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An Investigation of Earnings Management through Marketing Actions

Craig J. Chapman
Thomas J. Steenburgh

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AN INVESTIGATION OF EARNINGS MANAGEMENT THROUGH MARKETING ACTIONS[1]

Craig J. Chapman[2], Thomas J. Steenburgh[3]

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Abstract:

Prior research hypothesizes managers use 'real actions,' including the reduction of discretionary expenditures, to manage earnings to meet or beat key benchmarks. This paper examines this hypothesis by testing how different types of marketing expenditures are used to boost earnings for a durable commodity consumer product which can be easily stockpiled by end-consumers.

Combining supermarket scanner data with firm-level financial data, we find evidence that differs from prior literature. Instead of reducing expenditures to boost earnings, soup manufacturers roughly double the frequency and change the mix of marketing promotions (price discounts, feature advertisements and aisle displays) at the fiscal quarter-end when they have greater incentive to boost earnings.

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[2] Kellogg School of Management, Northwestern University, c-chapman@kellogg.northwestern.edu
[3] Harvard Business School

Our results confirm managers' stated willingness to sacrifice long-term value in order to smooth earnings (Graham, Harvey and Rajgopal, 2005) and their stated preference to use real actions to boost earnings to meet different types of earnings benchmarks. We estimate that marketing actions can be used to boost quarterly net income by up to 5% depending on the depth and duration of promotion. However, there is a price to pay, with the cost in the following period being approximately 7.5% of quarterly net income.

Finally, a unique aspect of the research setting allows tests of who is responsible for the earnings management. While firms appear unable to increase the frequency of aisle display promotions in the short run, they can reallocate these promotions within their portfolio of brands. Results show firms shifting display promotions away from smaller revenue brands toward larger ones following periods of poor financial performance. This indicates the behavior is determined by parties above brand managers in the firm.

These findings are consistent with firms engaging in real earnings management and suggest the effects on subsequent reporting periods and competitor behavior are greater than previously documented.

1. Introduction

Degeorge, Patel and Zeckhauser (1999) propose that earnings management behavior can be divided into two distinct categories:

- "misreporting" earnings management – involving merely the discretionary accounting of decisions and outcomes already realized; and
- "direct" or "real" earnings management - the strategic timing of investment, sales, expenditures and financing decisions.

In this paper, we observe an example of "real" earnings management. We present evidence of managers deviating from their normal business practices depending on their firms' fiscal calendars and financial performance. These managers increase the frequency and change the mix of retail-level marketing actions (price discounts, feature advertisements, and aisle displays) to influence the timing of consumers' purchases to manage reported earnings.

In the marketing literature, there are numerous papers studying how price discounts and other marketing actions affect customer buying behavior. Some marketing actions, such as television advertising, have a limited impact on short-term performance, but result in greater brand equity over time. Such actions are similar to research and development expenditures, as the benefits accrue long after the investment is made. In contrast, retail marketing actions such as price discounts, feature advertisements and aisle displays,[4] boost short-term performance while they are run, but bring little or no positive long-term

[4] Commonly referred to as 'sales promotions'

benefits to the brand. In fact, sales promotions often induce customer stockpiling which leads to a drop in sales in the period right after they are run, a phenomenon referred to as the "post-promotion dip" in the marketing literature.

Although marketing can be used tactically in response to changing demand conditions, the vast literature on both accounting and real earnings management suggests they might also be used to manage earnings. A limited amount of prior research has examined how firms reduce marketing expenditures when seeking to boost earnings in the short-term. These studies, however, have focused on reductions in advertising expenditures, which sacrifice value far in the future.[5] In contrast, we provide evidence that managers increase other types of marketing expenditures in order to boost earnings in the short-term, using sales promotions to induce customer stockpiling.[6] Thus, firms are willing to bear an immediate cost to shift income across time periods.

