Can We Infer "Trial and Repeat" Numbers From Aggregate Sales Data?

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Abstract

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Central to both monitoring and forecasting the performance of a new product is the decomposition of total sales into its trial (i.e., first-purchase) and repeat (or replacement) purchase components. Several researchers have developed models of new product sales that specify submodels for trial and repeat sales, yet can be calibrated using only aggregate sales data (as opposed to data on the underlying sales components). Some researchers have used these models for forecasting purposes, while other researchers have used these models to make inferences about the underlying trial and repeat components of new product sales in situations where only the aggregate sales data are available.

In this paper, we demonstrate that extreme caution must be used when trying to make such inferences about the underlying trial and repeat components of a new product's total sales. Using panel data for twenty new products, we aggregate the household-level transaction data to arrive at aggregate sales data. We fit a model of new product sales to these data and compare the implied trial/repeat patterns to the actual patterns observed using the raw panel data. Looking at several different underlying model specifications, we find that the implied trial/repeat patterns to do not reflect the true patterns. Thus any inferences derived from the aggregate sales data using such models can be very misleading.

1 Introduction

Most diffusion models developed within the marketing literature are first-purchase models. A problem faced in any empirical evaluation of these models is that first-purchase (or penetration) data are often hard to find; most data sources only report total sales, which is the combination of first-time and subsequent (replacement and/or additional) purchases.

The standard response has been either (i) to ignore the problem and simply fit the first-purchase model to the aggregate sales data, or (ii) to estimate the model parameters using only the first few years of data for which the majority of total sales are first-purchases. The first approach clearly represents a misapplication of the model. The second approach suffers from two problems: (i) the parameter estimates can be unstable (due to the limited amount of data), and (ii) any forecasts generated using the model are of limited value as most users will want forecasts of total sales, not just first purchases.

Recognizing this problem, a number of researchers have developed total sales models that have components for first and additional/replacement purchases.[1] The basic idea is as follows. Let $T(t)$ = cumulative number of first-purchase sales at time t and $R(t)$ = cumulative replacement/additional sales at time t. (In a nondurable setting, $T(t)$ and $R(t)$ represent cumulative trial and repeat sales.) It follows that cumulative total sales at time t is given by $S(t) = T(t)+R(t)$. The researcher first specifies a functional form (e.g., the Bass model) for $T(t)$ with parameters θ_T. The next step is to specify an expression for $\Delta R(t) = R(t) - R(t-1)$ with parameters θ_R. This may simply be a constant repeat/replacement rate (e.g, $\Delta R(t) = \rho T(t-1)$) or involve the specification of a distribution, $Q(t)$, that characterizes the "failure rate" of the product with incremental replacement sales being computed as

$$\Delta R(t) = \sum_{i=1}^{t-1} \big[Q(i) - Q(i-1)\big] S(t-i)$$

Olson and Choi (1985) use a Rayleigh distribution, whereas Kamakura and Balasubramanian (1987) use a truncated normal distribution. (See Ratchford et al. (2000) for a review of this lit-

[1] It is recognized that the purchasing of replacement products is a different process from that of purchasing additional products. However, these processes can be grouped together for the purpose of characterizing this general class of model.

erature and a discussion of the subtleties of the various models.) Fitting the resulting expression for $S(t)$ to the aggregate sales data yields estimates of θ_T and θ_R.

This general type of model has been applied in both durable and nondurable (i.e., frequently purchased products) settings. Some of the researchers working in this area have tested their models by looking at the accuracy of the model in forecasting total sales (i.e., $S(t|\hat{\theta}_T, \hat{\theta}_R)$). Others have gone an extra step. First-purchase sales can be inferred by substituting $\hat{\theta}_T$ in the formula for $T(t)$ and replacement/additional/repeat sales inferred as $\hat{R}(t) = \hat{S}(t) - \hat{T}(t)$. Mahajan, Wind, and Sharma (1983) and Olson and Choi (1985), amongst others, have reported these inferred components of a new product's sales. Shankar, Carpenter, and Krisnamurthi (1998) go one step further, (implicitly) using the inferred first-purchase numbers for theory-testing purposes.

