Multinomial Logistic Regression

Chanyeong Kwak ▼ Alan Clayton-Matthews

- **Background:** When the dependent variable consists of several categories that are not ordinal (i.e., they have no natural ordering), the ordinary least square estimator cannot be used. Instead, a maximum likelihood estimator like multinomial logit or probit should be used.
- **Objectives:** The purpose of this article is to understand the multinomial logit model (MLM) that uses maximum likelihood estimator and its application in nursing research.
- **Method:** The research on "Racial differences in use of long-term care received by the elderly" (Kwak, 2001) is used to illustrate the multinomial logit model approach. This method assumes that the data satisfy a critical assumption called the "independence of irrelevant alternatives." A diagnostic developed by Hausman is used to test the independence of irrelevant alternatives assumption. Models in which the dependent variable consists of several unordered categories can be estimated with the multinomial logit model, and these models can be easily interpreted.
- **Conclusions:** This method can handle situations with several categories. There is no need to limit the analysis to pairs of categories, or to collapse the categories into two mutually exclusive groups so that the (more familiar) logit model can be used. Indeed, any strategy that eliminates observations or combines categories only leads to less efficient estimates.

- **Key Words:** long-term care • multinomial logit model • racial differences

Many health science research projects analyze data that are not continuous, but in the form of categories. If the research focus is categorical dependent variables, the ordinary least square (OLS) estimator is an inappropriate estimator for the coefficients on the independent variables. Instead, a maximum likelihood estimators (MLE) should be used. The multinomial logit model (MLM) is an MLE that is an extension of the simple logit model for dichotomous dependent variables; therefore, MLM can be used when a study involves polychotomous dependent variable.*

To understand the use of MLM and its application in nursing research, the research on "Racial differences in use of long-term care received by the elderly" (Kwak, 2001) is illustrated. This article also discusses the Hausman (Hausman & McFadden, 1984) diagnostic test for the independence of irrelevant alternatives assumption of MLM.

Background on Multinomial Logit Model

The MLM is not the only estimation methodology available for situations with unordered categorical dependent variables, but it has three important advantages over other methods: (a) it is widely available and almost every commonly used statistical package includes the MLM model; (b) computers can calculate estimates relatively quickly, especially when there are many categories; (c) the model results are easy to interpret, allowing for convenient odds measures in addition to probability measures. Another good candidate for an estimator is multinomial probit. Multinomial probit is also an MLE. The multinomial probit model assumes that the disturbance

**If the dependent variable categories are ordered, an alternative estimator such as ordered probit or logit is appropriate. However, in many situations, such as the one presented here, the categories have no natural ordering*

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terms in the underlying equations have a multivariate normal distribution, which is theoretically more appealing than the type II extreme bounds error distribution assumed by MLM. However, when the independence of irrelevant alternatives assumption is fulfilled, the two approaches yield models that give virtually identical results in terms of significance of independent variables and estimated probabilities. Since the multinomial probit model is not widely available and is not computationally feasible when there are more than a few categories, the MLM model is much more widely used. The following describes the steps in using MLM and its analysis.

$$
\begin{aligned}
y = 1 \quad &\mathit{iff} \quad y_1^* > y_2^* \text{ and } y_1^* > y_3^* \text{ and } y_1^* > y_4^* \text{ and } y_1^* > y_5^* \\
y = 2 \quad &\mathit{iff} \quad y_2^* > y_1^* \text{ and } y_2^* > y_3^* \text{ and } y_2^* > y_4^* \text{ and } y_2^* > y_5^* \\
y = 3 \quad &\mathit{iff} \quad y_3^* > y_1^* \text{ and } y_3^* > y_2^* \text{ and } y_3^* > y_4^* \text{ and } y_3^* > y_5^* \\
y = 4 \quad &\mathit{iff} \quad y_4^* > y_1^* \text{ and } y_4^* > y_2^* \text{ and } y_4^* > y_3^* \text{ and } y_4^* > y_5^* \\
y = 5 \quad &\mathit{iff} \quad y_5^* > y_1^* \text{ and } y_5^* > y_2^* \text{ and } y_5^* > y_3^* \text{ and } y_5^* > y_4^*
\end{aligned}
$$

FIGURE 1. Demonstrates how an individual chooses one type of long-term care. For example in y =1 equation, one person chooses nursing home care because her/his utility level reaches maximum with the choice.