We base our study on a widely used dataset that tracks the retail promotional activities for soup, a relatively durable good that consumers are willing to stockpile,[7] and we add to these data by hand collecting information about the soup manufacturers' financial performance and related analyst forecasts. We begin by showing how promotional activities observed in retail stores relate to soup manufacturers' fiscal calendars and earnings management incentives. We find that soup manufacturers increase the frequency and change the mix of marketing promotions when they need to meet earnings

[5] For example, see Mizik and Jacobson (2007) who find that firms reduce marketing expenditures prior to seasoned public offerings to boost short-term earnings or Cohen, Mashruwala and Zach (2009) who find that managers reduce their advertising spending to achieve the financial reporting goals.
[6] This behavior is consistent with Stein's (1989) myopic behavior model or the "borrowing of earnings" discussed by Degeorge, Patel and Zeckhauser (1999).
[7] See Narasimhan, Neslin and Sen (1996) and Pauwels, Hanssens and Siddarth (2002) for discussion of stockpiling ease.

targets. Specifically, manufacturers that: have just experienced small quarterly earnings decreases (year-on-year) in the prior quarter; report a small increase in year-on-year quarterly earnings for the current quarter; or report earnings that just beat analyst consensus forecasts are more likely to offer products at special prices or run specific promotions (including less attractive unsupported price promotions) towards the end of fiscal periods as they have greater incentive to increase short term earnings.

The willingness of firms to use marketing actions in this manner was evidenced in a recent statement by Douglas R. Conant, President and Chief Executive Officer of Campbell Soup Company during their quarterly earnings conference call "We then managed our marketing plans to manage our [earning][8]" (Campbell Soup Company, 2008).

A unique aspect of our research setting allows us to test who is responsible for the earnings management. While it is very difficult for firms to immediately increase the frequency of display promotions, they can readily reallocate these promotions within their portfolio of brands. We observe that firms switch their promotional slots from smaller revenue brands to larger brands in periods when we predict them to have incentives to manage earnings upwards. Since it is highly unlikely that a brand manager would voluntarily give up promotional support, this change is consistent with the actions being directed, at least in part, by parties higher in the organization than the brand managers.

[8] The word "earning" can be clearly heard at time 33:40 in the audio version of the conference call but has been redacted from the call transcript available at http://seekingalpha.com/article/77913-campbell-soup-f3q08-qtr-end-4-27-08-earnings-call-transcript?page=-1

2. Hypothesis Development

There have been many papers in the accounting and finance literature studying earnings management. Early examples include: Healy (1985) who asserts that accrual policies of managers are related to income-reporting incentives of their bonus contracts; Hayn (1995) who asserts firms whose earnings are expected to fall just below zero engage in earnings manipulations to help them cross the 'red line' for the year; and Burgstahler and Dichev (1997) who more generally find that firms manage earnings opportunistically to meet thresholds.[9]

Healy and Wahlen (1999) report that early research on earnings management mostly considered whether and when earnings management takes place by examining broad measures of earnings management (i.e. measures based on total accruals). They noted several studies of firms managing earnings using specific accruals which fall neatly into the "misreporting" category of earnings management proposed by Degeorge, Patel and Zeckhauser (1999).

More recent work by Graham, Harvey and Rajgopal (2005) provides support for arguments that managers also use "real" earnings management techniques. Not only do they find that the majority of managers surveyed (78%) admit to taking actions that sacrifice long-term value to smooth earnings, but they also find that managers prefer to use real actions over accounting actions to meet earnings benchmarks. In a similar vein,

[9] Durtschi and Easton (2005) suggest that the shapes of the frequency distributions of earnings metrics at zero cannot be used as ipso facto evidence of earnings management and are likely due to the combined effects of deflation, sample selection, and differences in the characteristics of observations to the left of zero from those to the right.

Roychowdhury (2006) asserts that managers select operational activities which deviate from normal business practices to manipulate earnings and meet earnings thresholds.

How might marketing actions be used to boost earnings? Suppose a manager runs a short-term promotion to lift sales volume; if the associated increase in net revenue exceeds the cost of the promotion, short-term profits also rise. This raises the question of why the promotion is not run regularly. In the case of durable goods, at least some of the incremental sales are due to consumer stockpiling, which leads to subsequent reduced sales.[10] Thus, overall profits may actually fall, despite the current period gains.