One thing stands out when examining these papers: no one has examined whether these models yield valid estimates of the components of new product sales when the parameters have been estimated using only the aggregate sales data (cf., Kamakura and Balasubramanian 1987). At best, we have Hahn et al. (1994) discussing the face validity of the numbers they derive, and Bass and Bass (2001) focusing on the "plausibility" of their estimates (examining the similarity of various model-derived summary measures with industry estimates).

The apparent ability to extract the components of new product sales from the aggregate sales data is a very attractive property of these models. But if our estimates of the sales components are inaccurate, we must question the usefulness of this class of model. It is therefore important that we examine the accuracy of these model-based inferences.

The basic objective of this paper is to see how well the estimates of first-purchase and replacement/additional/repeat sales derived from such models compare to the actual numbers. Working in a nondurable setting, we have data from twenty separate year-long new product market tests conducted using the BehaviorScan® service operated by Information Resources, Inc. (A key characteristic of this controlled test market setting is that retail distribution is maintained at a 100% level over time.) Ten consumer packaged goods (CPG) categories are represented, including soap, shampoo, breakfast snacks, salad dressing, cookies, and candy. We have summary reports of the panel data collected in these markets that yield actual trial and repeat sales numbers (and therefore total sales) for the new product. In Section 2, we present a simple model of total sales. Using the aggregate sales only, we fit the model to obtain $\hat{\theta}_T$ and $\hat{\theta}_R$ for each dataset. We then compare the inferred (i.e., model-based) trial and repeat sales numbers to the true values collected via the panel data. We find that these inferred trial and repeat numbers are highly inaccurate. Allowing for the possibility that these errors could be due to the simplistic assumptions that we initially make about the nature of repeat sales, Section 3 considers a richer model of repeat purchasing, one that is widely used for sales forecasting in settings where we have access to the raw consumer panel data. Despite this improvement in the model specification, we find that it makes no meaningful difference in our ability to correctly extract estimates of the underlying sales components. In Section 4, we briefly discuss the implications of our findings.

2 Analysis: Part 1

The first step in developing a model for aggregate sales, $S(t)$, is to specify a submodel for first-purchases, $T(t)$. Drawing on the work of Hardie et al. (1998), which examined the performance of eight published models of trial purchasing across 19 CPG product datasets, there are two logical choices:

1. the exponential-gamma (EG) model,

$$T(t) = N \cdot \left\{1 - \left(\frac{\alpha}{\alpha + t}\right)^r\right\} \tag{1}$$

   where N is the market size

2. the exponential with "never triers" (ENT) model,

$$T(t) = N \cdot p \left(1 - e^{-\lambda t}\right) \tag{2}$$

   which is the continuous-time version of the basic Fourt and Woodlock (1960) trial model.

Both model specifications capture the concave nature of the penetration curve associated with the trial purchasing of a new CPG product in a constant distribution environment; furthermore, they provide almost equivalent fits to trial purchasing data. (Hardie et al. (1998) also examined a wider array of models, including the Bass model, but found that these two simple exponential forms were consistently best for the CPG datasets they used.)

The next step is to specify a submodel for repeat sales. Let

$$\Delta R(t) = \begin{cases} 0 & t = 1 \\ R(t) - R(t-1) & t = 2, 3, \ldots \end{cases}$$

The simplest structure is to assume a constant repeat purchase rate,

$$\Delta R(t) = \rho T(t-1) \tag{3}$$

which is the assumption made by Hahn et al. (1994), Mesak and Berg (1995), Shankar et al. (1998), Thepot (1988), and others. Thus cumulative total sales at time t is given by

$$\begin{aligned} S(t) &= T(t) + \sum_{i=1}^{t} \Delta R(i) \\ &= T(t) + \sum_{i=1}^{t} \rho T(i - i) \end{aligned} \tag{4}$$

where the expression for $T(t)$ is given by (1) or (2).

