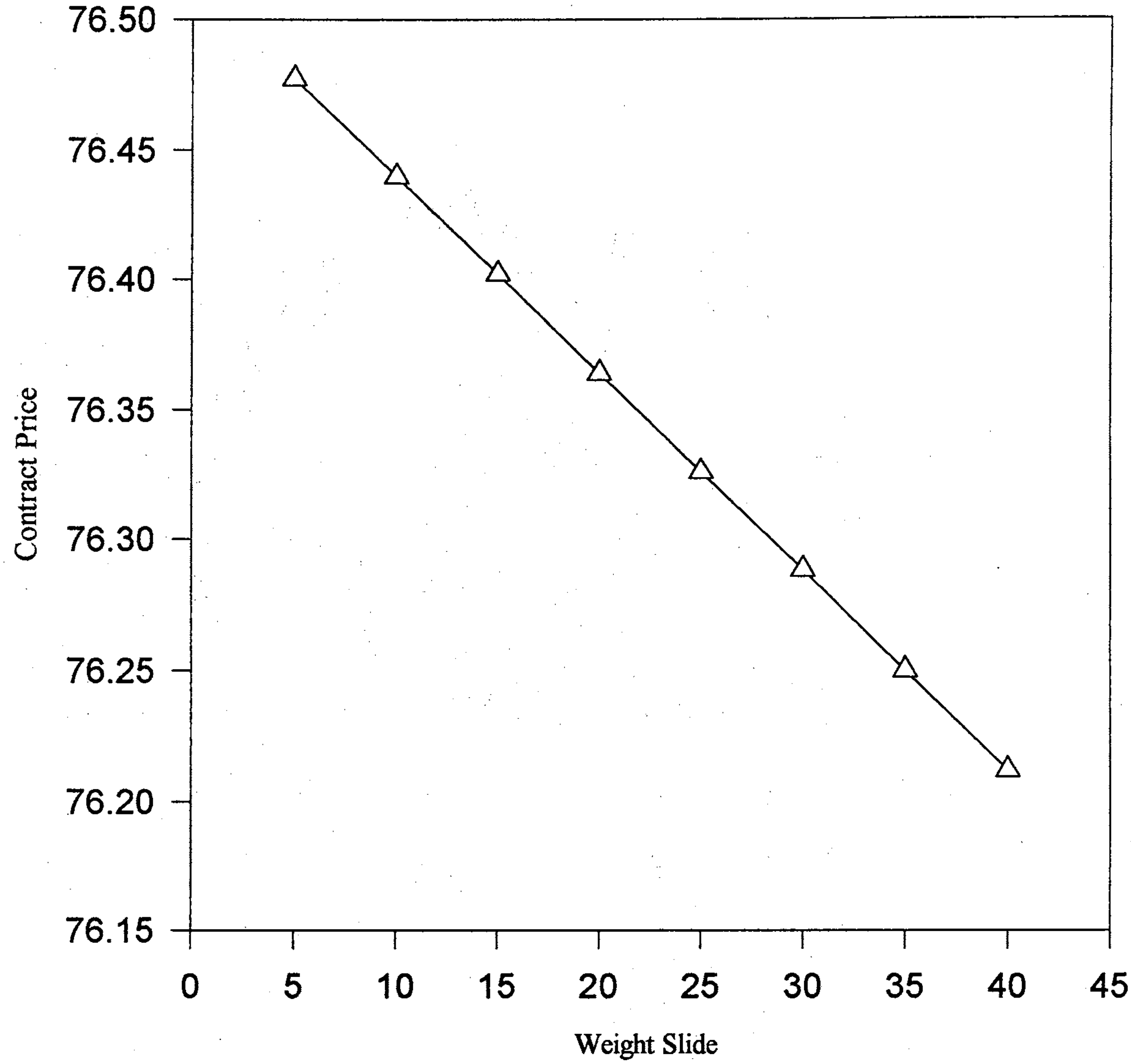

Figure 7. The effect of feeder cattle weight slides on the contract price

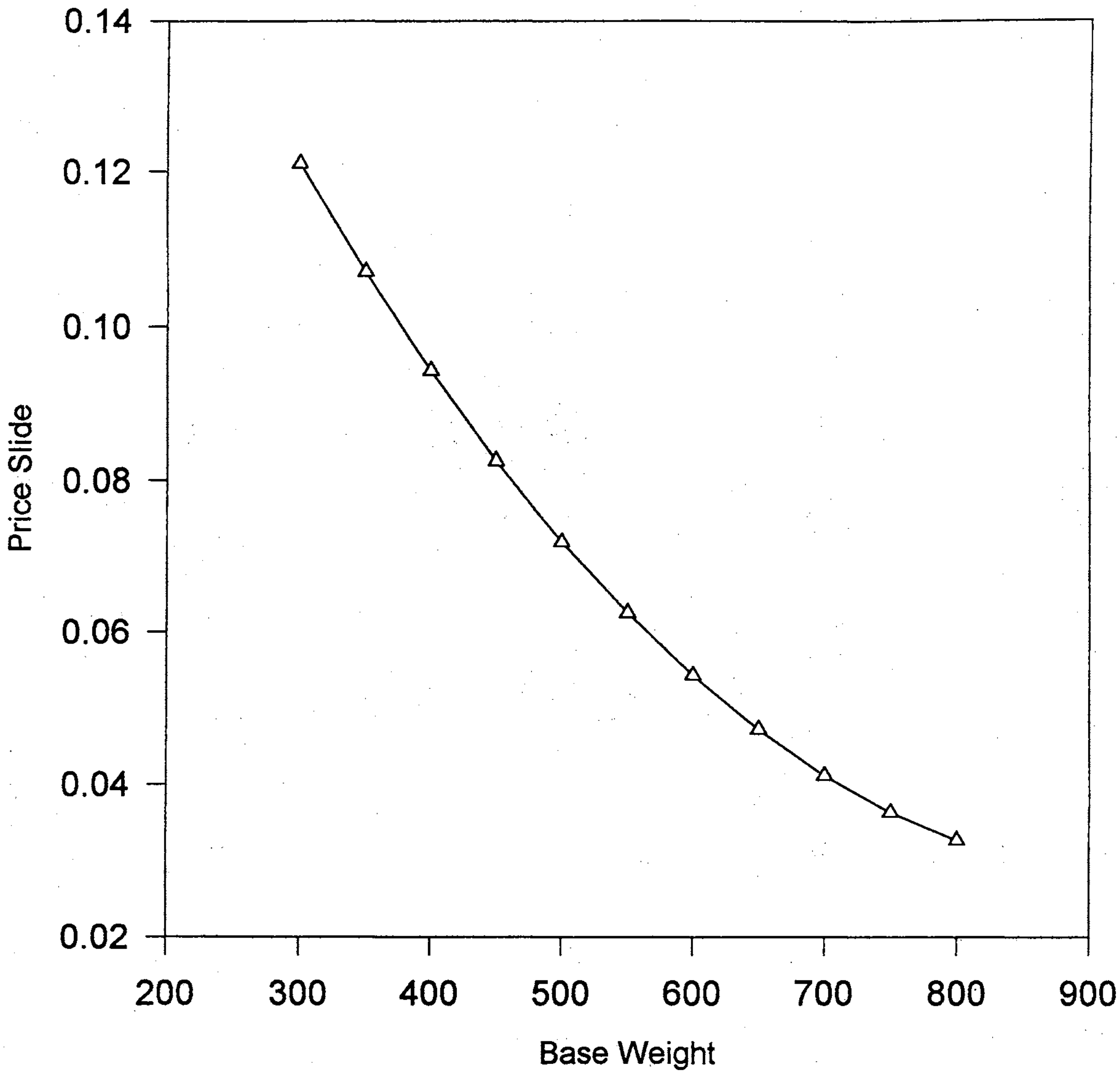

Figure 8. Price slide versus base weight

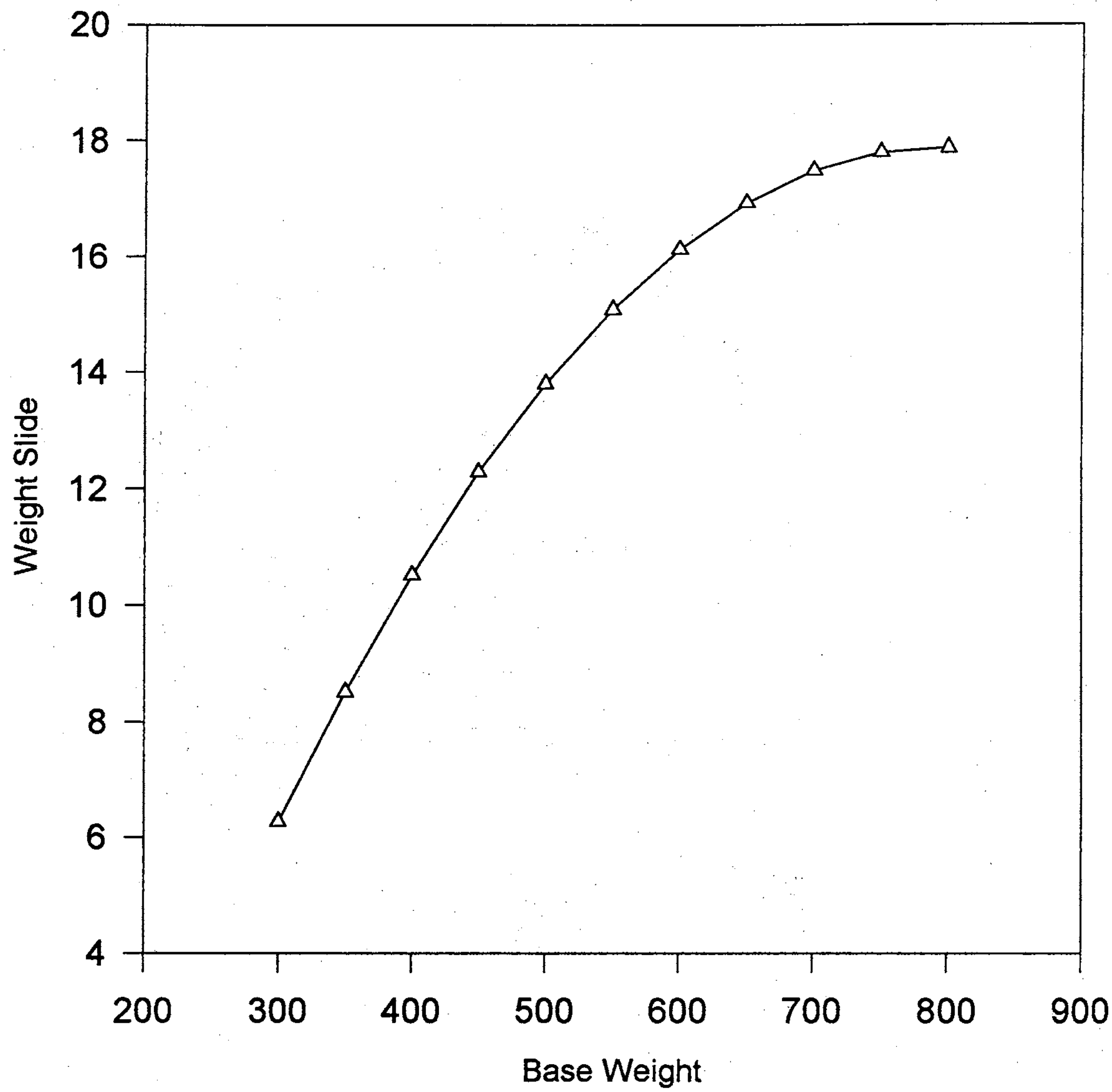

Figure 9. The effect of selected base weights on the weight slide

Appendix A

For all proofs, we will assume that changes in the principal and agent's subjective variances of weight (σ_P^2 and σ_A^2, respectively) are induced by changes in time to delivery.

