Joint modeling of primary and secondary action in database marketing[1]

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SOM-theme F Interactions between consumers and firms

Abstract

In this paper we discuss the issue of primary and secondary actions to direct mail offers. Primary action refers to the first responses consumers make toward a direct offer or solicitation. It might represent an order for a product, a request for a catalog or credit card, or a pledge to donate to a charity. As little money changes hands on primary actions, companies are also interested in secondary actions, i.e., bad debts, returns, or payments. A company concentrating solely on the prediction of primary actions might lose money on customers who do not ultimately pay. We present a model which jointly models primary and secondary action and incorporates the correlation between the two action probabilities. We also show how optimal selection should take place incorporating predicted primary and secondary action jointly. In an empirical study, the new joint model yields superior profits when compared to a split model assuming the independence of primary and secondary actions.

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1 Introduction

Database marketing involves a sequence of actions and reactions on the part of consumer and the supplier. Generally, the buyer-seller contact begins with an offer, received in the home, by mail, email, or telephone. We define *primary action* as the first expression of interest or disinterest shown in a product or service by the consumer. Primary action is most commonly an order for a product. In the context of charity fundraising it is the pledge to donate. If the primary action is negative, the transaction is complete. However, a positive primary action initiates a process which encompasses many further actions on the part of the buyer.

Secondary action refers to a subsequent action by the consumer. Secondary actions, such as payments, returns, bad debts, etc., often determine the profitability of the overall transaction. For companies selling one-shot products or services through direct solicitations, there are many secondary actions and variables. Series or club business represents the most complex sequence of consumer decisions after the order is made. After subscribing for a series or club membership, customers must often decide on which subsequent products they will order, how many they will order, and when to end the membership. The accurate prediction of both primary and secondary actions on an individual level enables firms to focus their offers on the consumers who will ultimately yield profits. This paper introduces a comprehensive model for jointly predicting primary and secondary actions to direct solicitations.

Many studies of models coupling prediction of primary and secondary *response* have been published previously. The distinction between secondary response and secondary action lies in that response is continuous, and action is binary. Courtheoux (1987) describes in detail a methodology for predicting customers' profitability for a book series mailing. He combines two regression models, one predicting the order action (binary response), the second predicting the number of books subsequently purchased. The method of combination of these two regressions is a simple cross-tabulation of ranked deciles of the two estimators. Otter, Van der Scheer, and Wansbeek (1999) develop a model to simultaneously predict donation (binary) and donation amount (continuous) in order to optimize charity fund raising solicitation investments. More recently, Levin and Zahavi (1998) report that a two-stage model for modeling primary action and a continuous secondary response (profitability) outperforms both linear regression and a Tobit model on the same data. The two-stage model incorporates the Mills' ratio into the regression of secondary response, see Heckman (1979).

The previous literature approaches the primary and secondary actions independently, except in the case of the two-stage model. This is not appropriate, given that a single individual makes both primary and secondary response decisions. Hence, we extend the literature by proposing a method that simultaneously models primary and secondary actions, thereby considering the likely correlation between the two decision probabilities.

The newly proposed joint model can be applied in situations where two binary actions are taken by individuals, and that only positive primary reactors have the opportunity to make a secondary action. This method is comprehensive in that it may be used in any direct marketing situation for which primary and secondary actions can be defined. Its strength is that it accounts for a possible correlation between the unobservable, random components determining primary and secondary action. We find that the joint model yields superior predictions and profits when compared to what we call the split model where this correlation is taken to be zero a priori.

The set-up of the paper is as follows. In section 2 we formally describe the joint model. This model implies probabilities for primary and secondary action, which can be used to identify, by their characteristics, individuals from the mailing list with positive and with negative expected profit. Section 3 is devoted to this. Section 4 describes an empirical example. The joint model is estimated, and the results for the joint model are confronted with those from the split model, showing higher profits to be had from the former. Section 5 contains conclusions. It indicates managerial implications, and points to a number of limitations that are still attached to the joint model.