Starting with the exponential-gamma trial model, we estimate the three model parameters (r, α, ρ) for each of the 20 datasets (labelled A–T) using nonlinear least squares (NLS) on incremental (i.e., week-by-week) total sales (Srinivasan and Mason 1986). For N we use the size of BehaviorScan® panel associated with each dataset. We then compute inferred trial and repeat sales and compare these to the actual trial and repeat numbers, which are observed in the panel data but obviously ignored for the purpose of model calibration.

To illustrate, we consider dataset J which was associated with a panel of 2273 households. The associated incremental NLS parameter estimates are $\hat{r} = 0.034$, $\hat{\alpha} = 6.111$, and $\hat{\rho} = 0.010$, with an R^2 of 49.5%. The fit of model, in terms of cumulative total sales, is illustrated in Figure 1a. Our estimate of trial sales is obtained by substituting $\hat{r}$ and $\hat{\alpha}$ into (1); subtracting this from the estimate of total sales yields our estimate of $R(t)$, cumulative repeat sales. These inferred sales components are plotted in Figure 1b.

[Figure 1 about here]

In Figure 1c, we compare these inferred trial and repeat numbers with the actual numbers observed from the raw panel data. The results are undeniably impressive, suggesting that we can indeed use a "repeat diffusion" model of this type to extract trial and repeat numbers from aggregate sales data. However, when we look across all 20 datasets, we clearly see that this is not the case. In Table 1 we report a set of summary measures for each dataset:

- model R^2 computed on the incremental total sales numbers used for model calibration,
- the mean absolute percentage error (MAPE) on cumulative total sales, computed over the whole year,
- actual and fitted cumulative total sales at the end of the year (and the corresponding percentage error),
- actual and inferred cumulative trial at the end of the year (and the corresponding percentage error), and
- actual and inferred year-end cumulative repeat sales, expressed as a percentage of total sales (and the corresponding percentage error).

This last error measure gives us some quick insight into the ability of the model to extract the trial and repeat components of sales from the aggregate sales numbers. Consequently, the table entries are sorted on the absolute value of this error measure.

[Table 1 about here]

In terms of overall model fit, the results are mixed but generally positive. Some of the R^2 numbers are quite good, but for others (especially datasets D, E, F, G, T) the model does not seem to be capturing much of the week-to-week variation in total sales. In these cases, the projected cumulative total sales curve is basically linear (i.e., constant incremental sales). However, even though we are fitting the model to incremental sales, the cumulative tracking plots (and the ability of the models manage to "hit" year-end total sales) are reasonably impressive.

Dataset J offers an interesting example: despite the fact that the R^2 from its week-to-week model estimation is slightly below the median across the 20 datasets, the quality of its cumulative tracking plot (shown in Figure 1a) is excellent.

But when we look at the columns that reflect the model's ability to capture the trial and repeat components, it is immediately clear that dataset J is an extreme outlier. Overall, there is a nearly universal bias towards the under-estimation of repeat sales (with a corresponding over-estimation of trial sales); in fact in 35% of the cases, the model infers no repeat sales at all. Furthermore, these biases are quite substantial; in 65% of the cases, the error in trial sales is greater than 50%. Every indication suggests that this modeling approach is unacceptable (and that the good results for dataset J are, most likely, attributable purely to chance).

We repeat this exercise using the exponential with "never triers" model, and report the same summary measures in Table 2. While we see a few more datasets that provide decent inferences for year-end cumulative repeat sales (expressed as a percentage of total sales) these point measures are slightly misleading as they don't give any insight into the quality of the inferences over time. For example, Figure 2 plots actual and inferred trial, repeat, and total sales for dataset I. Despite the impressive summary numbers shown in the top row of Table 2, we observe great error in the time-path of the trial and repeat components.