Consider model (8):

$$\underset{p_0}{Max} \int_{Y_{min}}^{Y_L} U_P[r_P(Y,\ p_0)]f(Y,\ \theta^*)dY + \int_{Y_L}^{Y_{max}} U_P[r_P(Y,\ p_0,\ Y_0,\ \gamma)]f(Y,\ \theta^*)dY$$

$$s.t. \int_{Y_{min}}^{Y_L} U_A[r_A(Y,\ p_0)]g(Y,\ \theta)dY + \int_{Y_L}^{Y_{max}} U_A[r_A(Y,\ p_0,\ Y_0,\ \gamma)]g(Y,\ \theta)dY \geq \bar{U}_A$$

For $p_0 \in \,]p_{0L},\ p_{0U}[$, the Kuhn-Tucker condition is:

$$\int_{Y_{min}}^{Y_{max}} U_P^{\prime}\frac{\partial r_P}{\partial p_0}f(Y,\ \theta^*)dY - \lambda \int_{Y_{min}}^{Y_{max}} U_A^{\prime}\frac{\partial r_A}{\partial p_0}g(Y,\ \theta)dY = 0$$

Since $\dfrac{\partial r_A}{\partial p_0} = -\dfrac{\partial r_P}{\partial p_0}$, the Kuhn-Tucker condition can be written as:

$$\int_{Y_{min}}^{Y_{max}} [U_P^{\prime}f(Y,\ \theta^*) + \lambda U_A^{\prime}g(Y,\ \theta)]\frac{\partial r_P}{\partial p_0}dY = 0.$$

Totally differentiating this first-order condition yields:

$$\int_{Y_{min}}^{Y_{max}} [(U_P''f(Y, \theta^*)\frac{\partial r_P}{\partial p_0} + \lambda U_A''g(Y, \theta)\frac{\partial r_A}{\partial p_0})\frac{\partial r_P}{\partial p_0} + (U_P'f(Y, \theta^*) + \lambda U_A'g(Y, \theta))\frac{\partial}{\partial p_0}(\frac{\partial r_P}{\partial p_0})]dp_0 dY$$

$$= A_\gamma d\gamma + A_{Y_0} dY_0 + A_\lambda d\lambda + A_t dt + A_\delta d\delta,$$

where the term A_i stands for the second partial derivative of $\int_{Y_{min}}^{Y_{max}} [U_P'f(Y, \theta^*) + \lambda U_A'g(Y, \theta)]\frac{\partial r_P}{\partial p_0}dY$ with respect to I. After rearranging and canceling terms, we obtain

$$\int_{Y_{min}}^{Y_{max}} [U_P''f(Y, \theta^*) - \lambda U_A''g(Y, \theta)](\frac{\partial r_P}{\partial p_0})^2 dp_0 dY = A_\gamma d\gamma + A_{Y_0} dY_0 + A_\lambda d\lambda + A_t dt + A_\delta d\delta.$$

From this equation, we obtain the following comparative results:

- only the price slide changes

$$\frac{dp_0^*}{d\gamma} = -\frac{\int_\Omega [U_P''f(Y, \theta^*) - \lambda U_A''g(Y, \theta)]\frac{\partial r_P}{\partial \gamma}\frac{\partial r_P}{\partial p_0}dY}{\int_\Omega [U_P''f(Y, \theta^*) - \lambda U_A''g(Y, \theta)](\frac{\partial r_P}{\partial p_0})^2 dY}$$

Note that the second-order condition for a maximum requires that the denominator be negative. Here, this means that $U_P''f(Y, \theta^*) - \lambda U_A''g(Y, \theta) < 0$. Given this condition, the numerator is positive. Thus, $\frac{dp_0^*}{d\gamma} > 0$.

- only Y_0 changes

$$\frac{dp_0^*}{dY_0} = -\frac{\int_\Omega [U_P'' f(Y, \theta^*) - \lambda U_A'' g(Y, \theta)] \frac{\partial r_P}{\partial Y_0} \frac{\partial r_P}{\partial p_0} dY}{\int_\Omega [U_P'' f(Y, \theta^*) - \lambda U_A'' g(Y, \theta)] (\frac{\partial r_P}{\partial p_0})^2 dY}$$

Both the numerator and the denominator are negative. Thus, $\frac{dp_0^*}{dY_0} < 0.$

- only δ changes

$$\frac{dp_0^*}{d\delta} = -\frac{\int_\Omega [U_P'' f(Y, \theta^*) - \lambda U_A'' g(Y, \theta)] \frac{\partial r_P}{\partial \delta} \frac{\partial r_P}{\partial p_0} dY}{\int_\Omega [U_P'' f(Y, \theta^*) - \lambda U_A'' g(Y, \theta)] (\frac{\partial r_P}{\partial p_0})^2 dY}.$$ Similar to Y_0, $\frac{dp_0^*}{d\delta} < 0$.

- only time to delivery changes

It is assumed that time to delivery, t, affects both the distribution of Y and the per unit cattle value. We have the following result:

$$\frac{dp_0^*}{dt} = -\frac{\int_\Omega [U_P'' \frac{\partial r_P}{\partial v(Y)} \frac{\partial v(Y)}{\partial t} f(Y, \theta^*) + U_P' \frac{\partial f(Y, \theta^*)}{\partial \sigma_P^2} \frac{\partial \sigma_P^2}{\partial t} + U_A' \frac{\partial g(Y, \theta)}{\partial \sigma_A^2} \frac{\partial \sigma_A^2}{\partial t}] \frac{\partial r_P}{\partial p_0} dY}{\int_\Omega [U_P'' f(Y, \theta^*) - \lambda U_A'' g(Y, \theta)] (\frac{\partial r_P}{\partial p_0})^2 dY}.$$

The key factors here are the signs of $\frac{\partial v(Y, Z)}{\partial t}$, $\frac{\partial f(Y, \theta^*)}{\partial \sigma_P^2}$, $\frac{\partial g(Y, \theta)}{\partial \sigma_A^2}$, and $\frac{\partial \sigma_P^2}{\partial t}$. We assume that $\frac{\partial \sigma_P^2}{\partial t} > 0$ and $\frac{\partial \sigma_A^2}{\partial t} > 0$. Also, $\frac{\partial v(Y, Z)}{\partial t} = 0$ at the time of contracting and at delivery. With these assumptions, the effect of time to delivery on the optimal contract price depends on the signs of $\frac{\partial f(Y, \theta^*)}{\partial \sigma_P^2}$ and $\frac{\partial g(Y, \theta)}{\partial \sigma_A^2}$ which can be negative or positive.

Appendix B: *Optimal Risk-Sharing and Incentives*

Consider the last two constraints of model (8). They are the first order condition of the agent maximization problem:

$$\int_{Y_L}^{Y_{max}} U_A' \frac{\partial r_A(Y,\, p_0,\, Y_0,\, \gamma)}{\partial Y_0} g(Y,\, \theta) dY = 0$$

$$\int_{Y_L}^{Y_{max}} U_A' \frac{\partial r_A(Y,\, p_0,\, Y_0,\, \gamma)}{\partial \gamma} g(Y,\, \theta) dY = 0$$

Totally differentiating, we have

$$\int_{\Omega_2} U_A''\left(\frac{\partial r_A}{\partial Y_0}\right)^2 dY_0 g(Y,\, \theta) dY + \int_{\Omega_2} [U_A'' \frac{\partial r_A}{\partial \gamma}\frac{\partial r_A}{\partial Y_0} + U_A' Y] d\gamma g(Y,\, \theta) d(Y) = C1_{p_0} dp_0 + C1_\delta d\delta$$

$$+ C1_t dt$$

$$\int_{\Omega_2} [U_A'' \frac{\partial r_A}{\partial Y_0}\frac{\partial r_A}{\partial \gamma} + U_A' Y] dY_0 g(Y,\, \theta) d(Y) + \int_{\Omega_2} U_A''\left(\frac{\partial r_A}{\partial \gamma}\right)^2 d\gamma g(Y,\, \theta) dY = C2_{p_0} dp_0 + C2_\delta d\delta$$

$+ \; C2_{t}dt.$

The second-order conditions for a maximum require that

$$\int_{\Omega_2} U_A''(\frac{\partial r_A}{\partial Y_0})^2 g(Y,\ \theta)dY < 0, \quad \int_{\Omega_2} U_A''(\frac{\partial r_A}{\partial \gamma})^2 g(Y,\ \theta)dY < 0, \text{ and}$$

$$D = \int_{\Omega_2} U_A''(\frac{\partial r_A}{\partial Y_0})^2 g(Y,\ \theta)dY * \int_{\Omega_2} U_A''(\frac{\partial r_A}{\partial \gamma})^2 g(Y,\ \theta)dY - [\int_{\Omega_2} [U_A''\frac{\partial r_A}{\partial Y_0}\frac{\partial r_A}{\partial \gamma} + U_A'Y]g(Y,\ \theta)dY]^2$$

- only δ changes.

Then,

$$\frac{d\gamma^*}{d\delta} = \frac{\begin{vmatrix} \int_{\Omega_2} U_A''(\frac{\partial r_A}{\partial Y_0})^2 g(Y,\ \theta)dY & C1_\delta \\ \int_{\Omega_2} [U_A''\frac{\partial r_A}{\partial Y_0}\frac{\partial r_A}{\partial \gamma} + U_A'Y]g(Y,\ \theta)dY & C2_\delta \end{vmatrix}}{D}$$

Since D > 0, the sign of $\frac{d\gamma^*}{d\delta}$ depends on that of the numerator. By rearranging terms, it can be shown that the sign of the numerator depends on that of

$$E1 = \frac{\int_{\Omega_2} U_A''\frac{\partial r_A}{\partial \delta}\frac{\partial r_A}{\partial \gamma}g(Y,\ \theta)dY}{\int_{\Omega_2} U_A''\frac{\partial r_A}{\partial \delta}\frac{\partial r_A}{\partial Y_0}g(Y,\ \theta)dY} - \frac{\int_{\Omega_2} [U_A''\frac{\partial r_A}{\partial Y_0}\frac{\partial r_A}{\partial \gamma} + U_A'Y]g(Y,\ \theta)dY}{\int_{\Omega_2} U_A''(\frac{\partial r_A}{\partial Y_0})^2 g(Y,\ \theta)dY},$$

Similarly, the sign of $\frac{dY_0^*}{d\delta}$ depends on of the sign of

$$E2 = \frac{\int_{\Omega_2} U_A'' \frac{\partial r_A}{\partial \delta}\frac{\partial r_A}{\partial \gamma} g(Y, \theta)dY}{\int_{\Omega_2} U_A'' \frac{\partial r_A}{\partial \delta}\frac{\partial r_A}{\partial Y_0} g(Y, \theta)dY} - \frac{\int_{\Omega_2} [U_A'' \frac{\partial r_A}{\partial Y_0}\frac{\partial r_A}{\partial \gamma} + U_A' Y] g(Y, \theta)dY}{\int_{\Omega_2} U_A'' (\frac{\partial r_A}{\partial \gamma})^2 g(Y, \theta)dY},$$

- only time to delivery changes

$$C1_t dt = -\int_{\Omega_2} U_A' \frac{\partial r_A}{\partial Y_0} \frac{\partial g(Y, \theta)}{\partial \sigma_A^2} \frac{\partial \sigma_A^2}{\partial t} dY dt \text{ and } C2_t dt = -\int_{\Omega_2} U_A' \frac{\partial r_A}{\partial \gamma} \frac{\partial g(Y, \theta)}{\partial \sigma_A^2} \frac{\partial \sigma_A^2}{\partial t} dY dt$$

So, $$\frac{d\gamma^*}{dt} = \frac{C2_t * \int_{\Omega_2} U_A'' (\frac{\partial r_A}{\partial Y_0})^2 g(Y, \theta)dY - C1_t * \int_{\Omega_2} [U_A'' \frac{\partial r_A}{\partial Y_0}\frac{\partial r_A}{\partial \gamma} + U_A' Y] g(Y, \theta)dY}{D}.$$

The sign of the numerator depends on the sign of

$$E3 = \frac{C2_t}{C1_t} - \frac{\int_{\Omega_2} [U_A'' \frac{\partial r_A}{\partial Y_0}\frac{\partial r_A}{\partial \gamma} + U_A' Y] g(Y, \theta)dY}{\int_{\Omega_2} U_A'' (\frac{\partial r_A}{\partial Y_0})^2 g(Y, \theta)dY}.$$

E3 can be positive or negative. Thus, the sign of $\frac{d\gamma^*}{dt}$ is ambiguous. Similarly, $\frac{dY_0^*}{dt}$ cannot be signed a priori.

Substituting for the expressions of Y_0 and γ into (7) and the individual rationality constraint, the principal's optimization problem becomes

$$\underset{p_0}{Max} \int_{\Omega} U_p[r_P(Y, Y_0^*(p_0), \gamma^*(p_0))] f(Y) dY$$

$$s.t. \quad \int_{\Omega} U_A[r_A(Y, Y_0^*(p_0), \gamma^*(p_0))] f(Y) dY \geq \bar{U}_A$$

Proceeding as in appendix A, the effects of time to delivery, allowable weight difference, and the principal's subjective variance of weight on the optimal contract price can be determined.