Multinomial Logit Model

Step 1. Understanding and Choosing Multinomial Logit Model

The researcher needs to understand MLM to decide whether research subjects are appropriate to this model. For example, suppose the researcher wants to examine the factors influencing an elder's decision for long-term care (LTC). Five types of LTC service are observed: (a) nursing home care, (b) paid home care, (c) informal care from family/friend, (d) mixed care with paid home care and informal care, and (e) independent with LTC. These categories in the dependent variable are truly discrete, nominal, and unordered. When the data are this type, MLM is appropriate (Liao, 1999) because different people rank the alternative choices differently to maximize their satisfaction for LTC. The model assumes that people select the type of LTC that gives them the highest utility. For example, a person who is in a nursing home is there because he or she derives higher utility for being in a nursing home than any other alternative, accounting for his or her characteristics.

In order to understand the estimation problem and the MLE, it is useful to interpret the model as having several continuous dependent variables, one for each dependent variable category, that are unobserved, or *latent*. These variables represent the person's utility index for each alternative. In Figure 1, y1* is the utility derived from being in a nursing home, y2* is the utility for receiving paid home care, y3* for receiving informal care from family or friend, y4* for receiving both paid home care and informal care, and y5* is the utility derived from living independently. The individual's utility level for different alternatives cannot be observed. Instead, what is observed is a censored variable that simply indicates which LTC service is selected by the person.

To the extent that persons' utilities are systematically related to observable characteristics and other factors, these are included as the independent variables, the, in each equation of the model. In this article, the independent variables include factors that have an effect on useation of LTC, such as demographic characteristics, health status indicators, sociocultural characteristics, healthcare system factors, living pattern factors, environmental factors, and availability of resource. The disturbance term of the equations, the ϵ's, are assumed to be independent across both individuals and equations.

Step 2. Testing the Independence of Irrelevant Alternatives Assumption

To use MLM, data need to meet the independence of irrelevant alternatives (IIA) assumption. The IIA property holds that the ratio of the choice probabilities of any two alternatives (in response categories) are not influenced systematically by any other alternatives (Kennedy, 1998; Liao, 1999). In other words, the inclusion or exclusion of any category in model should not affect the relative odds or probabilities of any other two categories. This assumption is questioned in many published articles that used MLM because they do not provide any diagnostic test to rule out the possibility of violation of IIA assumption. The IIA assumption is satisfied by performing a Hausman (Hausman & McFadden, 1984) diagnostic test.

The test is performed by comparing the estimated coefficients of the model with all dependent categories (called the "unconstrained" model). If the IIA is correct, dropping a category from the dependent variable and estimating a model with observations in the remaining categories only should result in estimated coefficients that are statistically identical, for the remaining categories left in the model, to the "full" model that includes all dependent variable categories. The Hausman test is performed by doing precisely that. The coefficients in the full, or "unconstrained" model are compared to the coefficients from each of several constrained models, where each constrained model results from dropping one of the categories from the dependent variables. The equation for the test is given in Figure 2, and the test statistics from this study are given in Table 1. Since the *P*-values for each of the comparisons are high, the IIA assumption is accepted. Failure would imply that the disturbances are not independent across categories. In that case, the model should be reestimated with another method such as multinomial probit, that allows for such nonindependence.

Step 3. Specifying the Model

Once the diagnostic test indicates that data satisfies IIA assumption, specification of the research model can proceed. Based on previous research and

$$\left(b_c - b_u\right)'\left[COV\left(b_c\right) - COV\left(b_u\right)\right]^{-1}\left(b_c - b_u\right)$$

FIGURE 2. The Hausman test statistic where b_c and b_u are the constrained and unconstrained coefficient estimates, and COV(b_c) and COV(b_u) are their estimated covariance matrices. This statistic has an approximate chi square distribution with the number of degrees of freedom equal to the number of coefficients estimated in the constrained model (Hausman & McFadden, 1984)

relevant theory, the researcher tries several regression models and performs various tests to approach the best one. Although such specification searches rely on experience and "art," and there is no well-specified procedure for building models, there are strategies and guidelines such as those described in Kennedy (1998).