2.1. The Relation between Financial Performance, the Fiscal Calendar and Promotions

Past literature suggests multiple circumstances in which managers may change behavior when they have incentive to manage earnings upwards.[11] Although price discounting may lead to customer stockpiling, some have proposed that firms reduce prices towards the end of reporting periods to smooth or boost earnings.[12]

Provided that demand is sufficiently elastic to boost short-term earnings (which we show to be the case in section 4.6), managers may use price reductions to boost sales and earnings just prior to the end of the fiscal quarter (year). We therefore propose the following hypothesis:

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[10] See Macé and Neslin (2004) and Van Heerde et al. (2004) for discussion of the post-promotion dip.
[11] See Healy (1985), Jones (1991), Burgstahler and Dichev (1997) and Bushee (1998) for general examples.
[12] See Fudenberg and Tirole (1995), Oyer (1998) and Roychowdhury (2006) .

H1 During the final month of a manufacturer's fiscal quarter (year), special price discounts will occur more frequently and the depth of these discounts will be greater for manufacturers expected to be managing earnings upwards.

Other authors have focused on the strategic reduction of discretionary spending prior to financial reporting deadlines. Graham, Harvey and Rajgopal (2005) find that 80% of survey respondents report they would decrease discretionary spending on R&D, advertising, and maintenance to meet an earnings target. Roychowdhury (2006) finds evidence of firms reducing discretionary spending to avoid losses. Dechow and Sloan (1991), Bushee (1998) and Cheng (2004) draw similar conclusions and show changes in R&D expenditure to be systematically related to reported earnings. Focusing exclusively on advertising and marketing expenditures, Mizik and Jacobson (2007) observe reductions in marketing expenditures at the time of seasoned equity offerings and Cohen, Mashruwala and Zach (2009) find that managers reduce their advertising spending to achieve the financial reporting goals.

We should not conclude from this literature, however, that firms reduce all marketing expenditures prior to financial reporting deadlines. The benefits from different types of expenditures are realized over vastly different time horizons. Television advertising investments build the long-term equity of a brand, but typically have little impact on short-term sales. Therefore, firms may reasonably choose to reduce this type of spending in order to meet short-term goals. In contrast, sales promotions, including price reductions, feature advertisements and aisle display promotions, can have a dramatic and measurable short-term impact on sales. Firms may therefore choose to increase this type of spending in order to meet short-term goals.

In describing the difference between television advertising and sales promotions, Aaker (1991) notes:

> It is tempting to "milk" brand equity by cutting back on brand-building activities, such as [television] advertising, which have little impact on short-term performance. Further, declines in sales are not obvious. In contrast, sales promotions, whether they involve soda pop or automobiles, are effective – they affect sales in an immediate and measurable way. During a week in which a promotion is run, dramatic sales increases are observed for many product classes: 443% for fruit drinks, 194% for frozen dinners, and 122% for laundry detergents.

In spite of these differences, we are unaware of any research that demonstrates how the timing and frequency of sales promotions relate to the fiscal calendar. Given that our research setting is a highly durable good with relatively low storage costs where stockpiling is likely, we propose the following hypothesis:

H2 *During the final month of a manufacturer's fiscal quarter (year), feature and display promotions will occur more frequently for manufacturers expected to be managing earnings upwards*.

We predict that firms and managers have stronger incentive to manage earnings upwards when the firm is seeking to meet or beat the EPS figure from the same quarter in the previous year and when the firm reports (ex-post) earnings that just beat analyst consensus estimates.[13] We base these predictions, in part, on Graham, Harvey and Rajgopal (2005), who find these the two most important earnings benchmarks in their survey, with 85.1% and 73.5% of respondents citing them, respectively.

[13] We thank the anonymous referee for proposing the inclusion of the analyst consensus forecasts.

Evidence confirming the previous two hypotheses would be consistent with the "strategic timing of investment, sales, expenditures and financing decisions" part of Degeorge, Patel and Zeckhauser's (1999) definition of earnings management. However, our research setting also permits estimation of the costs and benefits of promotions being run in different combinations. In line with prior literature, we show that special price promotions are most effective when offered with feature advertisement and aisle display promotions. [14] Not surprisingly, therefore, we observe special price promotions frequently supported by contemporaneous feature and/or display promotions. However, we also observe unsupported (and less effective) price promotions.[15]

Industry experts have told us that display promotions are usually scheduled several months in advance and it is very difficult for firms to increase their frequency at short notice. This means that price promotions planned at short notice are less likely to be supported with display promotions. We therefore test the following hypothesis:

H3 *During the final month of a manufacturer's fiscal quarter (year),* ***unsupported*** *special price discounts will occur more frequently and the depth of these discounts will be greater for manufacturers expected to be managing earnings upwards.*

[14] See Hypotheses H_7 and H_8 in Mela, Gupta and Lehmann (1997) for example.
[15] Approximately ⅔ of special price promotions are supported with a feature advertisement and ⅓ are supported with an aisle display with 15% being unsupported altogether.