Appendix C

Assuming a negative exponential utility and a normal distribution function for Y, the principal's expected utility function can be written as:

$$EU(rP) = -\int_{Y_{min}}^{Y_0+\delta} e^{-\lambda_P[v(Y) - p_0]Y} * \frac{e^{\frac{-(Y-\bar{Y})^2}{2\sigma_P^2}}}{\sqrt{2\pi}\sigma_P} dY - \int_{Y_0+\delta}^{Y_{max}} e^{-\lambda_P[v(Y) - (p_0 - \gamma(Y - Y_0 - \delta))]Y} * \frac{e^{\frac{-(Y-\bar{Y})^2}{2\sigma_P^2}}}{\sqrt{2\pi}\sigma_P} dY$$

Let $Z = \frac{Y - \bar{Y}}{\sigma_P}$. Then, the expected utility of the principal can be rewritten as follows:

$$EU(rP) = -\frac{1}{\sqrt{2\pi}}[\int_a^b e^{-\lambda_P(v(Y) - p_0)(\sigma_P Z + \bar{Y}) - .5Z^2} dZ + \int_b^c e^{-\lambda_P[v(Y) - (p_0 - \gamma(\sigma_P Z + \bar{Y} - Y_0 - \delta))](\sigma_P Z + \bar{Y}) - .5Z^2} dZ],$$

where $a = \frac{Y_{min} - \bar{Y}}{\sigma_P}$, $b = \frac{Y_0 + \delta - \bar{Y}}{\sigma_P}$, *and* $c = \frac{Y_{max} - \bar{Y}}{\sigma_P}$. Each of the integrals in the square brackets can be evaluated by using Gauss Legendre quadrature formulas. To do so, we use the following change of variable $Z = \frac{x(d_1 - d_0) + d_1 + d_0}{2}$ (Gerald and Wheatley, p. 344). Then, using the fact that $\int_{d_0}^{d_1} f(Z)dZ = \frac{d_1 - d_0}{2}\int_{-1}^{1} f(\frac{x(d_1 - d_0) + d_1 + d_0}{2})dx$, the expected utility of the principal can be expressed as:

$$EU(rP) = -\frac{1}{\sqrt{2\pi}}[\frac{b - a}{2}\int_{-1}^{1} e^{-\lambda_P(v(Y) - p_0)(\sigma_P\frac{x(b - a) + b + a}{2} + \bar{Y}) - \frac{(x(b - a) + b + a)^2}{8}} dx$$

$$+ \frac{c - b}{2}\int_{-1}^{1} e^{-\lambda_P[v(Y) - (p_0 - \gamma(\sigma_P\frac{x(c - b) + c + b}{2} + \bar{Y} - Y_0 - \delta))](\sigma_P\frac{x(c - b) + c + b}{2} + \bar{Y}) - \frac{(x(c - b) + c + b)^2}{8}} dx].$$

With the Gauss Legendre quadrature approach, $\int_{-1}^{1} f(x)dx = \sum_{i=1}^{n} w_i f(x_i)$, where w_i and x_i are Gauss-Legendre quadrature weights and points, respectively. Thus,

$$EU(rP) = -\frac{1}{\sqrt{2\pi}}\Big[\frac{b-a}{2}\sum_{i=1}^{n} w_i e^{-\lambda_P(v(Y) - p_0)(\sigma_P \frac{x_i(b-a)+b+a}{2} + \bar{Y}) - \frac{(x_i(b-a)+b+a)^2}{8}}$$

$$+ \frac{c-b}{2}\sum_{i=1}^{n} w_i e^{-\lambda_P[v(Y) - (p_0 - \gamma(\sigma_P \frac{x_i(c-b)+c+b}{2} + \bar{Y} - Y_0 - \delta))](\sigma_P \frac{x_i(c-b)+c+b}{2} + \bar{Y}) - \frac{(x_i(c-b)+c+b)^2}{8}}\Big].$$

Proceeding the same way, the expected utility of the agent can be approximated as:

$$EU(rA) = -\frac{1}{\sqrt{2\pi}}\Big[\frac{b-a}{2}\sum_{i=1}^{n} w_i e^{-\lambda_A(p_0)(\sigma_A \frac{x_i(b-a)+b+a}{2} + \bar{Y}) - \frac{(x_i(b-a)+b+a)^2}{8}}$$

$$+ \frac{c-b}{2}\sum_{i=1}^{n} w_i e^{-\lambda_A(p_0 - \gamma(\sigma_A \frac{x_i(c-b)+c+b}{2} + \bar{Y} - Y_0 - \delta))(\sigma_A \frac{x_i(c-b)+c+b}{2} + \bar{Y}) - \frac{(x_i(c-b)+c+b)^2}{8}}\Big].$$

The last two expressions of EU(rP) and EU(rA) are the ones used in the mathematical programming examples.

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Paper III

WHAT SHOULD BE BELIEVED ABOUT GENERIC MEAT ADVERTISING?

WHAT SHOULD BE BELIEVED ABOUT GENERIC MEAT ADVERTISING?

ABSTRACT

United States producer organizations spend large amounts of money on generic advertising of both beef and pork and other promotion programs designed to stimulate consumers' demand for meat. Producers need to know if the money allocated to generic advertising and these promotion programs is effective in increasing the demand for meat. Past research has disagreed about the effectiveness of generic advertising. Models of Ward and Lambert and Brester and Schroeder are reestimated and subjected to misspecification testing. The conflicting findings about generic advertising effectiveness are shown to be primarily due to the data transformation used by Ward and Lambert. The results of a correctly specified Rotterdam model (similar to Brester and Shroeder's model), show that generic advertising does not play an important role in explaining meat consumption.

Key Words: beef, confirmation, demand, generic and branded advertising, misspecification testing, pork, Rotterdam model.

WHAT SHOULD BE BELIEVED ABOUT GENERIC MEAT ADVERTISING?

United States producer organizations spent about 190 million dollars on beef checkoff programs over the 1987-1993 period. Expenditures on generic beef and pork advertising exceeded 200 and 70 million dollars over the 1970-1993 period, respectively. These advertising programs are designed to stimulate consumers' demand for beef and pork. Producers need to know if the money allocated to advertising is effective in increasing the demand for meat. Past research disagreed about the effectiveness of generic advertising. While some studies report that generic advertising effectively increases meat demand, other studies find that generic advertising has no substantial effect on meat demand. For example, Brester and Schroeder and Kinnucan et al. found that generic beef and pork advertising has little effect on demand. Ward and Ward and Lambert, however, found that generic advertising has substantially increased beef demand. The question that arises from these contradictory findings is what should be believed about the effectiveness of generic meat advertising? Industry groups apparently believe that generic advertising is a wise investment since they allocate enormous amounts of money to it. If advertising is not effective then the money should be spent elsewhere or returned to producers.

Generic advertising effectiveness is assessed by estimating advertising elasticities. These elasticities are used to determined if advertising has a substantial effect on demand or not. The econometric models used to estimate the advertising response equations differ from one study to another. For example, Brester and Schroeder, Kinnucan et al., and Ward and Lambert all used different functional forms. Different functional forms may lead to different conclusions about the effectiveness of generic advertising (see e.g., Green et al.). Other factors that may lead to different inferences about the effectiveness of generic advertising are the use of different data and the variables included in the demand model.

Of the studies evaluating the effectiveness of U.S. generic meat advertising only Kinnucan and Venkateswaran included misspecification testing. Reliable elasticity estimates can only be obtained if the models used are correctly specified (McGuirk et al., 1993; 1995). McGuirk et al. (1993; 1995) misspecification test procedures can be used to test if all of the underlying assumptions of the models hold. The test procedures help identify possible problems with parameter stability, omitted relevant variables, and functional form, for example. Importantly, these misspecification tests can be used to guide model respecification.

This paper aims to determine why current studies on the effectiveness of U.S. generic meat advertising has reached conflicting conclusions. Demand models of Brester and Schroeder and Ward and Lambert that have led to different conclusions about the effectiveness of U.S. generic meat advertising are reestimated and tested for misspecification. Brester and Schroeder used generic advertising expenditures while Ward and Lambert used beef checkoff expenditures data. In this paper, each model is estimated using both data. Specific problems related to the modeling approach used by Brester and Schroeder and Ward and Lambert are discussed. Correctly specified models are developed and used to reassess the effectiveness of generic meat advertising. Implications for future research on evaluating the effectiveness of U.S. generic meat advertising are discussed.

Background on Incorporating Advertising in Demand Models and Related Literature

Advertising in Single-Equation Models

Generic advertising of a particular good is intended to enhance consumers' demand for that good. Thus, generic advertising has been included in single-demand models as a demand shifter. In general, advertising is included in these models using current and/or lagged advertising expenditures as explanatory variables. The inclusion of lagged advertising expenditures accounts for the advertising carry over effects . Distributed lag models or the lag of the dependent variable have also been used to account for advertising carry-over effects (see, e.g., Capps and Smith; Kinnucan and Venkateswaran).

Single-equation models are not consistent with consumer demand theory. With the exception of homogeneity, all of the restrictions implied by demand theory cannot be incorporated into these models. Demand systems, however, allow incorporating these restrictions for consistency with theory.

Advertising in Demand Systems

The most common demand systems used in applied work are the Almost Ideal Demand System (AIDS) and the Rotterdam model. Contrary to the case of single-equation models, advertising can be incorporated into these demand systems in a way that is consistent with consumer demand theory (Brown and Lee; Selvanathan). Piggot et al. used the AIDS model to determine the effects of advertising on Australian meat demand. The Rotterdam model has been mostly used in the case of U.S. generic meat demand (e.g., Kinnucan et al.; Brester and

Schroeder).

Three major approaches for incorporating advertising into the Rotterdam model are reviewed here. The first approach is to consider advertising as a demand shifter. In this case, the Rotterdam model can be formulated as (Selvanathan; Brown and Lee):

$$(1) \quad w_i d\ln q_i = \alpha_i d\ln Q + \sum_j \beta_{ij} d\ln p_j + \sum_j \gamma_{ij} d\ln A_j + e_i,$$

where w_i is the budget share of the i^{th} good, q_i is per capita consumption of good I, p_j is the nominal price of good j, A_j is real advertising expenditures on good j, $d\ln Q = \sum_i w_i \, d\ln q_i$ is the DIVISIA volume index, and e_i is the error term. Note that current and lagged advertising expenditures or a "goodwill" variable can be used in lieu of A_j.

The second and third approach to incorporating advertising in the Rotterdam model use scaling and translating techniques (Brown and Lee). In the case of scaling, advertising is viewed as affecting consumers' perceptions of the quality of the good being advertised (Brown and Lee). Scaling then consists of adjusting the price of the good to account for the effects of advertising on consumers' perceptions of quality (Brester and Schroeder). The Rotterdam model with scaling effects is (Brown and Lee):

$$(2) \quad w_i d\ln q_i = \alpha_i (d\ln Q + \sum_j w_j \delta_j d\ln A_j) + \sum_j \beta_{ij} (d\ln p_j - \delta_j d\ln A_j) - w_i \delta_i d\ln A_i + e_i,$$

where all of the variables are defined as before.

In the translating approach, advertising is considered as affecting consumers' perceptions of basic needs (Brown and Lee). In this case, advertising has a income-like effects on demand. Advertising is therefore incorporated in the demand system by augmenting the income variable with a "need or subsistence parameter" (Brown and Lee, p. 424). The Rotterdam model with translating is formulated as (Brown and Lee):

$$(3) \quad w_i d\ln q_i = \alpha_i (d\ln Q - \sum_j \delta_j d\ln A_j) + \sum_j \beta_{ij} d\ln p_j + \delta_i d\ln A_i + e_i,$$

where all of the variables are defined as previously.

Brown and Lee showed that the scaling and translating models are restricted versions of the model specified in (1). They proposed a procedure for testing the scaling and translating models against the unrestricted model (equation 1). The test procedure only requires estimating the unrestricted model. The parameter estimates of this model and the budget shares are used to calculate the test statistics (see Brown and Lee).

Kinnucan et al. used the unrestricted model in (1) to determine the effectiveness of generic advertising on U.S. meat demand. The basic model in (1) was expanded to include a health information index and seasonal dummies as explanatory variables. They found that income, prices, and health information significantly affect meat demand, but generic advertising of beef and pork does not. Brester and Schroeder used the scaling model and found similar conclusions about the effectiveness of generic advertising. Brester and Schroeder's model is discussed in detail in the next section.

The Models

To achieve our objective, the studies conducted by Brester and Schroeder and by Ward and Lambert are considered. The data used by Brester and Schroeder were requested and obtained from Brester. The beef checkoff expenditures data used in Ward and Lambert were obtained from Lambert. Ward declined to provide any additional data. Contrary to Brester and Schroeder, Ward and Lambert used a single-equation model. As mentioned earlier, these two studies reached conflicting conclusions about the effectiveness of generic beef advertising.