In the example study, model specification is formed based on Orem's (Orem, 1995) Self Care Deficit Theory and other relevant findings in previous research. Bivariate analyses provide supportive information for designing the model. The variables that are significant in the bivariate analysis (chi-square test and *t*-test) were chosen based on the significance level of 0.05. Also the variables that are expected to be important factors in LTC based on the Orem's theory are included in the model regardless of the significance in the bivariate analysis.

There are five categories in the dependent variable, as described in Step 1, and 17 independent variables chosen to enter into the MLM model. The relationship between the dependent variable and the independent variables appears linear, excluding the income variable. The relationship between income and use of LTC may be parabolic because there is a turning point at the same income level (Figure 3). Low-income people may prefer nursing home care because it is free once they are eligible for Medicaid, while middle-income people may prefer informal care because they cannot afford to be in a nursing home. High-income people may prefer nursing home care because they have enough money to pay for the service or to purchase private LTC insurance. To reflect this parabolic relationship between the dependent variable and the income variable, the square of income was created and included in the model. In addition, to address interaction effects (i.e., effect of one variable may depend on the level of another) several variables accounting for interactions between income, education, race, and sex were created and entered into the regression model. However, since their *P*-values were too high, they were deemed insignificant and dropped from the final model.

Step 4. Running the Multinomial Logit Model

Although the model specification requires knowledge in statistics, running regressions is simple owing to the availability of statistics computer software packages. To run MLM, a reference category is chosen from the categories of the dependent variable. The estimated coefficients are *relative to the reference category*, so the choice is usually determined by which is most convenient for analysis. In this study, the informal care was chosen as a reference category. It is important to note that the choice of reference category makes no difference in the estimated coefficients, calculated probabilities, or significance of variables.

TABLE 1. The Result of Hausman Test

Excluded Dependent Variable	χ^2	*p*
Nursing home care	23.595	.999
Paid home care	24.160	1.0
Informal care	23.468	.909
Mixed (paid home care and informal care)	46.533	.989
Independent	21.526	.987

Once the coefficients are determined after running the MLM, the probability of selecting one type of LTC service can be predicted by the mathematical equation (Figure 4), where **x** is the vector of independent variables and β_k is the vector of corresponding coefficients for choice *k*.

Step 5. Interpretation of Coefficients

The regression output provides the coefficient for each independent variable and *P*-value for each coefficient. In a simple logistic regression that contains a dichotomous dependent variable, the coefficient represents the effect of a unit change in the independent variable on the natural logarithm of the odds of using one type of LTC service. In the MLM model, the coefficients and their exponential transformations that yield the odds ratios are always relative to the reference category. For example, in this study, comparing the odds of (a) event A (nursing home) versus event C (informal care), (b) event B (paid home care) versus event C, (c) event D (mixed care) versus event C, and (d) event E (independent) versus event C (Miller, McFall, & Campbell, 1994) where the odds of being in a nursing home versus informal care is the probability of being in a nursing home divided by the probability of receiving informal care, and so on.

Interpreting the result for continuous variable. As presented in Table 2, the coefficient for age in nursing home category is 0.0600514. Exponentiating it to obtain the odds ratio (also known as the relative risk ratio), we get 1.061891. This finding should be interpreted as "each additional year of age increases the odds of receiving nursing home care versus informal care by 6%." To interpret a categorical or dummy variable, let us examine the language variable. In this study, the language variable contains two categories: English speakers and non-English speakers, and non-English speakers is the reference category. The coefficient for English speakers in the nursing home category is 1.457826, and the odds ratio is 4.296609. This means that the odds of using nursing home care versus informal care for English speakers is 4.30 times that of non-English speakers. Thus, language does matter in the decision of nursing