2.2. Who is Behind the Earnings Management Behavior?

Our research also sheds light on a question that prior literature has found difficult to answer: *who* within the organization is responsible for the earnings management behavior?

Healy (1985) suggests that it is the managers who select accounting procedures and accruals that have the incentives to maximize the value of their bonus awards and will therefore use their discretion to manage earnings. Oyer (1998) finds results consistent with both upper management *and* salespeople affecting fiscal seasonality. However, he clearly states that his results do not prove that top management is the main cause of the fiscal-year effects, nor does he make a clear distinction between the roles of managers and salespeople.

Oberholzer-Gee and Wulf (2006), using various measures of earnings manipulation including discretionary accounting accruals, show that higher-powered incentives for division managers can lead to greater accounting manipulation than similar changes for CEOs. This work points more towards divisional managers than CEOs being responsible for earnings manipulation.

The question of who is responsible for allocating marketing resources has not been answered in the marketing literature either. As discussed in Blattberg and Neslin (1990), corporate and division objectives serve as the starting point for planning all marketing activities and senior managers are taking a more active role in this area.[16] However, the establishment of a total marketing budget requires negotiation between both brand

[16] Blattberg and Neslin (1990) p.382

managers and senior management.[17] This suggests that national brand managers and other senior executives are responsible for deciding which of the brands within the company are promoted and when these promotions occur, not lower-level managers. This was confirmed during unstructured interviews with representatives of multiple durable goods manufacturers. During these discussions, it became apparent that large promotions generally need explicit C-level executive approval.

In our research setting, we are able to examine differences in promotion activity within each sample firm by considering how promotion behavior differs based upon the importance of a brand to the company and the importance of a product within a brand as measured by their relative revenue contributions. This allows us to test the following hypotheses:

H4 *In the final month of the fiscal year when manufacturers are expected to be managing EPS upwards, prices will be cut more for: a) higher revenue UPC codes within a brand; and b) higher revenue brands within a manufacturer.*

While evidence in favor of these hypotheses may provide interesting information about manager selectivity in price promotion, it is unlikely to answer who in the organization is responsible for these decisions since both the CEO and the brand managers are likely to have incentives to take these pricing actions.

Nevertheless, our data also contain information about the frequency of display promotions. Industry experts have told us that display promotions are usually scheduled several months in advance and it is very difficult for firms to increase their frequency at

[17] Blattberg and Neslin (1990) p.391

short notice. Yet, it is possible for firms to *switch* their display promotions within their own suite of brands. Using a sub-sample of our data which contains only products with multiple UPC codes within each brand and also multiple brands within each manufacturer, we test the following hypotheses:

H5 *In the final month of the fiscal year of manufacturers expected to be managing EPS upwards, display promotions will occur more frequently for: a) higher revenue UPC codes within a brand; and b) higher revenue brands within a manufacturer.*

As with the previous hypotheses, it is difficult to draw conclusions as to responsibility if we simply observe an increase in promotion for the higher revenue UPC codes within brands or brands within manufacturers. However, if we observe promotions switching from lower revenue brands to higher revenue brands, we propose that senior managers are making the decisions. All brand managers would like to increase their display promotions, but only some are allowed to do so while others are forced to reduce theirs.

3. Data and Methodology

The data used in this study were collected between 1985 and 1988 by the ERIM marketing testing service. The data contain the purchase patterns of 2,500 households in Sioux Falls, SD and Springfield, MO. These data have been widely studied in the past and can be downloaded from the University of Chicago Graduate School of Business website.[18]

[18] http://research.chicagogsb.edu/marketing/databases/dominicks/index.aspx.

We chose to base our study on the use of promotions in the soup product category. Prior research by Narasimhan, Neslin and Sen (1996) and Hanssens, Pauwels, and Siddarth (2002) shows that soup is easily stockpiled and is purchased in greater quantities when it is offered at a discount. Therefore, the hypothesized earnings management behavior should be observable here.