Ward and Lambert Study

Ward and Lambert estimated three models to determine the economic impact of U.S. beef checkoff efforts on demand. The first model was at the liveweight level and the second and third were at the boxed beef and retail market levels, respectively. The retail market model is the one considered here. The model estimated by Ward and Lambert is:

$$(4) \quad \ln P_{bt} = \alpha_0 + \alpha_1 \ln Q_{bt} + \alpha_2 \ln Q_{kt} + \alpha_3 \ln Q_{pt} + \alpha_4 \ln I_t + \alpha_5 T_{1t} + \alpha_6 T_{2t} + \alpha_7 S_{1t} + \alpha_8 S$$

$$+ \alpha_9 S_{3t} + \alpha_{10} FR_t + \delta_1 \ln[1 + \exp(-\beta/E_t)] + \delta_2 \ln[1 + \exp(-\beta/E_{t-1})] + \epsilon_t$$

where P_{bt} is the real price of beef at the retail level, Q_{bt}, Q_{kt}, and Q_{pt} are the per capita disappearances of beef, pork, and poultry, respectively, I_t is real per capita income, the S_{it} are quarterly dummy variables, E_t and E_{t-1} are the current and lagged beef checkoff expenditures (used as proxies for current and lagged generic beef advertising expenditures), T_{1t} and T_{2t} are time trends, FR_t is the feeder steer ratio, and ϵ_t is the error term. The variable T_1 increases one unit each quarter, starting with $T_1 = 58$ in 1979:2. T_2 equals one before 1990:1 and increases in units of one thereafter.

Application of Ward and Lambert's Model to Pork Data

The effectiveness of generic pork advertising was determined in Brester and Schroeder's study but not in Ward and Lambert's. For comparison, a pork response function is estimated here using Ward and Lambert's model. The demand equation used is:

$$(5)\quad lnP_{kt} = \alpha_0 + \alpha_1 lnQ_{bt} + \alpha_2 lnQ_{kt} + \alpha_3 lnQ_{pt} + \alpha_4 lnI_t + \alpha_5 T_1 + \alpha_6 S_1 + \alpha_7 S_2 + \alpha_8 S_3$$

$$+ \delta_1 \ln[1 + \exp(-\beta/A_t)] + \delta_2 \ln[1 + \exp(-\beta/A_{t-1})] + \epsilon_t,$$

where P_{kt} is the real price of pork, A_t and A_{t-1} are current and one-period lagged per capita generic pork expenditures, and all other variables are defined as before. Here, T_1 starts at 1 in 1970:1 and increases in units of one until 1993:4. The time trend T_2 is not used. It was used in (4) as an additional variable to account for intercept parameter instability (see Ward and Lambert, p. 458).

Brester and Schroeder Study

The purpose of Brester and Schroeder's study was to determine the effects of both branded and generic advertising on consumer demand for beef, pork, and poultry. Using a Rotterdam model with scaling, all of the advertising expenditures were incorporated in the form of a stock of investment. The stock variable was obtained using a procedure proposed by Cox. This procedure allows accounting for advertising carry-over effects without imposing too much restriction on the shape of the advertising response function (see Cox).

The Rotterdam model with scaling is nonlinear in the parameters. The specification of the advertising stock variable makes this model even more nonlinear. Although Cox explains how end point restrictions can be used to make the model easier to estimate, it is still very intractable in the context of system misspecification testing. Brester and Schroeder indicated that they estimated a linear Rotterdam model without scaling effects. The price elasticities were similar to those obtained with the nonlinear model, suggesting that the scaling effects are negligible.

To simplify matters and given the linear model yields similar results with the nonlinear model, the unrestricted linear Rotterdam model is used here to conduct the misspecification tests. The specific model is formulated as:

$$(6) \quad w_i d\ln q_i = \alpha_i d\ln Q + \sum_j \beta_{ij} d\ln p_j + \sum_j \gamma_{ij} d\ln A_j + \sum_j \sum_{m=1}^{3} \delta_{ijm} d \ln A_{jm} + \sum_{k=1}^{3} \phi_{ik} D_k + e_i,$$

where A_{jm} is the m-period lagged advertising expenditures, the D_k's are quarterly dummy variables, and all other variables are defined as previously. Note that, here, the contemporaneous advertising variables include both brand and generic advertising. The lagged advertising variables, however, only include generic advertising expenditures. This is done to be consistent with the fact that no lagged branded advertising variable was used in Brester and Schroeder's model (see Brester and Schroeder).

As in Brester and Schroeder, model (6) has four equations. The fourth equation represents other consumption goods. It is used to make the demand system weakly integrable (see Brester and Schroeder). Being linear, model (6) is relevant for applying McGuirk et al. (1996) system misspecification test procedures.

Procedures

This section discusses the general approach used to determine if the conflicting conclusions about the effectiveness of generic meat advertising are due to different data, different variables, or different functional forms. In discussing each case, specific econometric and/or modeling issues that need to be addressed before a definitive conclusion can be drawn are also discussed.

Different Data

Ward and Lambert used beef checkoff expenditures as a proxy for generic advertising expenditures. Both beef checkoff and generic advertising expenditures are available to us. These expenditures are shown in figures 1 and 2 for the 1970:1-1993:4 (sample size used by Brester and Schroeder) and 1979:2-1991:2 periods (sample size used by Ward and Lambert). These figures seem to indicate that the use of different data on advertising may not lead to conflicting conclusions about the effectiveness of generic beef advertising. However, we argue that given the two models used here (Ward and Lambert and the Rotterdam model), the presence of many zero observations in the checkoff expenditures data may lead to differences in results. To provide some empirical evidence, the two models are estimated using both beef checkoff and generic advertising expenditures. For each model, the checkoff effect is calculated and compared to that of generic advertising.

Consider Ward and Lambert's model. The transformed checkoff variable takes the value of zero when the checkoff expenditures are zero and a value greater than zero but less than one otherwise. Thus, the checkoff variable has a dummy variable-type of effect. This is not the case for the generic advertising expenditures variable as shown in figure 3. It is apparent from this graph that, with Ward and Lambert model, differences in advertising effects may be due to the way zero observations are treated rather than to data *per se*.

The problem of zero advertising expenditures also exists in the Rotterdam model since logarithms of the data are used for estimation. The problem is generally addressed by adding a small number to each observation in the advertising data set (see, e.g., Brester and Schroeder). As in Brester and Schroeder, here, 100 is added to all observations (zero and non zero advertising expenditures). The same number is added to the checkoff expenditures data for estimation of the Rotterdam model. Looking at the checkoff expenditures data, it appears that when the first differences are taken, one observation will be very large compared to the others. This is due to the fact that there many consecutive zeros in the data and the first non-zero observation is a very large number. Since the number added to the observations is the same, the first differences of the logarithms yield zeros for all observation where the original number was zero. This problem does not occur in the generic advertising data (see plot later). Thus, with the Rotterdam model too, the treatment of the data for the purpose of estimation may lead to substantial differences in results.

Functional Forms, Variables, and Advertising Effects

Ward and Lambert's model does not include generic pork advertising. Neither does it include branded advertising for pork, beef, and poultry. Generic and branded advertising may sometimes be related (Kinnucan et al). If this is the case, then there will be an upward bias in Ward and Lambert's estimates of the advertising effects, irrespective of what data are used.

Apart from the variables and irrespective of the data used, Ward and Lambert's model may yield high advertising effects due to the way advertising is incorporated into the model. To determine if this is the case, advertising effects must be compared across functional forms. However, since Ward and Lambert's model is price dependent, its advertising effects cannot be directly compared to the Rotterdam model. Brester and Schroeder used price flexibilities of the Rotterdam model to compare the two advertising effects. These price flexibilities were obtained as the inverse of the directly estimated price elasticities. Huang showed that inverting a matrix of elasticities (in the case of demand systems) or taking the reciprocal of an elasticity (in the case of single-demand models) leads to incorrect estimates of flexibilities. Huang recommended using directly estimated flexibilities or elasticities "in agricultural policy and program analysis" (p. 313). Here, to compare the advertising effects obtained from the Rotterdam and the Ward and Lambert's models, directly estimated elasticities are used. Single-equation models are estimated using Ward and Lambert's data transformation and beef and pork quantities as dependent variables. The effects of advertising on beef and pork demand calculated from these models are then compared to those obtained from the Rotterdam model to determine if different functional forms lead to different conclusions about the effectiveness of advertising.

Estimation, Confirmation, and Misspecification Testing

Ward and Lambert's model is estimated using beef checkoff and generic advertising expenditures over the 1979:2-1991:2 sample period. Following Ward and Lambert, the model is estimated using ordinary least squares holding the checkoff coefficient β fixed. The value of β used is the one for which the sum of squared errors are minimized. This procedure does not bias the parameter estimates, but it may bias the hypothesis tests. The parameter estimates of our beef checkoff model are compared with those of Ward and Lambert to see how closely we replicate their results. Note that only the checkoff expenditures used by Ward and Lambert are available to us. The feeder steer ratio is computed from 1990 revised cattle slaughter data available in the USDA agricultural marketing service weekly publication. The other data are from Brester and Schroeder's study. A confirmation study can be conducted by fitting the original model to original data or "to revised data for the same sample period or to data for a new sample period" (Tomek p. 7).

Although estimating Ward and Lambert's model using OLS leads to biased standard errors, the model is still subjected to misspecification testing. McGuirk et al.'s (1993) approach to misspecification testing in single linear regression models are used.

For the Rotterdam model, the following modeling approach is used. The linear Rotterdam model is considered with the "other consumption goods" equation included. This demand system is subjected to misspecification testing. If the model is misspecified, efforts are made to respecificy it. If it cannot be correctly respecified, an alternative linear Rotterdam model is considered. The misspecification testing process is repeated until a correctly specified model is found. The misspecification tests used here are those proposed by McGuirk et al. (1995) for system of linear equations. Note that these tests are different from the single-equation misspecification tests. These tests are well described in McGuirk et al. (1995). They are conducted using the SAS/IML software.

The correctly specified Rotterdam model is estimated using the PROC SYSLIN procedure in SAS/ETS. As in Brester and Schroeder, the price symmetry and homogeneity conditions are imposed. Since branded advertising for beef, pork, and poultry are included in the model, advertising homogeneity is imposed for these variables (see Kinnucan et al.). Advertising homogeneity is not imposed for the generic advertising variables since poultry advertising is branded advertising.

Results

Different Data

Ward and Lambert's Model. The parameter estimates of the beef model are reported in table 1 for each type of advertising data. For the checkoff expenditures, the parameter estimates of the quantity and income variables are similar to those of Ward and Lambert. The parameter estimates of the checkoff variable are different. These parameter estimates suggest an even larger effect of checkoff expenditures than was found by Ward and Lambert. This fragility in results is probably due to the fact that the feeder steer ratio used here may not be the same as the one used by Ward and Lambert.

The results in table 1 show that the maximum percentage impacts that beef advertising can have on prices is 5.1% with the checkoff data and 0.502% with the generic advertising data, suggesting that different data lead to different conclusions about advertising effectiveness. As discussed in the procedures section, this difference may simply be due to the way zero advertising expenditures are treated in this model (see also figure 3).

The misspecification test results are reported in table 2. Models 1 and 2 are Ward and Lambert's beef models for the checkoff and generic advertising data, respectively. These models are estimated using the 1979:2-1991:2 sample period. Models 3 and 4 are the same as 1 and 2 except that the 1970:1-1993:4 sample period is used. Model 5 is the Ward and Lambert's pork model. For this model, the 1970:1-1991:4 sample period is used.

The functional form of the beef model estimated using the checkoff expenditures data (Model 1) is misspecified. The Beef model estimated using the generic advertising expenditures data (Model 2) is not misspecified. For the 1970:1-1993:4 data, the beef models (Models 3 and 4) are all misspecified. The p-values indicate that the dynamic homoskedasticity and no autocorrelation assumptions are rejected at the 5% significance level for Model 3. The assumptions of functional form, dynamic homoskedasticity, parameter stability, and no autocorrelation do not hold for Model 4. For the pork model, the functional form and no autocorrelation assumptions do not hold.

Models 6 to 10 are the same models as above except that women labor force participation and the cholesterol information index are included (these variables are defined below in more details). Model 6 is correctly specified. For Models 8, 9, and 10, the individual and joint tests indicate that only the assumption of no autocorrelation does not hold.[6] Table 3 reports the parameter estimates of the respecified Ward and Lambert's beef model when the checkoff expenditures data and the 1979:2-1991:2 sample period are used.