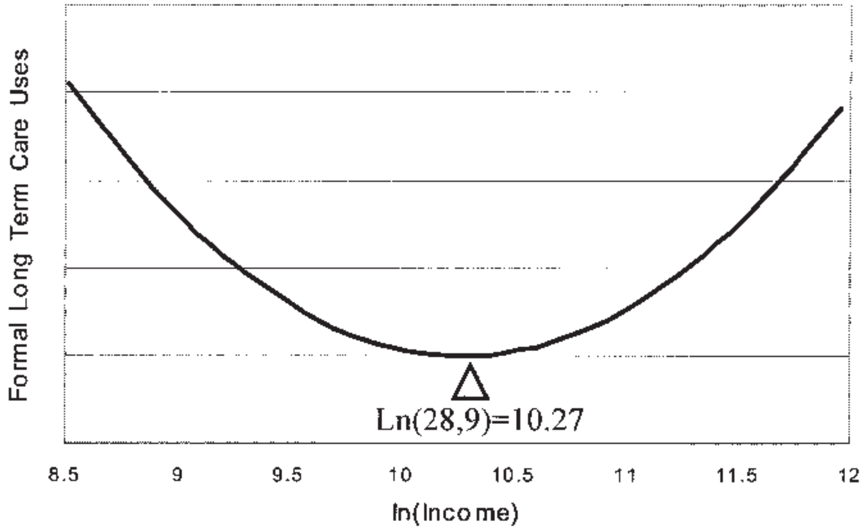

FIGURE 3. The relationship between log form of income level and formal long-term care use.

home placement. The coefficient for White in the "Independent" category is 0.409, giving an odds ratio of 1.505. This means that the odds ratio of being independent with LTC versus using informal care for Whites is 1.505 times that of non-Whites.

The researcher can decide which variables are significant in the use of LTC services by examining the *P*-values for the Wald z statistics in the regression output. As listed in Table 2, the significant variables in the nursing home category at the level of 0.05 are (a) age, (b) education, (c) activities of daily living (ADL), (d) cognition impairment, (e) English as the first language, (f) receiving Medicaid, (g) living with a spouse, (h) having children, and (i) living in an urban area. Those variables are the significant factors in the use of nursing home care versus informal care. Hypotheses about linear combinations of coefficients, for example, whether or not the coefficients on a variable or variables are the same for two categories, or whether or not a group of variables are significant, can often be performed conveniently as Wald tests in most statistics packages, or can sometimes be performed as likelihood ratio tests by comparing the reported likelihoods for a model and a constrained model that is nested within it.

Step 6. Predicted Probabilities Given a Set of Value

The calculation of odds ratios and their interpretation is very quick and easy, but the researcher should also calculate how changes in the independent variables affect the estimated probabilities of choices given by the model, using the equations in Figure 4. This is important because odds and probabilities need not change in the same direction. For example, the odds can be increasing even if both the probabilities that form it are decreasing, if the probability in the denominator of the odds is decreasing faster than that of the numerator. Also, a large odds ratio does not necessarily mean that the change in probabilities is large. The underlying change in probability may be proportionately large, but small in absolute terms.

Using the MLM, the predicted probability of being in each category can be estimated for hypothetical

$$\Pr(y = j) = \frac{e^{\beta_j \mathbf{x}}}{1 + \sum_{k=1}^{J-1} e^{\beta_k \mathbf{x}}} \quad \text{for } j = 1, 2, \cdots, J-1,$$

$$\Pr(y = J) = \frac{1}{1 + \sum_{k=1}^{J-1} e^{\beta_k \mathbf{x}}},$$

where there are J categories and J is the reference category.

$$\Pr(y = j) = \frac{e^{\beta_j \mathbf{x}}}{1 + \sum_{k=1}^{J-1} e^{\beta_k \mathbf{x}}}$$

FIGURE 4. The probability equation of long-term care choice category.