2 Joint modeling of primary and secondary action

In this section we formulate a bivariate probit model that jointly models the probability to perform primary and secondary actions. We refer to this model throughout as the joint model. We omit subscripts for individuals. Let

$$\begin{aligned} u_1 &= x_1'\beta_1 + \alpha_1 + \varepsilon_1 \\ u_2 &= x_2'\beta_2 + \alpha_2 + \varepsilon_2 \end{aligned}$$

where u_1 is the utility of performing the primary action and u_2 is the utility of performing the secondary action. The two vectors x_1 and x_2 represent characteristics of the individuals. One makes the primary action if $u_1 > 0$. If $u_1 > 0$, one makes the secondary action if also $u_2 > 0$. Further, let

$$\begin{bmatrix} \varepsilon_1 \\ \varepsilon_2 \end{bmatrix} \sim N\left(\begin{bmatrix} 0 \\ 0 \end{bmatrix}, \begin{bmatrix} 1 & \rho \\ \rho & 1 \end{bmatrix} \right),$$

where ρ is the correlation between ε_1 and ε_2. The error terms ε_1 and ε_2 represent factors that influence the decision of the consumer, but that are not observed by the researcher. If ε_1 and ε_2 are interpreted as the sum of a random individual effect η (that is the same in both error terms), and random effects ζ_1 and ζ_2 (that are uncorrelated with η), the correlation coefficient ρ can be interpreted as variance of the random individual effect, and we expect ρ to be positive. The parameters of the model are estimated with standard maximum likelihood.

If one assumes that ε_1 and ε_2 are independent, i.e., $\rho = 0$, maximum likelihood estimation can be utilized to estimate two separate probit models, which yield estimates of p_1 $(= \Pr(u_1 > 0))$ and $p_{11}|u_1 > 0$ $(= \Pr(u_2 > 0|u_1 > 0))$. Due to the assumed independence, the estimate of p_{11} is simply the product of the estimates of p_1 and $p_{11}|u_1 > 0$.

3 Optimal selection policy

Let p_0 $(= \Pr(u_1 \leq 0))$ be the probability of not performing the primary action, p_{11} the probability of making both the primary and secondary action, and p_{10} the probability of performing the primary action, but not the secondary action. Hence, $p_{10} = \Pr(u_1 > 0, u_2 < 0)$. Let R be the profit corresponding to performing the primary and secondary action, C the cost of performing only the primary action, and M the cost of the mailing, or more generally, the contact. Let the indices q_1 and q_2 be defined such that $q_1 \equiv x_1'\beta_1 + \alpha_1$ and $q_2 \equiv x_2'\beta_2 + \alpha_2$.

The breakeven point, or cutoff, is determined by $\pi = 0$, where

$$\pi \equiv Rp_{11} - M - Cp_{10}, \tag{1}$$

the expected profit. This equation needs to be solved for x_1 and x_2. Given the model assumptions, we can express p_{11} in terms of individual characteristics and model parameters:

$$
\begin{aligned}
p_{11} &= \int_{-q_2}^{\infty}\int_{-q_1}^{\infty} f(\varepsilon_1,\varepsilon_2)\mathrm{d}\varepsilon_1\mathrm{d}\varepsilon_2 \\
&= \int_{-q_2}^{\infty}\int_{-q_1}^{\infty} f(\varepsilon_1|\varepsilon_2)f(\varepsilon_2)\mathrm{d}\varepsilon_1\mathrm{d}\varepsilon_2 \\
&= \int_{-q_2}^{\infty}\left\{\int_{-q_1}^{\infty} f(\varepsilon_1|\varepsilon_2)\mathrm{d}\varepsilon_1\right\} f(\varepsilon_2)\mathrm{d}\varepsilon_2 \\
&= \int_{-q_2}^{\infty}\Phi\left(\frac{q_1+\rho\varepsilon_2}{\sqrt{1-\rho^2}}\right) f(\varepsilon_2)\mathrm{d}\varepsilon_2, \\
&= \int_{-q_2}^{\infty}\Phi\left(q^\dagger\right) f(\varepsilon_2)\mathrm{d}\varepsilon_2,
\end{aligned}
$$