For each individual UPC code (product), we expanded the dataset by identifying the product producer and ultimate parent company. We then hand collected information regarding the financial performance of these companies from multiple sources including Thompson Financial, Corporate Websites, Compustat and One Source. When these data were unavailable from public sources, we contacted the companies directly seeking to obtain the information required. We were able to obtain these data regarding 38 different brands (out of the 50 that we can identify in the full dataset) representing 27 distinct manufacturers. Analyst forecasts were obtained from Zacks Investment Research database (adjusted for stock splits) with the consensus estimate calculated as the mean of the last forecast of the fiscal quarter's earnings made by each analyst prior to the beginning of the quarter and not more than one year prior to the end of the quarter.

Table 1 shows summary statistics of our dataset which contains a total of over 233,000 individual item purchases from 36 different stores. From these, we are able to identify the manufacturer for just over 200,000 observations (85.7%) and the fiscal calendar for 197,000 (84.5%). Given the significant market share garnered by Campbell's products in the soup category (>80% in each of our sub-samples), we consider separately the effects of Campbell's products in the data to ensure that the results are not being driven entirely by this dominant player in the marketplace.

For the firms under consideration, the percentage of revenues associated with soup as disclosed in their business segment report contained in the 10-K filing[19] represents an average of 52.5% of sales with a range of 2–100% and a standard deviation of 15.0%.

Due to concerns about lack of independence of observations within the dataset, we use a single randomly selected observation for each product-week-store triplet. This allows us to draw conclusions as to the probability of a promotion activity within a store for a particular product. Collectively, these constraints restrict our sample to a total of 114,870 observations. Within this sample, the probability of a product being offered with some form of promotion is 2.7% overall with the probability of a special price, feature or display being 2.0%, 1.5% and 1.3% respectively.

We recognize that many products are never promoted during their lifecycle. To increase test power, we therefore report additional results based upon a restricted sample of products offered at a special price at some point during the observation period, representing 38,262 observations. Within this sample, the probability of a product being offered with some form of promotion is 7.6% overall with the probability of a special price, feature or display being 5.9%, 4.5% and 3.3% respectively.

For tests of hypotheses *H4* and *H5*, we use a sub-sample of our data which contains multiple UPC codes within each brand and also multiple brands within each manufacturer.

[19] This often incorporates related businesses such as sauces and sometimes beverages.

As shown in figure 1, there is significant calendar seasonality of demand in the products studied here. We therefore control for calendar month fixed effects and seek identification for our regression models from the differences in fiscal calendars of the companies manufacturing the products.[20] This research design is similar to the one used by Oyer (1998) and controls for seasonality of the data. In the event that a random sample of competitors responded contemporaneously in a similar fashion to a promotion, this would bias the coefficients of interest towards zero and against finding results.

Our interpretation of results is based upon the assumption that the supermarket chains are passing through at least some of the discounts/promotions from the manufacturers as opposed to selectively targeting specific months within each manufacturers' fiscal calendars with their promotional activities.

We report t-statistics calculated using standard errors corrected for autocorrelation using the Newey-West procedure for the OLS regressions[21] and Huber-White adjusted standard errors for the logistic regressions allowing for lack of independence between observations for each product. Where quoted, pseudo-R^2 is the McKelvey-Zavonia pseudo-R^2.[22]

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[20] The frequency distribution of fiscal year-ends is shown in figure 2.

[21] Consistent with Stock and Watson (Eqn 13.17), we use a 4 week truncation parameter being estimated as $\frac{3}{4}n^{1/3}$ where n is the number of weeks in the sample. Use of alternative truncation parameters does not change the results materially.

[22] The McKelvey-Zavonia pseudo-R^2 is defined as $\mathrm{var}(\hat{y}_i) / [1+ \mathrm{var}(\hat{y}_i)]$ where $\mathrm{var}(\hat{y}_i)$ is the variance of the forecasts values for the latent dependent variable (Hagle and Mitchell (2001)).

4. Results and Discussion

4.1 Marketing Actions when Incentives to Manage Earnings Relating to Prior Earnings Target and Analyst Earnings Forecasts are Higher

We first examine whether marketing actions are more likely to occur at the fiscal Quarter-end (Year-end) than they are in other months for firms which we expect are more likely to be managing EPS upwards. We examine behavior at the end of the fiscal quarter because prior literature[23] shows a significant post-promotion dip in sales occurs right after a promotion is run. Running promotions early in reporting periods would not be an effective way to manage earnings because some of their effects would reverse before the period closed.