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[6]Model 7 is of no interest here. It is used only for illustration purposes. Recall that Model 2 was not misspecified.

The Rotterdam Model. The misspecification test results of the Rotterdam model including the other-good equation are reported in tables 4 and 5. All figures reported are p-values. Model 1 includes only the variables used by Brester and Schroeder. The full-system joint test results show that both the conditional mean and variance of this model are misspecified. This misspecification is confirmed by the individual equation-by-equation system tests. There are problems with all of the underlying assumptions of the model, except dynamic heteroskedasticity and autocorrelation.

Model 1 is respecified by including women labor force participation and cholesterol information index as additional explanatory variables (Model 2). It has been argued that the increased participation of women in the labor force may have caused structural change in meat demand (McGuirk et al., 1995). Health information has also been found to be a significant factor in explaining structural change in meat demand in the United States (McGuirk et al., 1995). The women labor force participation variable used here is different from the one used by McGuirk et al. (1995). Here, this variable is the ratio of civilian women in the labor force who are married or who maintain a family to the total civil labor force. These data were obtained from the World Wide Web site of the *Bureau of Labor Statistic.* Contrary to the ratio used in previous studies, the one used here is not highly correlated with a linear time trend (the correlation here is 0.57 compared to the 0.98 of past studies). The cholesterol information index used here is the same as the one used by Kinnucan et al. These data were requested and obtained from Kinnucan.

The test results show that Model 2 is also misspecified. The problems are similar to the one of Model 1. An alternative linear Rotterdam model is considered. This model simply does not include the "other goods" equation. A similar model specification was used by Kinnucan et al. Kinnucan et al., however, do not include branded advertising in their model although they recognize that this may lead to an upward bias in the parameter estimates.

The misspecification tests are carried out on the alternative Rotterdam model as above. Table 6 and 7 report the test results. Model 3 does not include women labor force participation and the cholesterol information index variables. The p-values of the full-system joint tests indicate that the conditional mean and variance are misspecified. The equation-by-equation system tests indicate that the problems may be due to dynamic heteroskedasticity, parameter stability, and/or functional form. Model 4 includes women labor force participation and the cholesterol information index. The p-values of the tests show that all of the assumption hold, except maybe the assumption of parameter stability for the mean and variance equations. The equation-by-equation tests, however, indicate that the parameters of the mean equation are stable. Only the variance-covariance may not be stable. McGuirk et al. (1995) indicated that the full-system test can point to a misspecification problem simply because the variance-covariance is often inflated with those tests, or because the "cross-equation residual covariances may not be stable" (p. 15). In the present case, an alternative explanation of unstable variance-covariances is that the advertising parameters may vary randomly over time.

Model 5 is estimated with both checkoff and generic advertising expenditures. The results are reported in tables 8 and 9 for the 1970:1-1993:4 and 1979:2-1991:2 sample periods, respectively. In each case, most of the parameter estimates of the economic variables are significantly different from zero. The parameter estimate of the women labor force participation and cholesterol information index variables are also generally significant.

The advertising elasticities are reported in table 10. The advertising elasticities reported here are lower than those obtained by Brester and Schroeder. They are generally similar to those calculated by Kinnucan et al.

The advertising elasticities differ depending on the measure of advertising expenditures. To see why this might be the case, the first differences of the logarithm of these two data series are plotted in figure 4. This figure shows that there is an outlying observation in the checkoff expenditures as discussed earlier. This might cause substantial differences in the estimation results.

Different Functional Forms

The parameter estimates of the quantity-dependent single-demand models are reported in table 11. The beef advertising elasticities are 0.002 and 0.0001 for the checkoff and generic advertising data, respectively. The pork advertising elasticity is 0.0001. For the Rotterdam model, the beef checkoff and generic advertising elasticities are 0.000272 and 0.000011. The pork advertising elasticity is negative with the checkoff data and zero with the generic advertising data. These results indicate that the effects of advertising obtained from the two functional forms are different.

To determine if advertising is a good investment, marginal returns to advertising can be calculated as $p\frac{\partial q}{\partial A}$, where p, q, and A are the price, quantity, and advertising expenditures of the good of interest (Piggot et al.). Marginal returns greater than one indicate advertising is a good investment (Piggot et al.). Here, $p\frac{\partial q}{\partial A}$ is approximated as $p\frac{\Delta q}{\Delta A}$. The marginal returns are calculated at the mean of the data. For beef, the marginal returns to generic advertising are $2.29 and $0.73 with the 1970-1993 and 1979:2-1991:2 data, respectively. Similarly, the marginal returns to pork advertising are $33.74 and nearly zero dollars. These results indicate that advertising may have been profitable over the 1970-1993 period.

Different Sample Periods

The advertising elasticities of the Rotterdam model indicate that the effects of generic advertising on meat demand are sensitive to the sample period used. The parameter estimates of Ward and Lambert's price dependent model are reported in table 12 for the 1970:1-1993:4 sample period. For beef, the maximum effects that advertising can have on prices are 0.078% and -0.011% with the checkoff and generic advertising data, respectively. The results for the 1979:2-1991:2 sample period were 5.1% and 0.502%. These results also show that different sample periods lead to different generic meat advertising effects. Similar conclusions were reached by Kinnucan et al.

Summary and Implications

United States producer organizations spent about 190 million dollars on beef checkoff programs over the 1987-1993 period. Expenditures on generic beef and pork advertising exceeded 200 and 70 million dollars over the 1970-1993 period, respectively. The advertising programs are designed to stimulate consumers' demand for beef and pork. Producers need to know if the money allocated to generic advertising is a good investment. Past research has disagreed about the effectiveness of generic advertising. While some studies report that generic advertising effectively increases meat demand, other studies find that generic advertising has no substantial effect on meat demand. If advertising is not effective then the money should be spent elsewhere.

Past studies have used different functional forms, different data on advertising, different observation periods, and different variables. Two models (a single-equation model like that used by Ward and Lambert and a Rotterdam model like that used by Brester and Schroeder and Kinnucan et al.) are used to determine why past studies have reached different conclusions about the effectiveness of generic advertising. The primary factor causing the differing conclusions was Ward and Lambert's highly unconventional transformation of the advertising variable. Every model estimated without this transformation yielded low advertising elasticities. When more recent data were used with the Ward and Lambert's specification, the estimated effects of beef advertising turned negative. Furthermore, Ward and Lambert's transformation yielded very different conclusions with Brester and Schroeder's data. With Ward and Lambert's data, their variable was essentially a dummy variable. Slight differences in Brester and Schroeder's data caused the conclusions to be totally changed. Given the fragility of Ward and Lambert's results, their model does not seem appropriate. Ward and Lambert's and Brester and Schroeder's models were both misspecified. They were both made correctly specified by adding additional variables, however the correctly specified models did not yield materially different conclusions.

The generic advertising elasticities estimated from the Rotterdam model are generally very small. Similar results were obtained by Brester and Schroeder and Kinnucan et al. These advertising elasticity estimates suggest that advertising does not play a major role in meat consumption behavior (Kinnucan et al.; Brester and Schroeder). Results show that, besides prices and meat expenditures, health information and the participation of women in the labor force play a very important role in meat consumption behavior. The results with the Rotterdam model are not fragile.

The findings of this paper have important implications. Since there is now some evidence that generic meat advertising does not have a substantial effect on demand, industry groups should tightly monitor and perhaps reduce the money they allocate to generic advertising. Time series models like those considered are always subject to the criticism that advertising may be positively correlated with some omitted factor which has reduced meat demand. One way around such a criticism is to use designed experiments. The one such study available by Jensen and Schroeter used split-cable data and also found little effect of advertising on beef demand. Therefore, the evidence suggests that the millions spent on generic advertising of beef and pork have done little to increase demand.

Table 1. Parameter Estimates of the Ward Model For Beef, 1979:2-1991:2 Data

	Checkoff Expenditures		Generic Adv. Expenditures	
Variable	Coefficient	t-Ratio	Coefficient	t-Ratio
Constant	8.0206*	3.1250	7.6785*	2.7110
$\ln Q_k$	-0.0708	-0.8005	0.0181	0.2063
$\ln Q_b$	-0.8066*	-5.0250	-0.9370*	-5.3770
$\ln Q_c$	-0.2558	-1.3320	-0.0622	-0.3074
lnI	0.2874	0.6076	0.2124	0.3981
T1	-0.0049	-0.4736	-0.0023	-0.2013
T2	0.0187*	3.8070	0.0137*	2.6450
Current Advertising	0.0210	0.5567	-0.0335	-1.1570
Lag Advertising	0.0718	1.7770	0.0072	0.2409
S1	-0.0509*	-1.9250	-0.0277	-0.9833
S2	-0.0193	-1.0790	-0.0012	-0.0608
S3	0.0063	0.3575	0.0351*	2.0700
FR	0.0119	1.7580	0.0188*	2.7300
R-Square	0.97		0.96	
R-Square Adjusted	0.96		0.95	

Note: Single and double asterisks denote significant at the 5% and 10%, respectively.

Table 2. P-Values of the Misspecification Tests, Ward and Lambert's Models

		Model				
Assumptions	Test	1	2	3	4	5
Individual Tests						
Normality	Skewness	0.300	0.995	0.634	0.593	0.845
	Kurtosis	0.703	0.415	0.639	0.554	0.749
Functional Form	RESET 2	0.050	0.084	0.001	0.001	0.005
Static Homoskedasticity	RESET 2	0.953	0.471	0.033	0.044	0.000
Dynamic Homoskedasticity	ARCH 1	0.459	0.190	0.003	0.002	0.000
Parameter Stability		-	-	0.000	0.000	0.009
Independence		0.191	0.193	0.000	0.000	0.000
Joint Tests						
Conditional Mean	Overall F-test	0.088	0.152	0.000	0.000	0.000
Parameter Stability	Parameter Shifts	-	-	0.182	0.196	0.981
Functional Form	RESET 2	0.077	0.150	0.118	0.056	0.023
Independence		0.333	0.306	0.000	0.000	0.000
Conditional Variance	Overall F-test	0.108	0.258	0.031	0.042	0.441
Parameter Stability	Variance Shifts	-	-	0.094	0.211	0.127
Static Homoskedasticity	RESET 2	0.144	0.683	0.291	0.749	0.594
Dynamic Homoskedasticity	ARCH 1	0.102	0.109	0.042	0.024	0.603

Note: Models 1 and 2 are Ward and Lambert's beef models for the checkoff and generic advertising data, respectively, 1979:2-1991:2 sample period. Models 3 and 4 are the same as 1 and 2 except that the 1970:1-1993:4 sample period is used. Model 5 is the Ward and Lambert's pork model. For this model, the 1970:1-1991:4 sample size is used.

The parameter stability test is conducted using a dummy variable. The Chow and CUSUMSQ tests were not reliable when the beef model and the 1979:2-1991:2 sample were used. Also in this case, the parameter stability test cannot be conducted using a time trend or a dummy variable because of the use of T_1 and T_2 in the model.

Table 2. Continued

Assumptions	Test	Model 6	7	8	9	10
Individual Tests						
Normality	Skewness	0.199	0.887	0.968	0.819	0.601
	Kurtosis	0.818	0.436	0.910	0.503	0.251
Functional Form	RESET 2	0.121	0.268	0.495	0.408	0.405
Static Homoskedasticity	RESET 2	0.336	0.106	0.000	0.001	0.000
Dynamic Homoskedasticity	ARCH 1	0.822	0.091	0.011	0.006	0.000
Parameter Stability		-	-	0.102	0.170	0.475
Independence		0.757	0.617	0.000	0.000	0.000
Joint Tests						
Conditional Mean	Overall F-test	0.269	0.460	0.000	0.000	0.000
Parameter Stability	Parameter Shifts	-	-	0.095	0.086	0.371
Functional Form	RESET 2	0.114	0.257	0.274	0.135	0.023
Independence		0.869	0.794	0.000	0.000	0.000
Conditional Variance	Overall F-test	0.369	0.137	0.210	0.326	0.292
Parameter Stability	Variance Shifts	-	-	0.390	0.827	0.367
Static Homoskedasticity	RESET 2	0.299	0.402	0.213	0.459	0.222
Dynamic Homoskedasticity	ARCH 1	0.236	0.051	0.201	0.097	0.314

Note: Models 6 and 7 are Ward and Lambert's beef models for the checkoff and generic advertising data, respectively, 1979:2-1991:2 sample period. Models 8 and 9 are the same as 1 and 2 except that the 1970:1-1993:4 sample period is used. Model 10 is the Ward and Lambert's pork model. For this model, the 1970:1-1991:4 sample size is used.