where Φ is the standard normal integral, and f is the (univariate or bivariate) standard normal density function, and

$$
q^\dagger \equiv \frac{q_1+\rho\varepsilon_2}{\sqrt{1-\rho^2}}.
$$

Clearly,

$$
\begin{aligned}
p_{10} &= \int_{-\infty}^{-q_2}\Phi\left(q^\dagger\right) f(\varepsilon_2)\mathrm{d}\varepsilon_2 \\
p_1 &= p_{11}+p_{10} = \int_{-\infty}^{\infty}\Phi\left(\frac{q_1+\rho\varepsilon_2}{\sqrt{1-\rho^2}}\right) f(\varepsilon_2)\mathrm{d}\varepsilon_2 = \Phi\left(q_1\right),
\end{aligned}
$$

p_1 being the probability of performing the primary action. Further, making substitutions into (1) we have,

$$
\begin{aligned}
\pi &= R\int_{-q_2}^{\infty}\Phi\left(q^\dagger\right) f(\varepsilon_2)\mathrm{d}\varepsilon_2 - M - C\int_{-\infty}^{-q_2}\Phi\left(q^\dagger\right) f(\varepsilon_2)\mathrm{d}\varepsilon_2 \\
&= R\int_{-\infty}^{\infty}\Phi\left(q^\dagger\right) f(\varepsilon_2)\mathrm{d}\varepsilon_2 - M - (R+C)\int_{-\infty}^{-q_2}\Phi\left(q^\dagger\right) f(\varepsilon_2)\mathrm{d}\varepsilon_2 \\
&= R\Phi(q_1) - M - (R+C)(1-\Phi(q_2))\mathrm{E}\left\{\Phi\left(q^\dagger\right) \mid \varepsilon_2 \le -q_2\right\}. \qquad (2)
\end{aligned}
$$

The last, complicated term can be interpreted as the expected cost of uncertainty of secondary action.

For the split case, where $\rho = 0$, (2) reduces to

$$
\pi = R\Phi(q_1) - M - (R+C)(1-\Phi(q_2))\Phi(q_1). \qquad (3)
$$

This again reduces to

$$\pi = R\Phi(q_1) - M$$

if the probability of performing the secondary action is 1, so $q_2 = \infty$, which is the basic case studied by e.g. Bult and Wansbeek (1995). Equations (2) and (3) for $\pi = 0$ can be very simply put in a graph, i.e. a (q_1, q_2) box. This graph separates the individuals to be selected for a mailing from those who should not be selected in order for the direct marketing company, after running a test mailing in order to obtain the various parameters, to maximize its profits.

Expected profits π can also be written differently, in a way that identifies profitable contacts by a lower bound on the probability of secondary action. Let A be the event of primary action, and B the event of secondary action. In this notation, we have $p_{11} = \Pr(AB) = \Pr(B|A)\Pr(A)$, and $p_{10} = \Pr(A\bar{B}) = \Pr(\bar{B}|A)\Pr(A)$. Note that $\Pr(B|\bar{A}) = 0$. Now (1) can be written as

$$\begin{aligned} \pi &= R\Pr(A)\left(\Pr(B|A) - \frac{C}{R}\Pr(\bar{B}|A)\right) - M \\ &= R\Pr(A)\left(\frac{\Pr(B)}{\Pr(A)} - \frac{C}{R}\left(1 - \frac{\Pr(B)}{\Pr(A)}\right)\right) - M \\ &= \Pr(B)(R + C) - C\Pr(A) - M. \end{aligned} \tag{4}$$

From the last equation, it follows that expected profits are greater than zero if

$$\Pr(B) > \frac{C}{C+R}\Pr(A) + \frac{M}{C+R}. \tag{5}$$

A contact with an unconditional probability of secondary action less than $\frac{M}{C+R}$, will not be profitable. This restriction holds both for the split case and the joint model.