TABLE 2. The Result of Multinomial Logistic Regression

Dependent Variable	Independent Variable	Coefficient	*p* value	Odds Ratio
Nursing Home	Age	.0600514	0.001*	1.061891
	Female	−.1967696	0.467	.8213798
	Education	.0948187	0.002*	1.09946
	ADL	.1382368	0.039*	1.148247
	IADL	−.1617989	0.113	.8506122
	Self-assessed health rate	−.1642144	0.157	.84856
	Cognition impairment	.3063144	0.000*	1.358409
	White	.5050331	0.093	1.65704
	English	1.457826	0.027*	4.296609
	Income (log form)	−1.283871	0.420	.2769631
	(Income)2 (log form)	.0622849	0.445	1.064478
	LTC insurance	−.1971957	0.771	.8210299
	Medicaid	1.347277	0.000*	3.846936
	Spouse	−1.310349	0.000*	.2697258
	Children	−.1386263	0.019*	.8705533
	Urban	.6609008	0.050*	1.936536
	Frequency of church attendance	.0206791	0.805	1.020894
Paid Home Care	Age	−.0156286	0.576	0.9844929
	Female	−.2477227	0.486	.7805764
Care	Education	.1085089	0.003*	1.114615
	ADL	−.071059	0.524	.9314069
	IADL	−.73855	0.001*	.4778062
	Self-assessed health rate	−.1441588	0.360	.8657502
	Cognition impairment	.0056883	0.957	1.005704
	White	.7857524	0.099	2.194057
	English	−.4354151	0.588	.646996
	Income (log form)	−1.394275	0.411	.24801279
	(Income)2 (log form)	.0765832	0.378	1.079592
	LTC Insurance	−.3461316	0.594	.7074194
	Medicaid	−1.615792	0.035*	.1987332
	Spouse	−1.495769	0.000*	.2240763
	Children	−.0532139	0.529	.9481772
	Urban	.1138058	0.789	1.120534
	Frequency of church attendance	.0791982	0.482	1.082419
	Age	.0620398	0.012*	1.064005
Mixed Care (Paid Home Care and Informal Care)	Female	.4671939	0.196	1.595511
	Education	.0095565	0.825	1.009602
	ADL	.2236773	0.007*	1.250667
	IADL	−.1069179	0.398	.8985995
	Self-assessed health rate	−.2358457	0.132	.7899025
Care	Cognition impairment	.1647716	0.112	1.179124
	White	.6557508	0.148	1.926588
	English	−.615162	0.270	.5405533
	Income (log form)	−.8180168	0.728	.441306
	(Income)2 (log form)	.0432375	0.720	1.044186
	LTC insurance	.5490361	0.315	1.731583
	Medicaid	−.617518	0.181	.5392813
	Spouse	−.0807356	0.821	.9224376
	Children	−.0613871	0.454	.9404591

Continues

TABLE 2. The Result of Multinomial Logistic Regression Dependent (Continued)

Variable	Independent Variable	Coefficient	p value	Odds Ratio
	Urban	−.2558579	0.472	.774252
	Frequency of church attendance	−.2062514	0.086	.8136285
Independent (No Help)	Age	−.0429964	0.001*	.9579149
	Female	−.3519131	0.027*	.7033412
	Education	.0085494	0.700	1.008586
	ADL	−.8726052	0.000*	.4178615
	IADL	−2.133831	0.000*	.1183829
	Self-assessed health rate	.2752005	0.000*	1.316795
	Cognition impairment	.0663106	0.170	1.068559
	White	.4090453	0.036*	1.50538
	English	.1087147	0.711	1.114844
	Income (log form)	−1.126853	0.279	.3240514
	(Income)2 (log form)	.058003	0.278	1.059718
	LTC insurance	−.0336168	0.903	.966942
	Medicaid	−.6159025	0.006*	.5401532
	Spouse	−.5261466	0.001*	.5908775
	Children	−.0380661	0.215	.9626493
	Urban	−.2434641	0.198	.7839076
	Frequency of church attendance	.2422398	0.000*	1.2741

Note. *Significant at the level of 0.05, log likelihood = −1372.932, N = 2,794, χ^2 = 1,752.80, Pseudo R_2 = 0.3896.
ADL = activities of daily living; IADL = instrumental activities of daily living; LTC = long-term care.

cases. Estimated probabilities in multiple-outcome models should be even more useful than those in binary-outcome models, for instead of just one schedule of nonredundant probabilities now there are at least two schedules of nonredundant probabilities (Liao, 1999). To examine the impact of a particular independent variable on each category of dependent variable, hypothetical values for the other independent variables should be fixed at reasonable levels. In this study, hypothetical values for most variables were assigned based on the mean value of each continuous variable. Other categorical values were set as female, no Medicaid nor private insurance, living alone, one child, and urban residency.

As shown in Table 3, the predicted probability of being in a nursing home for the hypothetical 85-year-old individual ($P = 0.098$) is more than three times higher than that of 70 years old ($P = 0.031$). Non-English speakers have only one fourth the probability of using nursing home service (0.015) as that of English speakers (0.064). Non-Whites have a lower probability of using nursing home care (0.05 vs. 0.064) or paid home care (0.046 vs. 0.078) than Whites, while having a higher probability of receiving informal care (0.510 vs. 0.394).