Based on Graham, Harvey and Rajgopal (2005), we predict that firms are more likely to manage earnings upwards to meet or beat the EPS figure from the same quarter in the previous year. We therefore consider how firms behave at the end of periods that immediately follow quarters in which they have reported a small reduction in EPS compared to the previous year. We predict these firms are more likely to experience a small reduction in current period EPS compared to the previous year (absent any Earnings Management) and may need to 'catch up' the shortfall before the end of the fiscal year and therefore have stronger incentive to manage earnings upwards. Graham, Harvey and Rajgopal (2005) also suggest that managers have incentive to beat Consensus Earnings Forecasts. We therefore predict that incentives to boost earnings are stronger for firms which report (ex-post) earnings that just beat analyst consensus estimates.

[23] See Macé and Neslin (2004) for example.

To test hypotheses *H1* and *H2*, we estimate the following logistic regressions for each of the three different marketing actions (special prices, feature advertisements or aisle displays):

$$\Lambda(Action_{ist}) = \alpha + \beta_1 QuarterEnd_{ist} + \beta_2 YearEnd_{ist} + \beta_3 MissedPriorQEPS_{ist} * QuarterEnd_{ist} + \beta_4 MissedPriorQEPS_{ist} * YearEnd_{ist} + \sum_{j=1}^{12} \gamma_j Month_{istj} + \epsilon_{ist}$$

$$\Lambda(Action_{ist}) = \alpha + \beta_1 QuarterEnd_{ist} + \beta_2 JustBeat_{ist} + \beta_3 JustBeat_{ist} * QuarterEnd_{ist} + \sum_{j=1}^{12} \gamma_j Month_{istj} + \epsilon_{ist}$$ [24]

where *Action* is substituted by *Special Price, Feature* or *Display*, three dummy variables which equal one if the sale is associated with a special price, feature or display promotion respectively, zero otherwise. *QuarterEnd* (*YearEnd)* is a dummy variable which equals one if the sale is during the last month of the manufacturer's fiscal quarter (year), zero otherwise. *MissedPriorQEPS* is a dummy variable which equals one if EPS for the previous quarter was 80-100% of the EPS for the same quarter in the previous year, zero otherwise.[25] Within the full (restricted) sample, the mean value of *MissedPriorQEPS* is 5.4% (5.8%).[26] *JustBeat* is a dummy variable which equals one if the manufacturer reports (ex-post) earnings for the quarter are between zero and 10% above the consensus

[24] For completeness, an expanded version of this model containing *YearEnd* and *JustBeat**YearEnd* variables was also estimated. It provides no incremental significant results over the simpler model except that products were generally promoted on display with higher frequency at the fiscal year end such that no incremental year-end effect was noted for firms just beating their 4th quarter earnings forecast.

[25] Robustness tests using the Earnings per Share figures for the nine months prior to the observation provide similar results.

[26] We also compared the behavior of firms with current quarter EPS just above (0-20% above) the same quarter in the previous year with firms with EPS just below (0-20% below) the prior year - See Burghstahler and Dichev (1997) for a further discussion as to why the first category might be expected to have managed earnings to achieve their targets. We therefore estimated the following regression:

$$PriceChange_{ist} = \alpha + \beta_2 YearEnd_{ist} + \beta_5 JustAbove_{ist} * YearEnd_{ist} + \beta_6 JustBelow_{ist} * YearEnd_{ist} + \sum_{j=1}^{12} \gamma_j Month_{istj} + \varepsilon_{ist}$$

Although not reported, results show that β_5 is significantly lower than β_6 in both the full and restricted model settings suggesting that those who report ex-post small increases in EPS reduce prices more than those firms which just miss the targets. We do not report results of tests regarding the frequency of special price, feature and displays promotions for the small-EPS-increase/decrease firms as these results are generally not significant.

analyst forecast at the beginning of the quarter and zero otherwise.[27] Within the full (restricted) sample, the mean value of *JustBeat* is 34.0% (34.8%). Calendar month fixed effects are included to control for seasonality.