4 Empirical example

The model of primary and secondary action is illustrated on a direct mail one-shot offer. The offer package cost, M, is 1.45 NLG for production and delivery. Since the copy guaranteed the quality of the product, customers could return the product at no charge if they found it unsatisfactory.

A cross-section of approximately 30,000 customers were mailed the direct offer. The mailing yielded 1,154 orders, and ultimately, 517 customers paid for the product. The 637 non-payers were mostly returns, along with a few bad debts. We do not distinguish between the cost of a bad debt or a return, instead choosing to combine these into the non-payers group. We model payment as the secondary action. The cost to the company for an order, which did not result in a payment, C, is 14.70 NLG. The profit, R, of a paying customer is 57.20 NLG.

Five characteristics, x_{11} through x_{15}, are employed to predict the order response. They include a number of measures of frequency and recency of orders and other contacts. A further five characteristics, x_{21} through x_{25}, serve as predictors for the secondary action. Since the secondary action refers to payment, the explanatory variables represent frequency and recency of payments, and frequency of various money-losing secondary actions such as rejects or bad debts. There was no overlap between x_1 and x_2. The descriptions of the predictive variables have purposely been left vague at the request of the firm donating the data.

We estimated parameters for the data utilizing both the joint and the split models. Table 1 shows the parameter estimates for the joint and split models. Note that the coefficients β_{11} through β_{15} and α_1 are very similar between the two models. (Here and beyond we make, for simplicity, no notational distinction between parameters or functions of parameters and their estimates or estimators.) Greater differences are seen for β_{21} through β_{25} and α_2. The parameter ρ is estimated for only the joint model. According to expectations, it is positive. Its t-value is 3.7, so it is clearly significant.

4.1 Gains charts

Tables 2 and 3 display gains charts for the joint and split models, respectively. (MQ stands for mailing quantity.) Gains charts are created by ranking individuals in a test sample according the expected profit prediction according to (1). Individuals are then placed into groups, known as buckets, of equal size (we employ 15 buckets), still maintaining the descending predicted profit. Ties in predicted profit can result in buckets of unequal size, as we see in Table 3. Tables 2 and 3 both contain the same individuals, only the ranking of those individuals differs between the two gains charts. The first bucket of Table 2 represents the 1974 individuals with the highest π given by (3). The second bucket contains the 1975 individuals with the next highest values of π, etc. Various predictions and observed actions are also given by bucket. The rightmost column gives the observed profit in the test data set.

Table 1: Parameter estimates

Parameter	Joint model Coefficient	Split model Coefficient
α_1	-2.4647	-2.4618
β_{11}	0.5806	0.5574
β_{12}	1.0670	1.0859
β_{13}	0.2013	0.1942
β_{14}	0.0169	0.0177
β_{15}	0.0996	0.0976
α_2	-0.6672	0.0415
β_{21}	0.2098	0.0940
β_{22}	-0.0526	-0.0906
β_{23}	-0.3420	-0.4259
β_{24}	0.0658	0.0828
β_{25}	0.6455	0.6623
ρ	0.3261	—

Insight into one shortcoming of the split model can be obtained from the gains charts. The predicted profit for the top bucket of Table 3 is severely overestimated. The average predicted profit in that bucket is NLG 2.86, while in actuality, a profit of just NLG 1.85 is obtained. The top bucket generated by the joint model predicts profit much more accurately, NLG 1.80 vs. 1.76. We studied this phenomenon on another direct mail test, and also found superior prediction in the joint model. It appears that the assumption of zero ρ can lead to inaccurate profit predictions.