Step 7. Analysis of the Results

As a final step, the researcher needs to analyze the results and draw the implications of practice in nursing. For example, this study found that people who speak English as a second language use nursing home services at one-quarter the rate of English speakers after controlling for other variables. Language here is serving as a proxy for one's culture, immigration status, and social economic status, all of which impact one's access to health services

TABLE 3. Predicted Probabilities of Being Each Category for Hypothetical Case

	Nursing Home	Paid Home Care	Informal Care	Mixed Care	Independent
Age					
70	0.031	0.076	0.333	0.012	0.547
85	0.098	0.076	0.422	0.038	0.364
Race					
Non-White	0.050	0.046	0.510	0.017	0.378
White	0.064	0.078	0.394	0.025	0.439
English					
No	0.015	0.124	0.406	0.048	0.406
Yes	0.064	0.078	0.395	0.025	0.439

and the practice of health (Guo, 1999; Zhan, 1999). This implies that health policy makers should recognize cultural and social heterogeneity among the elderly population and design culturally, ethnically, and linguistically appropriate services to fit them. The study results also suggest that nurses and other healthcare providers solve communication problems so that all elders are provided culturally appropriate services.

The MLM can be used in nursing research as a model containing a dependent variable with several unordered categories. For example, the researcher may investigate the influencing factors of a student's career choice after graduation (e.g., medical, surgical, pediatric, psychiatric, or maternity nursing fields). This dependent variable of fields contains categories only, thus, MLM would be appropriate. Because of the mathematical characteristics of the MLM model, and current software, alternatives can be treated in a computationally convenient manner (Hausman & McFadden, 1984). However, the MLM estimator may be biased if data does not satisfy the IIA assumption. Therefore, it is necessary to perform a diagnostic test (Hausman & McFadden) prior to running the model. ▼

Accepted for publication June 12, 2002.

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STATEMENT OF OWNERSHIP, MANAGEMENT, AND CIRCULATION (Act of August 12, 1970; Section 3685; Title 39 United States Code) Date of Filing—October 1, 2002; Title of Publication—*Nursing Research*; Frequency of Issue—Bimonthly; Annual Subscription Price—$67.00; Location of Known Office of Publication—Lippincott Williams & Wilkins, Inc., 16522 Hunters Green Parkway, Hagerstown, MD 21740-2116; Location of the Headquarters or General Business Offices of the Publisher—Lippincott Williams & Wilkins, Inc., 530 Walnut Street, Philadelphia, PA 19106; Publisher—Lippincott Williams & Wilkins, Inc., 530 Walnut Street, Philadelphia, PA 19106; Editor—Molly C. Dougherty, PhD, RN, FAAN, School of Nursing CB #7460, University of North Carolina at Chapel Hill, Chapel Hill, NC 27599-7460; Managing Editor—Karyn Crislip; Lippincott Williams & Wilkins, 530 Walnut Street, Philadelphia PA 19106; Owner—Wolters Kluwer, Stadouderskade 1, 1054 FS Amsterdam, The Netherlands; Known Bond Holders, Mortgagees, and other security holders owning or holding 1 percent or more of the total amount of bonds, mortgages, or other securities—None. A. Total no. of copies printed (net press run), average 6975, actual 6700. B. Paid and/or requested circulation. Paid/requested outside–county mail subscriptions stated on form 3541, average 3971, actual 3991; 2. Paid in–county subscriptions, average none, actual none; 3. Sales through dealers and carriers, street vendors, counter sales, and other non–USPS paid distribution, average 1515, actual 1519; 4. Other classes mailed through the USPS, average none, actual none. C. Total paid and/or requested circulation [sum of B (1), (2), (3), and (4)], average 5486, actual 5510. D. Free distribution by mail (samples, complimentary, and other free). 1. Outside–county as stated on form 3541, average 167, actual 342; 2. In–county as stated on form 3541, average none, actual none; 3. Other classes mailed through the USPS, average none, actual none. E. Free distribution outside the mail (carriers or other means), average 33, actual 134. F. Total free distribution (sum of D and E), average 200, actual 476. G. Total distribution (sum of C and F), average 5686, actual 5986. H. Copies not distributed, average 1289, actual 714. I. Total (sum of G and H), average 6975, actual 6700. J. Percent paid and/or requested circulation, average 96%, actual 92%. I certify that the statements made by me above are correct and complete. *Jeffrey Brown, Manager, Periodicals Operations*