[Table 2 about here]

[Figure 2 about here]

Furthermore, when we put aside the (same) five datasets with very poor R^2 values, there is little relationship between the trial-and-repeat inferences provided by one model versus the other. In other words, the decompositional inferences are highly sensitive to the specification of the trial model[2], and thus there is little reason to have faith in the estimates provided by either model.

The general conclusion we must draw is that we cannot use this particular "repeat diffusion" model to extract trial and repeat numbers from aggregate sales data. However, before we

[2]It is important to recall that the two trial models (EG and ENT) provide almost equivalent fits to actual trial purchasing data (Hardie et al. 1998).

completely write-off any possible application of this overall modeling approach, let us consider an alternative specification of the repeat sales submodel.

3 Analysis: Part 2

The above analysis was based on the assumption of a constant repeat purchase rate, $\Delta R(t) = \rho T(t-1)$. While this is an assumption made in previous empirical work (e.g., Hahn et al. 1994; Shankar et al. 1998), anyone familiar with the repeat buying patterns of new (nondurable) products will find such an assumption rather simplistic. We therefore consider a more realistic model of repeat sales, drawing on the work of Eskin (1973).

The development of repeat sales is conceptualized using the well-known depth-of-repeat decomposition:

$$R(t) = \sum_{j=1}^{\infty} R_j(t)$$

where $R_j(t)$ is the cumulative number of customers that have made at least j repeat purchases. Eskin (1973) decomposes $R_j(t)$ in the following manner:

$$R_j(t) = \sum_{i=1}^{t-1} F_j(t|i)\big[R_{j-1}(i) - R_{j-1}(i-1)\big]$$

In light of observed patterns in the empirical repeat purchase curves, Eskin (1973) proposes a model of the following form:

$$F_j(t|t_{j-1}) = p_j\left(1 - e^{-\gamma(t_j - t_{j-1})}\right),\ j \geq 1$$

$$\text{where } p_j = \begin{cases} p_1 & \text{if } j = 1 \\ p_\infty(1 - e^{-\theta j}) & \text{otherwise} \end{cases}$$

(See Kalwani and Silk (1980) for further discussion of this model.)

Coupling this model of repeat sales with the ENT trial model, we estimate the six model parameters $(p, \lambda, p_1, p_\infty, \theta, \gamma)$ for each of the 20 datasets using NLS on incremental total sales. We then compute inferred trial and repeat sales and compare these to the actual trial and repeat numbers observed in the panel data. The corresponding summary measures of model performance are reported in Table 3.

[Table 3 about here]

The basic story from Part 1 of our empirical analysis still holds — there are systematic biases and large errors in the trial and repeat inferences made using such a model. Note, however, that there now a universal bias towards the over-estimation of repeat sales (with a corresponding under-estimation of trial sales). As the Eskin repeat model has proven to be very robust in a panel data setting, we cannot lay the blame on its specification (or that of the trial model). Rather, the problem is simply the inability to estimate the combined set of parameters for both models using only aggregate data.

4 Discussion

The recognition that aggregate sales data for a new product represent both first-purchase and replacement/additional purchases (trial and repeat in nondurable settings) has led a number of researchers to develop models of total sales that explicitly recognize (but fail to validate) these underlying components. Many researchers have reported estimates of trial and repeat sales (as inferred using the model), and some have used these numbers for theory-testing purposes.

Yet it is clear from the analyses reported in this paper that these models cannot be used to obtain reliable and meaningful estimates of the underlying trial and repeat components of the observed total sales series. This suggests we should reconsider any empirical findings that have been based on such models. Furthermore, it suggests that more elegant (and complex) model specifications cannot be used to overcome inadequacies in the collected data. If we wish to fully understand the underlying components of a new product's performance, we must collect individual-level first and repeat purchasing data.