Note that inequality (5) is satisfied: buckets with a payment rate on the mailed quantity ($\Pr(B)$) that is lower than $\frac{M}{R+C}$ (approximately 2% in our example), are not profitable. This holds both for the joint model and the split model.

4.2 Results and interpretation

We now apply the rule of segmenting the sample into mail and do-not-mail groups based on the predicted profitability of individuals. We refer to mail and do-not-mail groups as pass and fail groups, respectively. The cutoff

Table 2: Gains chart: Joint model

Predicted profit	MQ	Orders	Order rate (%)	Predicted order rate (%)	Payments	Payment rate (%)	Predicted pmt. rate (%)	Pmt. rate (%) on MQ	Predicted Pmt. rate (%) on MQ	Actual Profit
1.80	1974	287	14.54	15.77	141	49.13	50.50	7.14	7.40	1.76
-0.06	1975	189	9.57	10.27	75	39.68	47.67	3.80	3.76	0.04
-0.49	1975	124	6.28	4.85	51	41.13	53.51	2.58	2.22	-0.41
-0.67	1975	84	4.25	3.75	40	47.62	54.41	2.03	1.77	-0.55
-0.78	1974	69	3.50	2.95	28	40.58	56.62	1.42	1.48	-0.88
-0.85	1976	59	2.99	2.70	28	47.46	55.55	1.42	1.33	-0.82
-0.89	1975	46	2.33	2.36	25	54.35	56.50	1.27	1.21	-0.85
-0.93	1975	45	2.28	2.13	24	53.33	57.50	1.22	1.11	-0.88
-0.96	1984	32	1.61	1.98	16	50.00	57.63	0.81	1.04	-1.08
-0.99	1966	26	1.32	1.77	12	46.15	58.63	0.61	0.97	-1.18
-1.01	1975	30	1.52	1.66	19	63.33	58.83	0.96	0.92	-0.97
-1.03	1975	24	1.22	1.62	14	58.33	57.88	0.71	0.88	-1.10
-1.06	1975	27	1.37	1.64	14	51.85	55.58	0.71	0.85	-1.12
-1.12	1975	35	1.77	1.78	12	34.29	47.78	0.61	0.78	-1.24
-1.29	1975	71	3.59	2.88	18	25.35	37.40	0.91	0.72	-1.25

Table 3: Gains chart: Split model

Predicted profit	MQ	Orders	Order rate (%)	Predicted order rate (%)	Payments	Payment rate (%)	Predicted pmt. rate (%)	Pmt. rate (%) on MQ	Predicted Pmt. rate (%) on MQ	Actual profit
2.86	1815	323	17.80	19.70	142	43.96	51.75	7.82	9.61	1.85
0.17	2134	159	7.45	7.92	71	44.65	52.90	3.33	3.70	-0.03
-0.50	1975	125	6.33	4.61	54	43.20	53.77	2.73	2.16	-0.31
-0.71	1981	79	3.99	3.70	35	44.30	53.62	1.77	1.71	-0.70
-0.83	1969	67	3.40	2.86	32	47.76	55.10	1.63	1.39	-0.73
-0.90	1975	59	2.99	2.58	25	42.37	54.26	1.27	1.24	-0.93
-0.95	1975	46	2.33	2.30	28	60.87	54.40	1.42	1.12	-0.75
-0.99	1977	38	1.92	2.04	19	50.00	54.95	0.96	1.02	-1.01
-1.02	1972	36	1.83	1.89	22	61.11	54.29	1.12	0.95	-0.90
-1.05	1976	29	1.47	1.78	15	51.72	53.70	0.76	0.89	-1.10
-1.07	1975	31	1.57	1.78	20	64.52	52.74	1.01	0.86	-0.94
-1.09	1975	22	1.11	1.68	14	63.64	51.63	0.71	0.81	-1.09
-1.12	1975	33	1.67	1.85	12	36.36	46.70	0.61	0.79	-1.23
-1.20	1975	48	2.43	2.10	12	25.00	39.30	0.61	0.73	-1.32
-1.35	1975	53	2.68	2.24	16	30.19	29.82	0.81	0.53	-1.21