If marketing actions occur more frequently at the fiscal quarter-end following quarters of slightly lower EPS (at the fiscal quarter-end in quarters when firms just beat analyst forecasts), the β_3 coefficients will be positive and significantly different from zero. If the promotions occur even more frequently at the fiscal year-end following quarters of slightly lower EPS, then we will also see positive β_4 coefficients which are significantly different from zero.[28]

To consider the part of *H1* which considers the depth of price reductions, we also estimate the following regressions:

$$PriceChange_{ist} = \alpha + \beta_1 QuarterEnd_{ist} + \beta_2 YearEnd_{ist} + \beta_3 MissedPriorQEPS_{ist} * QuarterEnd_{ist} + \beta_4 MissedPriorQEPS_{ist} * YearEnd_{ist} + \sum_{j=1}^{12} \gamma_j Month_{istj} + \epsilon_{ist}$$

$$PriceChange_{ist} = \alpha + \beta_1 QuarterEnd_{ist} + \beta_2 JustBeat_{ist} + \beta_3 JustBeat_{ist} * QuarterEnd_{ist} + \sum_{j=1}^{12} \gamma_j Month_{istj} + \epsilon_{ist}$$

where *PriceChange* equals the percentage change in mean price for the product at the store compared to the previous month.

[27] This definition differs from consensus forecast definitions used in some prior literature due to the nature of our study. For example, Bartov, Givoly and Hayn (2002) consider forecasts up to three days before the earnings announcement. This definition would not work in our setting because managers need time to receive a forecast, make a decision to manage earnings, and then run a marketing action before the period closes. We use the consensus at the beginning of the quarter to ensure that managers have sufficient time to take these 'real actions' following the forecast. Robustness checks using forecasts up to 45 days before the end of the quarter to determine the consensus provide similar results. However, reducing the minimum forecast horizon below 45 days results in coefficients of interest becoming non-significant.

[28] To estimate the difference in probability of promotion between a non fiscal-quarter-ending month with low earnings management incentive and the last month of the fiscal year with high earnings management incentive, readers must aggregate the effects of β_1, β_2, β_3 and β_4.

If prices are reduced at the fiscal quarter-end following quarters of slightly lower EPS (at the fiscal quarter-end in quarters when firms just beat analyst forecasts), the β_3 coefficient will be negative and significantly different from zero. If these reductions are even greater at the fiscal year-end following quarters of slightly lower EPS, then we will also see a negative β_4 coefficient significantly different from zero.[29]

Results are shown in tables 2 and 3. Our data show special prices and feature promotions occur more frequently at the fiscal quarter-end following small decreases in prior quarter EPS as evidenced by the positive and statistically significant β_3 in table 2, columns 1, 2, 5 and 6 and that special prices, feature and display promotions all occur more frequently at the fiscal quarter-end when firms just beat analyst forecasts as evidenced by the positive and statistically significant β_3 in table 3, columns 1, 2, 5, 6, 7 and 8. Given the negative coefficient on β_2 in the analyst consensus specifications, it appears that promotions are being moved to the last month of the fiscal quarter for these firms as opposed to being increased overall.

The probability of a product being offered at a special price triples from 1.8% at a typical quarter-end to 4.6% at a quarter-end following a small decrease in EPS; the probability of a feature promotion increases from 1.4% to 3.6%. Similarly the probability of a product being offered at a special price more than doubles to 3.8% at a quarter-end in which the firm just beats the consensus analyst forecast with the probability of a feature promotion increasing to 2.9% and an aisle promotion increasing from 1.0% to 1.7%. These quarter-

[29] To estimate the difference in price changes between a non fiscal-quarter-ending month with low earnings management incentive and the last month of the fiscal year with high earnings management incentive, readers must aggregate the effects of β_1, β_2, β_3 and β_4.

end levels of promotional activities are approximately the same as typical year-end levels.

Restricting the sample to products offered at a discount at some point during the observation period (presented in table 2, columns 2 and 6) strengthens the power of these tests with the probability of a special price (feature promotion) increasing from 5.3% (3.9%) in regular fiscal quarter-ends to 12.4% (10.3%) at a quarter-end following a small decrease in EPS with similar stronger effects being observed in relation to the analyst forecasts in the restricted sample in table 3, columns 2, 6 and 8.