There appears to be a fundamental problem of identifiability; we cannot estimate all the model parameters using only the aggregate sales data. Kamakura and Balasubramanian (1987) are, to the best of our knowledge, the only prior researchers to acknowledge this problem, stating that some additional information about the repeat (or, in their case, replacement) component of sales must be obtained exogenously. The challenge faced by the modeler is how to gain access to such information, especially for new products. In a forecasting setting, Mesak and Mikhail

(1988) suggest using decision calculus methods. In a CPG setting, it may be possible to make use of panel data for previously-launched new products to arrive at informed priors for the trial and repeat submodel parameters that can then be estimated in a Bayesian framework. This is clearly a topic worth considering as future research.

The analysis reported in this paper has not included the effects of marketing mix variable. The incorporation of covariates, per se, will not overcome the fundamental problem of identifiability. However, if it were possible to identify covariates that have an effect on the replacement/repeat process but not on adoption/trial (or vice-versa), it may be possible to identify these two sub-processes from the aggregate data — see, for example, the literature on models of partial observability (Van den Bulte and Lilien 2001). However, it is hard to conceive of such separate sets of variables existing for the adoption/trial and replacement/repeat processes for most durable and nondurable products.

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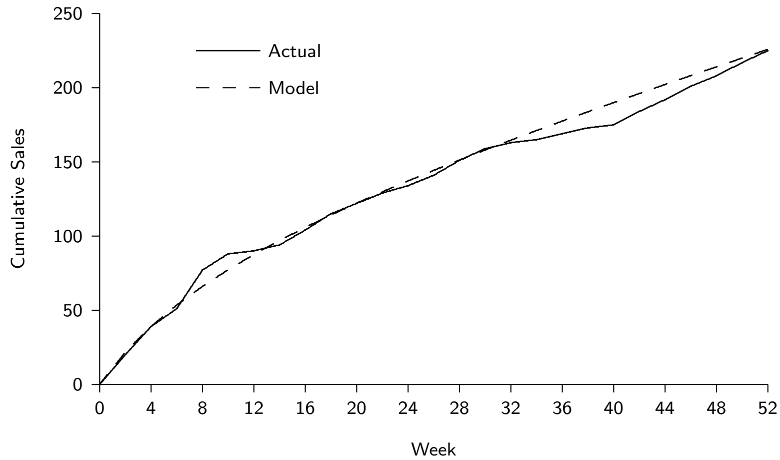
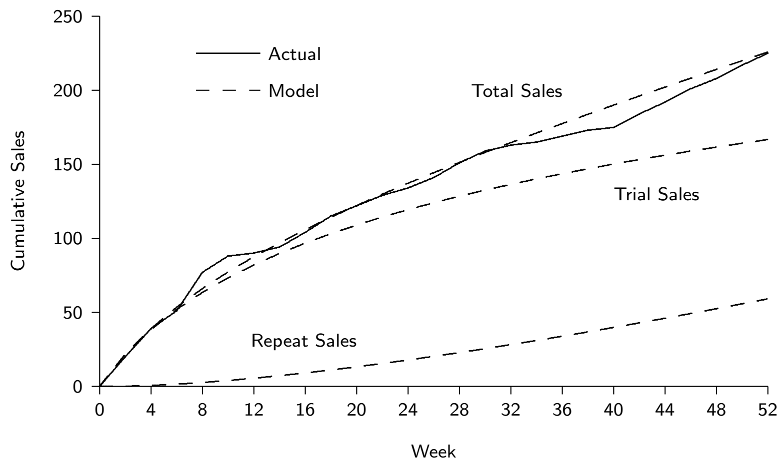


(a)