Table 4: Cross-tabulation of pass segments and profits

Joint model	Split model	Mail quantity	Orders	Payments	Actual profit per individual
pass	pass	2570	347	166	1.41
	fail	63	7	4	1.62
fail	pass	608	85	25	-0.26
	fail	26383	709	322	-0.92

point discerning pass and fail individuals is at zero predicted profits. The joint model yields 2633 *pass* mailed quantity and NLG 3,734 profit. The split model indicates an optimal mail quantity of 3178 passes and a profit of NLG 3,473. Thus, the joint model produces a more targeted mailing, while improving profits by about 10%. A more targeted mailing saves money on mailing investment and thereby reduces the risk of a mailing.

It is interesting to contrast the results of the two models in more detail. Table 4 is a cross-tabulation of passing strategy and results by model. The split model passes 545 individuals more than the joint model. However, not all individuals passing the criterion based on the joint model are deemed profitable by the split model. The joint model discerns profitable names (63) in the fail group of the split model. In addition, the split model passes 608 unprofitable individuals that the joint model does not. The overprediction of profits for the split model is the reason behind the split model segmenting unprofitable individuals into the pass group.

The cutoff points for the joint and for the split model can be put in a graph. This is done in Figure 1. It contains two curves, one for the joint model and one for the split model. By some simple algebraic manipulations from (2), it follows that both curves have a horizontal asymptote for

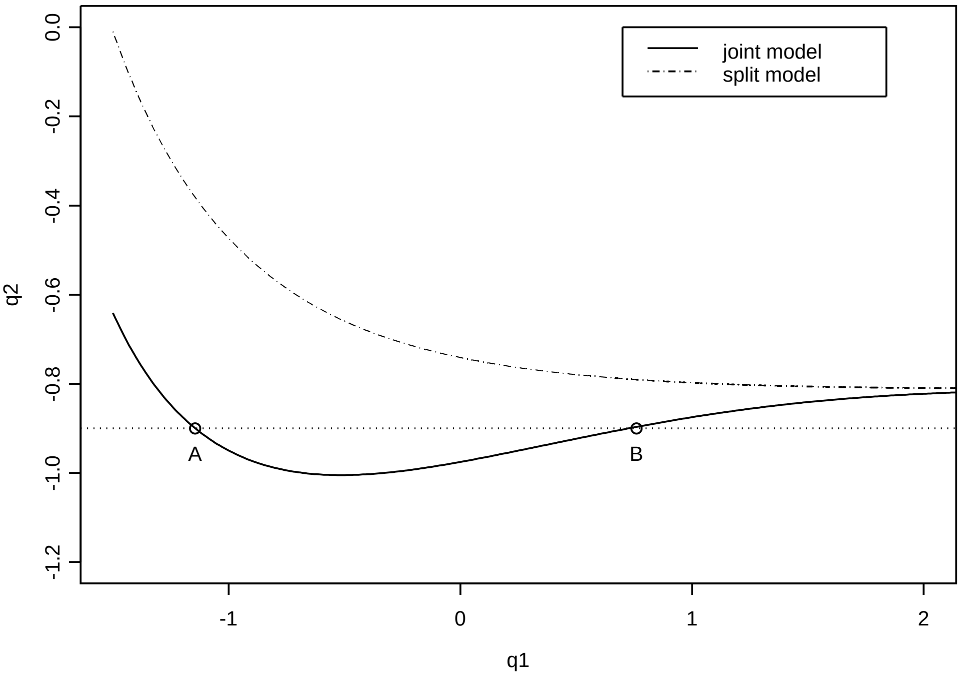
$$q_2 = \Phi^{-1}\left(\frac{M+C}{R+C}\right) = -0.7567,$$

since in our case $R = 57.20$, $C = 14.70$, and $M = 1.45$, and both curves have a vertical asymptote for

$$q_1 = \Phi^{-1}\left(\frac{M}{R}\right) = -1.954.$$

For both curves, the area to its northeast defines the pass group.