The parameter stability test is conducted using a dummy variable. The Chow and CUSUMSQ tests were not reliable when the beef model and the 1979:2-1991:2 sample were used. Also in this case, the parameter stability test cannot be conducted using a time trend or a dummy variable because of the use of T_1 and T_2 in the model.

Table 3. Parameter Estimates of the Correctly Specified Ward and Lambert's Model for Beef, Checkoff Expenditures Data, 1972:2-1991:2

Variable	Coefficient	t-Ratio
Constant	16.863*	4.741
$\ln Q_k$	-0.095	-1.166
$\ln Q_b$	-0.755*	-5.253
$\ln Q_c$	-0.053	-0.285
lnI	0.197	0.422
T1	0.009	0.639
T2	0.008**	1.577
Advertising	0.055	1.509
Lag Advertising	0.048	1.319
S1	-0.016	-0.610
S2	0.003	0.145
S3	0.015	0.904
FR	0.004	0.537
lnWLFP	-2.307*	-2.876
lnCHOL	-0.384	-1.255
R-Square	0.98	
R-Square Adjusted	0.97	

Note: Single and double asterisks denote significant at the 5% and 10%, respectively.

Table 4. **P-values of the Misspecification Tests for the Beef, Pork, Poultry, and Other Goods Equations, Full System Tests, 1970:1-1993:4**

Item	Model 1	Model2
Individual Tests		
Normality		
Skewness	0.0008	0.0007
Kurtosis	0.0000	0.0000
Functional Form		
RESET2	0.0000	0.0000
Heteroskedasticity		
Static: RESET	0.0006	0.0001
Dynamic	0.9455	0.9914
Autocorrelation	0.3256	0.4103
Parameter Stability		
Variance	0.0000	0.0000
Mean	0.0240	0.0054
Joint Tests		
Overall Mean Test	0.0035	0.0002
Parameter Stability	0.0000	0.0000
Functional Form	0.0000	0.0000
Autocorrelation	0.0000	0.0000
Overall Variance Test	0.1313	0.0408
Parameter Stability	0.3411	0.3237
Static Heteroskedasticity	0.0039	0.0001
Dynamic Heteroskedasticity	0.9996	0.9971

Table 5. P-values of the Misspecification Tests for the Beef, Pork, Poultry, and Other Goods Equations, Equation-by-Equation System Tests, 1970:1-1993:4

		Model 1				Model 2			
		Beef	Pork	Poultry	Other	Beef	Pork	Poultry	Other
Individual Tests									
Normality									
Skewness		0.0225	0.0048	0.1456	0.0072	0.0206	0.0029	0.0226	0.0110
Kurtosis		0.0311	0.0009	0.0562	0.0034	0.1511	0.0001	0.0038	0.0449
Functional Form									
RESET		0.0000	0.0005	0.0000	0.0000	0.0000	0.0279	0.0000	0.0407
Heteroskedasticity									
Static	Beef	0.0162	0.1867	0.6138	0.0430	0.0020	0.0004	0.3647	0.2857
RESET2	Pork		0.1056	0.1345	0.0288		0.2321	0.0022	0.2461
	Poultry			0.0000	0.0000			0.0000	0.0045
	Other				0.0000				0.0000
Dynamic	Beef	0.7311	0.9973	0.8515	0.0995	0.8891	0.9768	0.6274	0.7615
	Pork		0.9736	0.7256	0.0067		0.9334	0.4425	0.1207
	Poultry			0.1519	0.0007			0.5878	0.0628
	Other				0.0311				0.0760
Autocorrelation		0.6644	0.2320	0.5159	0.1913	0.6509	0.5226	0.4439	0.1650
Parameter Stability									
Variance		0.0230	0.9303	0.9660	0.5271	0.0380	0.9842	0.9937	0.3542
Mean		0.2101	0.4656	0.0054	0.9927	0.4057	0.4264	0.0013	0.9988
Joint Tests									
Overall Mean Test		0.0012	0.0193	0.0038	0.2498	0.0009	0.0805	0.0000	0.1794
Parameter Stability		0.5421	0.7093	0.8124	0.6735	0.9536	0.8381	0.7596	0.9465
Functional Form		0.0019	0.0236	0.0013	0.4930	0.0000	0.0251	0.0000	0.2063
Autocorrelation		0.7448	0.5498	0.6310	0.1931	0.4535	0.1392	0.2649	0.2177

Table 5. Continued

Overall Variance Test									
Beef	0.0044	0.0578	0.2233	0.0000		0.0003	0.0009	0.0210	0.0000
Pork		0.0592	0.0966	0.0053			0.0909	0.8029	0.0442
Poultry			0.0000	0.0000				0.0000	0.0442
Other				0.0000					0.5324
Parameter Stability									
Beef	0.1214	0.5222	0.3562	0.1792		0.3838	0.2782	0.5769	0.4359
Pork		0.3362	0.6551	0.5595			0.1332	0.8060	0.8925
Poultry			0.9217	0.4474				0.2363	0.2954
Other				0.9219					0.4680
Static Heteroskedasticity									
Beef	0.0042	0.0256	0.1249	0.0001		0.0004	0.0006	0.0116	0.0000
Pork		0.0157	0.2289	0.0904			0.0556	0.5804	0.1622
Poultry			0.0006	0.0015				0.0000	0.1170
Other				0.3547					0.2281
Dynamic Heteroskedasticity									
Beef	0.9743	0.5955	0.7902	0.0398		0.9744	0.2549	0.7745	0.0288
Pork		0.9869	0.3680	0.0840			0.8811	0.9421	0.4433
Poultry			0.8423	0.0059				0.7416	0.5769
Other				1.0000					0.9909

Table 6. P-values of the Misspecification Tests for the Beef, Pork, and Poultry Equations, Full System Tests, 1970:1-1993:4

Item	Model 3	Model 4
Individual Tests		
Normality		
Skewness	0.0000	0.1865
Kurtosis	0.0000	0.0000
Functional Form		
RESET2	0.0014	0.18461
Heteroskedasticity		
Static: RESET	0.1005	0.4325
Dynamic	0.0264	0.7538
Autocorrelation	0.0046	0.5965
Parameter Stability		
Variance	0.0000	0.0000
Mean	0.0006	0.0029
Joint Tests		
Overall Mean Test	0.0001	0.4195
Parameter Stability	0.1192	0.8050
Functional Form	0.0006	0.1492
Autocorrelation	0.0114	0.5152
Overall Variance Test	0.0000	0.0147
Parameter Stability	0.3491	0.3172
Static Heteroskedasticity	0.0291	0.1524
Dynamic Heteroskedasticity	0.0039	0.7537

Table 7. P-values of the Misspecification Tests for the Beef, Pork, and Poultry Equations, Equation-by-Equation System Tests, 1970:1-1993:4

		Model 3			Model 4		
		Beef	Pork	Poultry	Beff	Pork	Poultry
Individual Tests							
Normality							
Skewness		0.7194	0.0625	0.6692	0.1967	0.0762	0.1274
Kurtosis		0.3801	0.7873	0.6889	0.8070	0.2775	0.9172
Functional Form							
RESET2		0.0000	0.0004	0.0000	0.4284	0.0541	0.2284
Heteroskedasticity							
Static	Beef	0.8395	0.8104	0.6281	0.8729	0.5794	0.9054
RESET2	Pork		0.5659	0.6578		0.0381	0.7180
	Poultry			0.3385			0.8629
Dynamic	Beef	0.0532	0.3944	0.0367	0.1735	0.5000	0.2947
	Pork		0.6493	0.2459		0.7064	0.3824
	Poultry			0.0512			0.7685
Autocorrelation		0.4581	0.2260	0.1598	0.6788	0.8349	0.1121
Parameter Stability							
Variance		0.9097	0.2821	0.9985	0.9845	0.7771	0.8058
Mean		0.0163	0.0266	0.0128	0.1057	0.0042	0.5169
Joint Tests							
Overall Mean Test		0.0000	0.0192	0.0000	0.6462	0.5658	0.1609
Parameter Stability		0.9630	0.5466	0.7092	0.5909	0.3768	0.6586
Functional Form		0.0000	0.0228	0.0000	0.3171	0.2051	0.2686
Autocorrelation		0.4581	0.2260	0.1598	0.6442	0.5275	0.1373

Table 7. Continued

Overall Variance Test							
	Beef	0.0000	0.0000	0.0000	0.0000	0.0000	0.0282
	Pork		0.0017	0.0315		0.0000	0.5315
	Poultry			0.0000			0.0015
Parameter Stability							
	Beef	0.1214	0.2184	0.3022	0.3493	0.2122	0.8860
	Pork		0.2584	0.6615		0.4935	0.1720
	Poultry			0.4257			0.2012
Static Heteroskedasticity							
	Beef	0.2932	0.3389	0.2873	0.1098	0.0039	0.9393
	Pork		0.3485	0.4554		0.0002	0.8071
	Poultry			0.1639			0.1170
Dynamic Heteroskedasticity							
	Beef	0.0118	0.3100	0.0063	0.0953	0.6137	0.0734
	Pork		0.5333	0.2376		0.9626	0.4897
	Poultry			0.0052			0.2577

Table 8. Parameter Estimates of the Rotterdam Model for Beef, Pork, and Poultry, 1970:1-1993:4

Independent Variable	Checkoff Expenditures			Generic Advertising Expenditures		
	QBEEF	QPORK	QPOULTRY	QBEEF	QPORK	QPOULTRY
Prices:						
Beef	-0.188868*			-0.179816*		
	(-9.611)			(-9.580)		
Pork	0.195048*	-0.132642*		0.191956*	-0.137951*	
	(12.291)	(-8.408)		(12.902)	(-9.261)	
Poultry	-0.006180	-0.062406*	0.068586	-0.012140	-0.054005*	0.066145
	(-0.659)	(-7.800)		(-1.280)	(-6.787)	
Expenditures	0.236903*	0.082030*	0.681067	0.239316*	0.078869*	0.681815
	(17.048)	(6.886)		(18.196)	(7.131)	
Cholesterol Index	-0.001965**	0.000842	0.001251	-0.003295*	0.001159	-0.002136
	(-1.558)	(0.780)		(-2.785)	(1.168)	
Women Labor Force	0.005832*	-0.005243*	-0.000589	0.007891*	-0.005598*	-0.002293
	(2.415)	(-2.536)		(3.462)	(-2.925)	
Generic Adv.:						
Beef	0.000041*	0.000004	-0.000045	0.000018*	-0.000004	-0.000014
	(2.179)	(0.221)		(2.122)	(-0.514)	
Pork	-0.000009	-0.000019	0.000028	-0.000033	0.000002	0.000031
	(-0.303)	(-0.744)		(-0.860)	(0.062)	
Lag Gen. Adv.:						
Beef 1	-0.000016**	0.000003	0.000013	-0.000009**	0.000011*	-0.000002
	(-1.521)	(0.388)		(-1.537)	(2.446)	
Beef 2	0.000013	-0.000001	-0.000012	-0.000019*	-0.000001	0.000020
	(1.221)	(-0.161)		(-3.209)	(-0.358)	
Beef 3	-0.000027*	0.00001	0.000026	0.000022*	-0.000017*	-0.000005
	(-2.601)	(1.109)		(4.016)	(-3.556)	
Pork 1	-0.000009	0.000018	-0.000009	0.000005	-0.000021	0.000016
	(-0.441)	(0.985)		(0.163)	(-0.828)	
Pork 2	0.000031	-0.000008	-0.000023	0.001210*	-0.000004	-0.001206
	(1.468)	(-0.425)		(4.033)	(-0.174)	
Pork 3	0.000025	-0.000008	-0.000017	-0.000077*	0.000064*	0.000013
	(1.209)	(-0.418)		(-2.582)	(2.578)	

Table 8. Continued

Branded Adv.						
Beef	0.000026	0.000028	-0.000054	-0.000082	0.000019	0.000063
	(0.397)	(0.508)		(-1.418)	(0.382)	
Pork	-0.000015	-0.000024	0.000039	0.000071	-0.000014	-0.000057
	(-0.243)	(-0.456)		(1.275)	(-0.294)	
Poultry	-0.000011**	-0.000004	0.000015	0.000011*	-0.000005	-0.000006
	(-1.592)	(-0.728)		(1.988)	(-1.033)	
Seasonality						
D2	-0.001328	0.003617*	-0.002289	-0.001046	0.003217*	-0.002171
	(-0.624)	(1.988)		(-0.514)	(1.886)	
D3	0.004365*	0.014967*	-0.019332	0.006391*	0.013220*	-0.019611
	(1.842)	(7.311)		(2.806)	(6.825)	
D4	-0.028902*	0.031807*	-0.002905	-0.026657*	0.030920*	-0.004263
	(-12.405)	(15.728)		(-11.975)	(16.262)	

Note: Single and double asterisks denote significance at the 5 and 10 percent level, respectively.