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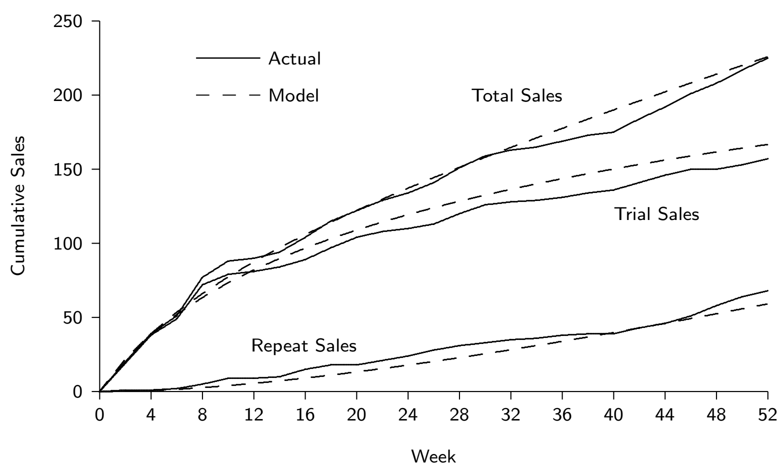

(c)

Figure 1: Model Fit and Sales Component Inferences: Dataset J, EG Trial Model

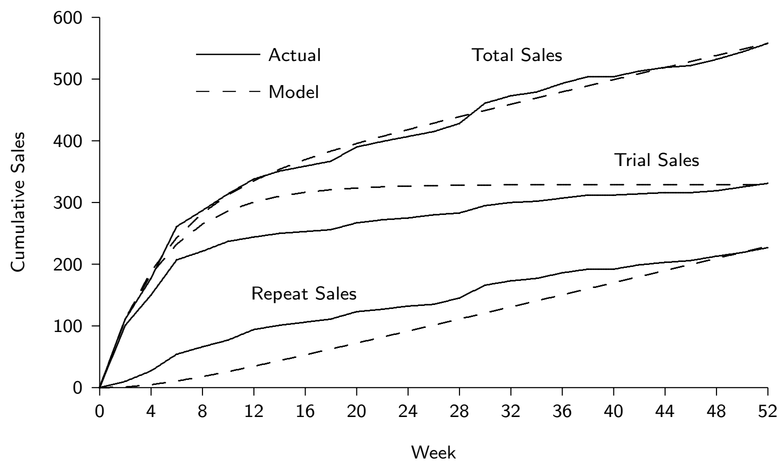

Figure 2: Model Fit and Sales Component Inferences: Dataset I, ENT Trial Model

	Model Fit		Week 52 Cum Sales			Week 52 Cum Trial			Week 52 Rpt as % Tot Sales		
Dataset	R^2 (incr.)	MAPE	Actual	Pred	% Error	Actual	Pred	% Error	Actual	Pred	% Error
J	49%	4	225	225.8	0	157	166.7	6	30	26	−13
Q	76%	3	263	263.8	0	148	220.6	49	44	16	−63
H	89%	4	461	463.5	1	286	399.5	40	38	14	−64
T	1%	14	1870	1869.7	0	642	1462.6	128	66	22	−67
S	69%	4	303	304.7	1	163	261.5	60	46	14	−69
G	0%	36	309	309.0	0	193	287.6	49	38	7	−82
F	0%	20	203	203.0	0	122	188.1	54	40	7	−82
K	20%	14	137	137.2	0	100	131.8	32	27	4	−86
L	53%	4	551	552.3	0	205	505.4	147	63	8	−86
E	2%	34	523	523.0	0	256	500.6	96	51	4	−92
I	85%	4	558	561.4	1	331	544.9	65	41	3	−93
C	73%	12	191	186.1	−3	170	145.8	−14	11	22	97
D	3%	55	829	829.0	0	433	818.4	89	48	1	−97
B	64%	8	421	469.8	12	349	469.8	35	17	0	−100
O	53%	10	144	156.2	8	98	156.2	59	32	0	−100
A	51%	11	306	314.0	3	193	314.0	63	37	0	−100
R	46%	12	291	296.1	2	167	296.1	77	43	0	−100
N	66%	12	398	434.0	9	213	434.0	104	46	0	−100
P	55%	6	220	222.9	1	102	222.9	119	54	0	−100
M	29%	4	306	306.3	0	139	306.3	120	55	0	−100