Figure 1: Cutoff curves



The figure has two seemingly anomalous aspects. In the first place, the area to the northeast of the curve for the joint model contains the area to the northeast of the split model, whereas the pass group for the joint model is smaller than for the split model. However, comparing both areas is meaningless since they are based on different parameter values. Hence, values of q_1 and q_2 for each individual differ under the two models.

Another seemingly anomalous aspect of the figure concerns the 'dip' in the graph for the joint model. It implies that (within a very limited range) some (q_1, q_2) points in the graph are in the pass group while there are points with both coordinates higher that are in the fail group.

To shed some light on this phenomenon, consider points A and B in the figure. Both are 'borderline' cases with zero expected profit. Points to the left of A are in the fail group, which is not surprising, but points to the right of B are also in the fail group, which certainly is counterintuitive. Basically, this is due to the high degree of nonlinearity of the joint model. Table 5 offers some clarification. It shows that, when moving from A to B, p_{11}, the probability of both primary and secondary action, increases. But also p_{10}, primary action but not secondary action, increases although q_2 remains constant, reflecting the just-mentioned high nonlinearity. The increase of p_{10} is much larger that the increase of p_{11}, such that the points to the right of B belong in the fail group.

Table 5: Seemingly anomalous behavior in the joint model

	q_1	q_2	p_{11}	p_{10}	p_1
A	−1.15	−0.90	0.04	0.08	0.12
B	0.76	−0.90	0.17	0.61	0.78

5 Conclusion

In this paper we have shown that in database marketing situations where profits rely on both primary and secondary actions, it is more profitable to fit a joint model, which does not assume the independence of the primary and secondary action. On actual direct marketing data, we show that profit predictions are overestimated using a split model, which assumes independence of the two response probabilities. Due to this overprediction, the some unprofitable individuals are segmented into the pass group using this strategy. The model considering the correlation between primary and secondary action passes fewer names, and yields higher profits.

5.1 Managerial implications

The joint presented in this paper allows the DBM practitioner to optimally model primary and secondary action while simultaneously allowing for the correlation between the two actions. Profits are increased using this model, which is any manager's foremost concern. However, the joint model requires more specialist software while the split model can be estimated using standard software. The added costs of additional software and expertise should be weighted into the decision to implement this new technique.

In the course of testing the model assuming ρ equal zero, we found that on two direct mail test samples, the profitability was overpredicted in the buckets most likely to perform both the primary and secondary action. The adoption of the new model presented in this paper would likely lead to reduced mailed quantity, as its predictions were much closer to the actual profitability. With a lower contacted quantity, less risk is taken on the part of the DBM firm.

5.2 Limitations

This research has various limitations. We mention three.

First, both actions considered are of a simple, bivariate discrete nature. An appealing extension is to generalize the nature of the first action, making it ordered discrete of continuous.

The second limitation deals with the short-sighted nature of the models we present and compare. Our strategy deals with only a single mailing, where a more comprehensive model would also develop a strategy for multiple mailings over time. In that case, consumer behavior can be modelled with random or fixed effects multinomial panel data models. However, such models are much more complex than the joint model we present in this paper.

The third limitation is of a more detailed, methodological nature and can be easily avoided if richer data were availble beyond those on a single test mailing. That is, the dataset on which we fit the two models was also used to evaluate their profitability. Ideally, a validation or holdout dataset would be employed to compare the profitability of the two models. Unfortunately, the test sample we employed was too small to allow us to divide it into two, thus creating both analysis and validation datasets.

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