The parameter estimates of the poultry equation are calculated from the adding-up condition.

Table 9. Parameter Estimates of the Rotterdam Model for Beef, Pork, and Poultry, 1979:2-1991:2

Independent Variable	Checkoff Expenditures QBEEF	Checkoff Expenditures QPORK	Checkoff Expenditures QPOULTRY	Generic Advertising Expenditures QBEEF	Generic Advertising Expenditures QPORK	Generic Advertising Expenditures QPOULTRY
Prices:						
Beef	-0.289173*			-0.278497*		
	(-8.566)			(-7.761)		
Pork	0.114072*	-0.085168*		0.103006*	-0.080627*	
	(4.409)	(-3.556)		(3.905)	(-3.475)	
Poultry	0.175101*	-0.028904*	-0.146197	0.175492*	-0.022379*	-0.153113
	(11.062)	(-2.369)		(10.520)	(-1.863)	
Expenditures	0.304043*	0.132128*	0.563829	0.302271*	0.134949*	0.562780
	(12.210)	(6.528)		(11.410)	(6.603)	
Cholesterol Index	-0.001478	0.003095	-0.001617	-0.001694	0.003489	-0.001795
	(-0.417)	(1.057)		(-0.458)	(1.205)	
Women Labor Force	0.005340	-0.010115**	0.004775	0.005809	-0.010864*	0.005055
	(0.772)	(-1.772)		(0.807)	(-1.931)	
Generic Adv.:						
Beef	0.000123*	-0.000024	-0.000099	0.000030	-0.000001	-0.000029
	(2.911)	(-0.701)		(1.392)	(-0.073)	
Pork	-0.000110**	-0.000027	0.000137	-0.000070	-0.000053	0.000123
	(-1.848)	(-0.554)		(-0.820)	(-0.807)	
Lag Gen. Adv.:						
Beef 1	0.000015	0.000002	-0.000017	-0.000013*	-0.000004	0.000017
	(1.599)	(0.282)		(-1.999)	(-0.742)	
Beef 2	0.000041*	-0.000007	-0.000034	-0.000029*	0.000006	-0.000023
	(4.111)	(-0.873)		(-4.660)	(1.274)	
Beef 3	-0.000024*	0.000024*	0.000000	0.000018*	-0.000015*	-0.000003
	(-2.448)	(2.998)		(2.928)	(-3.044)	
Pork 1	-0.000052*	0.000033*	-0.000019	0.000009	0.000050*	-0.000059
	(-3.028)	(2.374)		(0.293)	(2.085)	
Pork 2	-0.000025	-0.000015	-0.000040	0.000122*	-0.000047*	-0.000075
	(-1.451)	(-1.070)		(3.888)	(-1.941)	
Pork 3	0.000030**	-0.000029	-0.000001	-0.000065*	0.000050*	0.000015
	(1.734)	(-2.008)		(-2.030)	(1.990)	

Table 9. Continued

Branded Adv.						
Beef	0.000181	0.000054	-0.000235	-0.000169*	0.000112*	0.000057
	(1.549)	(0.570)		(-2.480)	(2.113)	
Pork	-0.000151	-0.000059	0.000210	0.000145	-0.000109*	-0.000036
	(-1.451)	(-0.690)		(2.358)	(-2.280)	
Poultry	-0.000029*	0.000044	-0.000015	0.000024*	-0.000003	-0.000021
	(-2.126)	(0.396)		(2.194)	(-0.389)	
Seasonality						
D2	-0.002975	0.007716*	-0.004741	-0.002096	0.007260*	-0.005164
	(-1.010)	(3.221)		(-0.715)	(3.212)	
D3	-0.001338	0.012760*	-0.011455	-0.002166	0.012678*	-0.124614
	(-0.397)	(4.717)		(-0.630)	(4.830)	
D4	-0.033280*	0.034895*	-0.001615	-0.031922*	0.034171*	-0.002249
	(-11.467)	(14.711)		(-10.805)	(14.911)	

Note: Single and double asterisks denote significance at the 5 and 10 percent level, respectively.

The parameter estimates of the poultry equation are calculated from the adding-up condition.

Table 10. Elasticity Estimates, Rotterdam Model for Beef, Pork, and Poultry

	Checkoff Expenditures			Generic Advertising		
Variable	Beef	Pork	Poultry	Beef	Pork	Poultry
Prices						
Beef	-0.251415	0.768753	-0.374082	-0.254268	0.753810	-0.335527
	-0.507321	0.422489	1.094381	-0.488591	0.381504	1.096825
Pork	0.343985	-0.688568	-0.144993	0.337298	-0.666292	-0.158253
	0.200126	-0.315437	-0.180650	0.180712	-0.298619	-0.139869
Poultry	-0.092569	-0.080186	0.519075	-0.083029	-0.087519	0.493781
	-0.307195	-0.107052	-0.913731	0.307881	-0.082885	-0.956956
Meat Expend.	0.398910	0.294450	4.704849	0.403247	0.286894	4.700986
	0.533409	0.489363	3.523931	0.530300	0.499816	3.517375
Generic Advertising						
Beef	0.000007	0.000106	-0.000219	0.000027	-0.000053	-0.000068
	0.000272	-0.000019	-0.000938	0.000011	-0.000052	-0.000238
Pork	0.000017	-0.000106	-0.000219	0.001920	0.000205	-0.008130
	-0.000275	-0.000141	0.000481	-0.000007	0.000000	0.000025
Branded Advertising						
Beef	0.000039	-0.000227	-0.000411	-0.000142	0.000057	0.000473
	0.000318	0.000200	-0.001469	-0.000296	0.000415	0.000356
Pork	-0.000019	-0.000167	0.000301	0.000125	-0.000042	-0.000432
	-0.000265	-0.000219	0.001313	0.000254	-0.000404	-0.000225
Poultry	-0.000020	0.000061	0.000110	0.000017	-0.000011	-0.000048
	-0.000051	0.000163	-0.000094	0.000042	-0.000011	-0.000131

Note: Price and meat expenditures elasticities are compensated elasticities. For each equation, elasticities are calculated as the ratio of the parameter estimates to the budget share. For the generic advertising variables, the coefficient of the lagged variables are added to those of the contemporaneous variables before calculating the ratio.

The elasticities are for the 1970:1-1993:4 and 1979:2-1991:2, respectively.

Table 11. Parameter Estimates of the Ward and Lambert Model for Beef and Pork, 1970:1-1993:4 Data, Quantity Dependent Model

	Beef Checkoff Expenditures		Generic Advertising Expenditures			
			Beef		Pork	
Variable	Coefficient	t-Ratio	Coefficient	t-Ratio	Coefficient	t-Ratio
Constant	1.268	0.825	0.961	0.638	5.193*	2.661
$\ln P_b$	-0.557*	-4.326	-0.506*	-5.462	0.375*	3.367
$\ln P_k$	0.075	1.425	0.083**	1.635	-0.723*	-12.430
$\ln P_c$	-0.010	-0.133	-0.011	-0.153	-0.112	-1.333
lnI	1.148*	4.002	1.147*	4.205	0.166	0.598
T1	-0.025*	-4.381	-0.025*	-4.661	-0.002	-0.383
T2	0.011*	2.405	0.010*	2.743	--	--
Current Adv.	-0.004	-0.081	-0.050	-0.556	0.055	1.591
Lag Adv.	0.035	0.610	0.142**	1.617	0.037	1.016
S1	-0.013	-1.527	-0.013**	-1.698	-0.064*	-7.023
S2	0.014	1.516	0.017*	1.962	-0.090*	-9.671
S3	0.034*	4.411	0.035*	4.730	-0.079*	-8.694
FR	0.003	0.504	0.003	0.478	--	--
R-Square	0.97		0.97		0.95	
R-Square Adjusted	0.96		0.96		0.93	

Note: Single and double asterisks denote significant at the 5% and 10%, respectively.

Table 12. Parameter Estimates of the Ward Model for Beef and Pork, 1970:1-1993:4 Data

	Beef Checkoff Expenditures		Generic Advertising Expenditures			
			Beef		Pork	
Variable	Coefficient	t-Ratio	Coefficient	t-Ratio	Coefficient	t-Ratio
Constant	4.0286*	2.1840	3.9559*	2.1840	6.6577*	4.8050
lnQ_k	-0.3644*	-3.3840	-0.3617*	-3.2160	-1.1626*	-12.0800
lnQ_b	-1.2457*	-7.5690	-1.2228*	-7.3770	-0.4453*	-3.3090
lnQ_c	-0.0283	-0.1374	-0.0983	-0.4702	0.0460	0.2453
lnI	1.4241*	7.9150	1.4741*	9.2990	0.8077*	5.9630
T1	-0.0263*	-6.0530	-0.0027*	-6.9330	-0.0128*	-3.7080
Current Adv.	-0.1385**	-1.5660	-0.0197	-0.4251	-0.0027	-0.0670
Lag Adv.	0.1087	1.2160	-0.0156	-0.3329	0.0551	1.3340
S1	-0.0483	-1.3960	-0.0604**	-1.7090	-0.0810*	-2.4510
S2	-0.0356	-1.4070	-0.0461**	-1.7310	-0.1058*	-4.4950
S3	0.0094	0.4562	0.0421	0.2013	-0.0775*	-3.7980
FR	0.0263	1.4000	0.0264	1.4010	--	--
R-Square	0.98		0.96		0.97	
R-Square Adjusted	0.97		0.95		0.97	

Note: Single and double asterisks denote significant at the 5% and 10%, respectively.