Table 1: Summary of Results: EG Trial Model

	Model Fit		Week 52 Cum Sales			Week 52 Cum Trial			Week 52 Rpt as % Tot Sales		
Dataset	R^2 (incr.)	MAPE	Actual	Pred	% Error	Actual	Pred	% Error	Actual	Pred	% Error
I	87%	2	558	558.0	0	331	329.0	−1	41	41	1
R	52%	9	291	291.0	0	167	170.2	2	43	42	−3
O	56%	6	144	144.0	0	98	104.3	6	32	28	−14
Q	77%	2	263	263.0	0	148	131.0	−11	44	50	15
S	71%	4	303	303.0	0	163	139.8	−14	46	54	17
H	91%	2	461	461.0	0	286	235.9	−18	38	49	29
L	54%	4	551	551.0	0	205	327.2	60	63	41	−35
P	57%	6	220	220.0	0	102	152.6	50	54	31	−43
A	54%	10	306	306.0	0	193	250.2	30	37	18	−51
C	63%	5	191	191.0	0	170	158.4	−7	11	17	55
M	29%	4	306	306.0	0	139	237.4	71	55	22	−59
K	20%	14	137	137.0	0	100	78.2	−22	27	43	59
N	69%	7	398	398.0	0	213	323.5	52	46	19	−60
T	1%	14	1870	1869.7	0	642	1462.8	128	66	22	−67
E	2%	34	523	523.0	0	256	500.8	96	51	4	−92
D	3%	55	829	829.0	0	433	819.1	89	48	1	−98
J	52%	4	225	225.0	0	157	89.6	−43	30	60	99
B	70%	5	421	438.6	4	349	438.6	26	17	0	−100
F	5%	9	203	203.0	0	122	1.5	−99	40	99	149
G	12%	11	309	309.8	0	193	0.0	−100	38	100	166

Table 2: Summary of Results: ENT Trial Model

	Model Fit		Week 52 Cum Sales			Week 52 Cum Trial			Week 52 Rpt as Tot Sales		
Dataset	R^2 (incr.)	MAPE	Actual	Pred	% Error	Actual	Pred	% Error	Actual	Pred	% Error
L	56%	3	551	550.8	0	205	187.4	−9	63	66	5
M	31%	3	306	305.9	0	139	99.2	−29	55	68	24
Q	77%	2	263	263.0	0	148	107.3	−27	44	59	35
T	27%	11	1870	1883.9	1	642	99.0	−85	66	95	44
I	87%	2	558	558.2	0	331	219.0	−34	41	61	49
P	68%	4	220	221.0	0	102	41.0	−60	54	81	52
H	91%	2	461	461.3	0	286	188.7	−34	38	59	56
F	8%	11	203	204.5	1	122	74.7	−39	40	63	59
N	84%	5	398	406.1	2	213	101.8	−52	46	75	61
E	19%	23	523	529.5	1	256	79.1	−69	51	85	67
G	20%	20	309	313.0	1	193	112.5	−42	38	64	71
D	20%	40	829	845.2	2	433	150.4	−65	48	82	72
S	78%	4	303	303.7	0	163	43.0	−74	46	86	86
R	71%	10	291	298.0	2	167	55.4	−67	43	81	91
A	74%	7	306	310.7	2	193	63.3	−67	37	80	116
O	67%	4	144	145.8	1	98	31.4	−68	32	78	146
J	54%	3	225	225.1	0	157	36.2	−77	30	84	178
B	74%	2	421	422.7	0	349	198.3	−43	17	53	210
K	32%	12	137	139.0	1	100	18.0	−82	27	87	222
C	80%	12	191	186.1	−3	170	42.7	−75	11	77	601

Table 3: Summary of Results: ENT Trial with Eskin Repeat Model