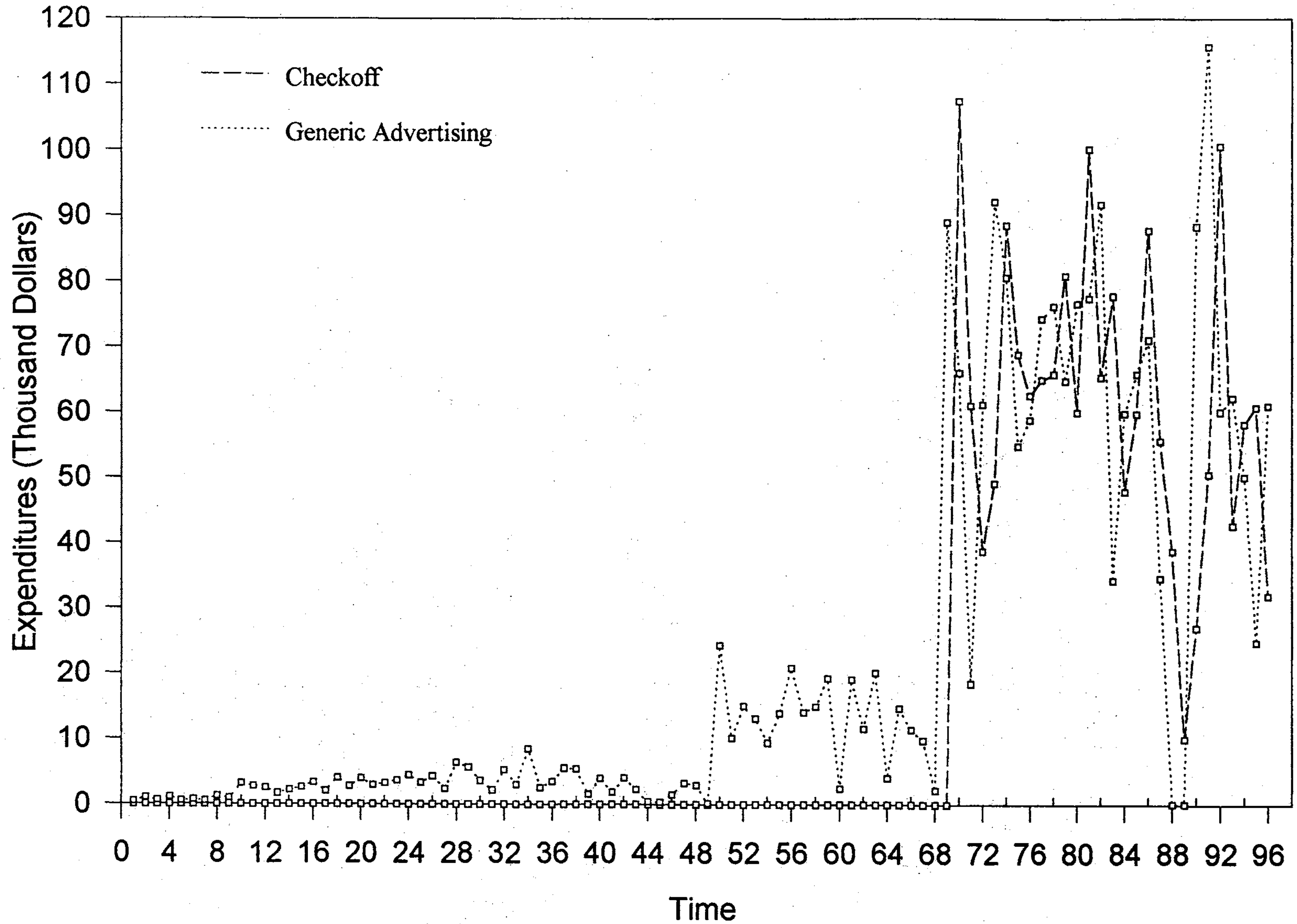

Figure1. Per capita checkoff and generic advertising expenditures, 1970:1-1993:4

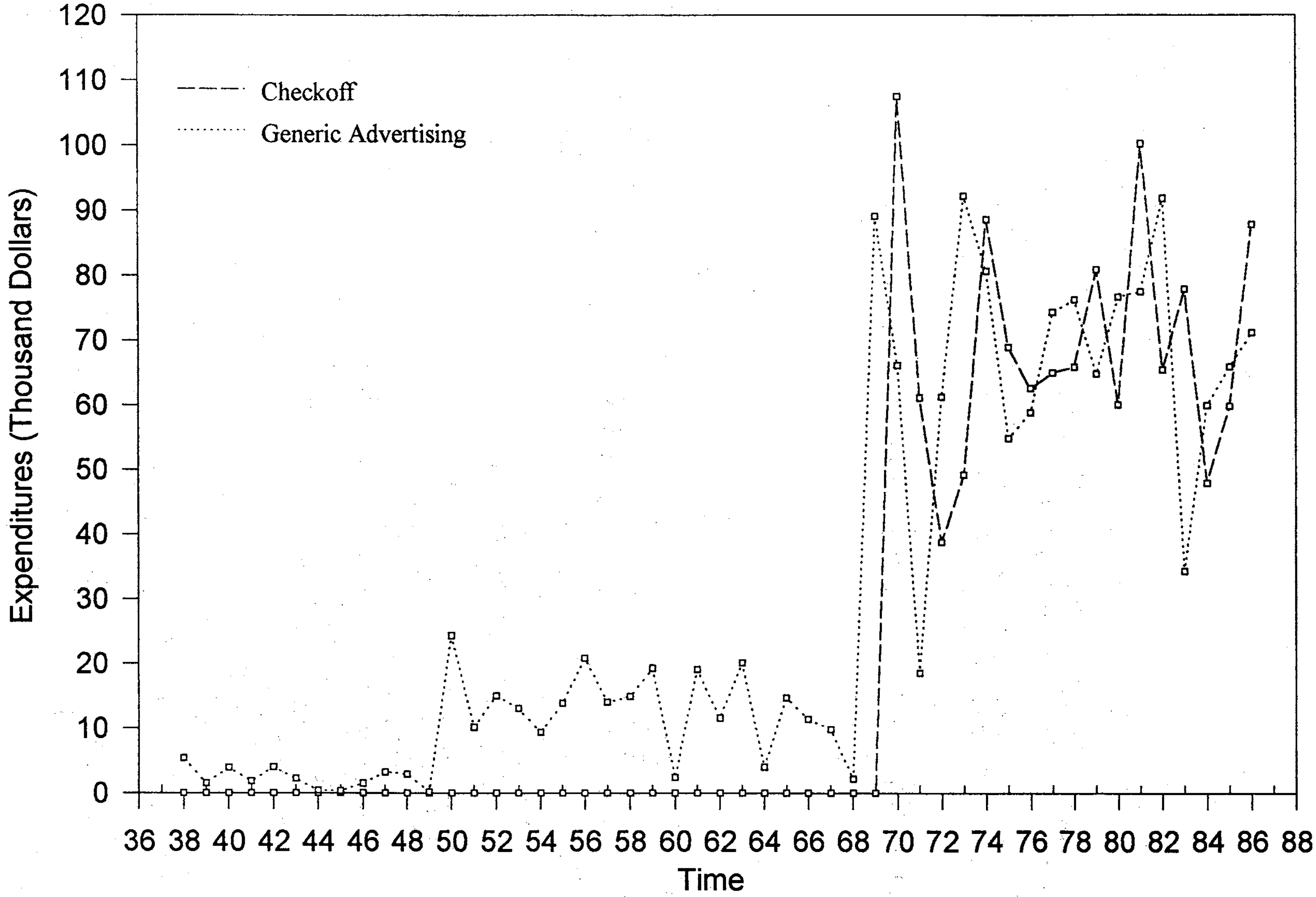

Figure 2. Per capita checkoff and generic advertising expenditures, 1979:2-1991:2

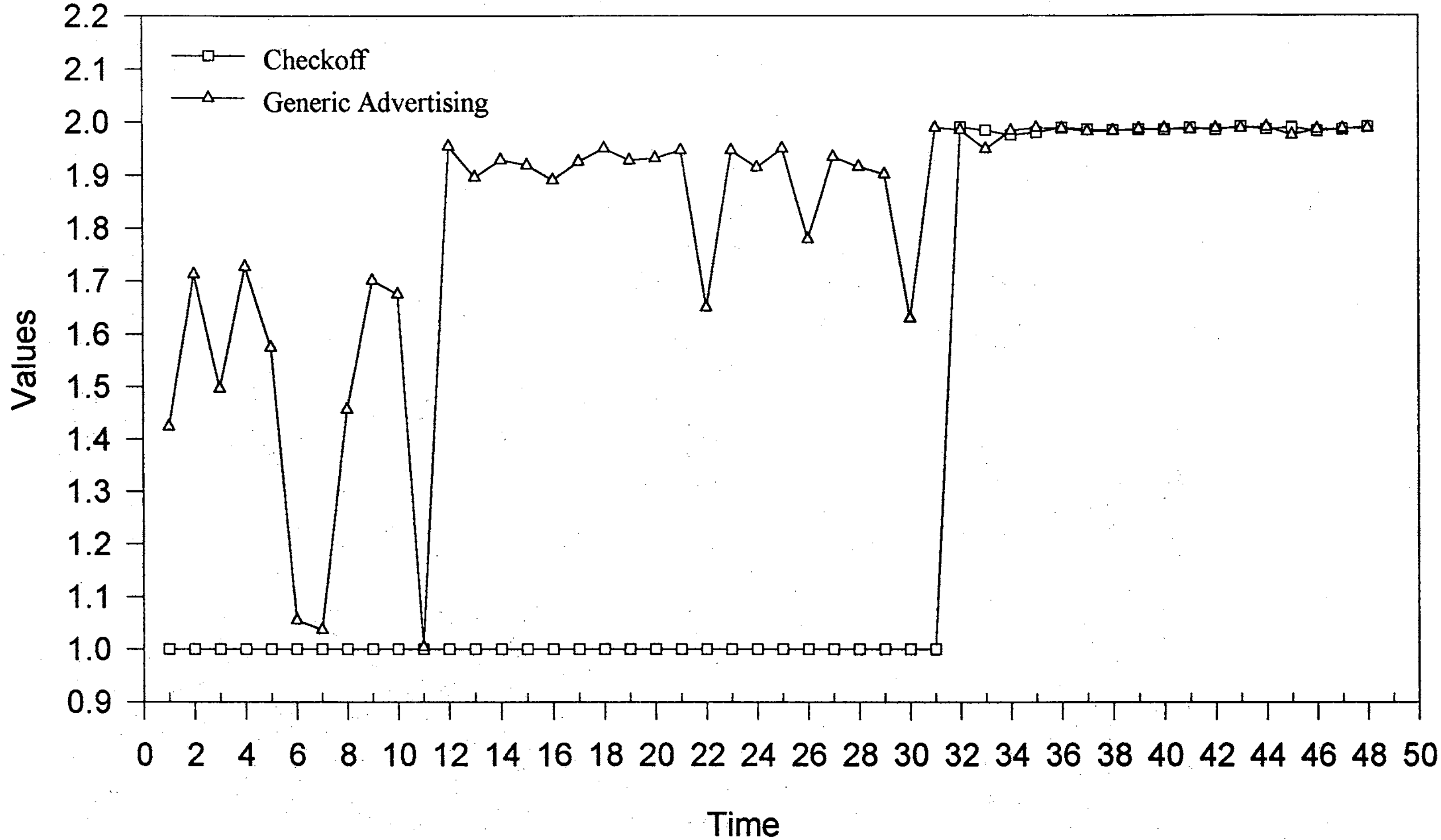

Figure 3. Values of the transformed advertising variable, Ward and Lambert's model, 1979:2-1991:2

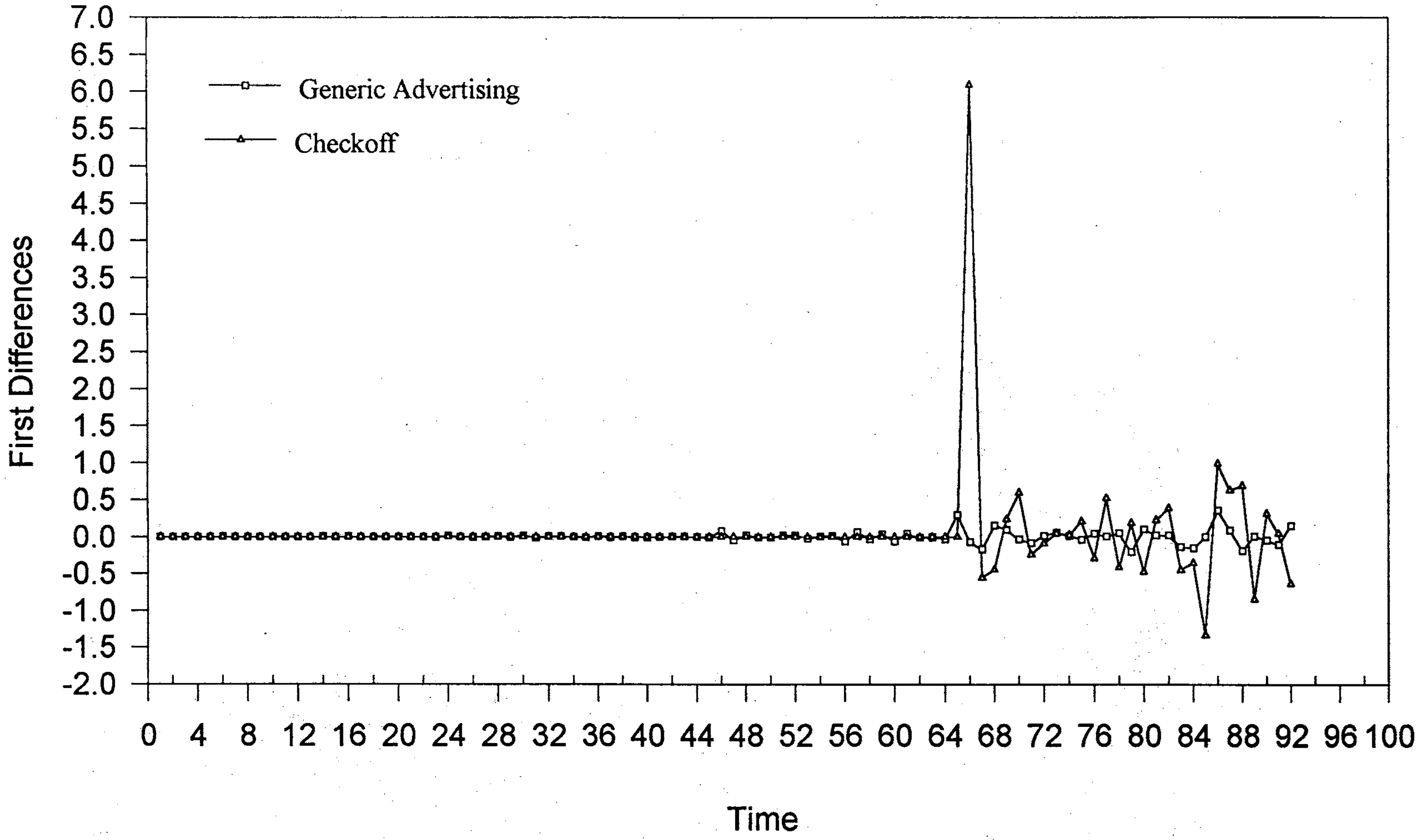

Figure 4. First differences of the logarithms of the checkoff and generic advertising expenditures, 1970:1-1993:1

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