In contrast, results show no evidence that the frequency of quarter-end display promotions changes following quarters of poor financial performance (β_3 is not statistically significant in table 2, columns 7 and 8). However, as discussed further below, the mix of products offered 'on display' does change. Interviews with representatives of multiple durable goods manufacturers suggest that although quarter-end promotions are widespread, the longer planning horizon required for display promotions is likely to be the reason for limited changes in their frequency in relation to recent financial performance.

Furthermore, we do not observe any significant change in the frequencies of year-end promotions following quarters of poor financial performance compared to a typical year-end (β_3+β_4 not statistically significant in table 2, columns 1, 2, 5, 6, 7 and 8). This suggests that year-end promotions may be so widespread that there is either no benefit or no ability for firms to increase such activities further, even following a period of poor performance. The similarity in magnitude and the relation of signs of the β_2, β_3 and β_4

coefficients suggests that firms increase quarter-end promotion frequencies to regular year-end levels following poor financial performance.

When considering the depth of price reductions at the fiscal year end, and in support of *H1*, table 2, column 3, shows that, above and beyond a fiscal calendar effect, firms which report a small reduction (0-20%) in prior quarter EPS are estimated (on average) to reduce prices by a further 0.9% (β_3+β_4) to 1.5% (β_1+β_2+β_3+β_4) in the final month of the fiscal year. These results represent price changes for an average firm in our sample. If we allocate the year-end price reduction of 1.5% to the 4.6%[30] of firms which are estimated to offer products at special prices, we calculate the magnitude of the overall year-end discount to be approximately 33% compared to an average 17.5% fiscal year-end discount across all products.

When considering depth of price reductions at the fiscal quarter-end, results are not as predicted in that they show firms increasing prices at the fiscal quarter-end following poor performance (when just beating consensus forecasts) (β_3 is positive and significant in table 2 columns 3 and 4 and positive but not significant in table 3, columns 3 and 4). This result is caused by a small number of observations from Campbells' products in a one month period.[31]

Additional tests (not reported) show that the frequency of quarter-end promotions is lowest in the first quarter of the fiscal year. These first quarter frequencies are less

[30] Estimated from the regression in table 2, column 1.
[31] These relate to price increases observed for a limited number of Campbell's condensed soup products (including Cream of Chicken, Cream of Celery and Chicken Noodle) in April 1986 (the last month of Campbell's third quarter). These followed price cuts in the prior month which resulted in high values (>200%) for month on month price increases for April that lead to the positive coefficient on β_3. Re-estimation of the models excluding these observations causes the coefficient to turn negative and significant as predicted consistent with *H1*.

affected by prior quarter financial performance than other quarters. This is consistent with the catch-up motivation being weaker in the first quarter than other periods in the fiscal year.

Overall, in support of our hypotheses *H1* and *H2*, we conclude that the frequency of special price and feature promotions at fiscal quarter-ends following recent poor financial performance increases to levels normally seen only at the fiscal year-end. Furthermore, price cuts are smaller at fiscal quarter-ends but deeper at the fiscal year-end for these products. In contrast, the data show no variation in the frequency of display promotions associated with recent poor financial performance. We suggest this may be due to the longer planning horizon needed for this type of promotional activity. In the next section we explore this further and investigate if firms switch their promotions within their brand portfolio when faced within the constraint of a limited number of display promotions and increased earnings management incentives.

When considering the alternative measure of earnings management incentive linked to analyst forecasts we find strong support for the hypotheses that frequency of special price, feature and display promotions all increase for firms which report ex-post earnings just beating their analyst forecasts.

We conduct several tests to explore the robustness of these results. First, we confirm that the results were not being driven solely by Campbell, a dominant player in the market. Thus, we re-estimate the regressions allowing the effects to differ between Campbell's and other brands (results not shown).[32] With the exception noted above, we conclude that Campbell's products do not drive the results as there is no statistical difference between Campbell's and other brands.

Next, we test our assumption that firms use marketing actions more frequently at the fiscal year-end in order to induce consumer stockpiling. Thus, we conduct a similar analysis on a sample of non-durable products (yogurt) purchased in the same stores during the same period of time. Given that consumers cannot stockpile yogurt due to its lack of durability, we expect to find that marketing actions do not occur with greater frequency at the fiscal year-end in this category. We find that they do not (results not shown).

Finally, we note that Chapman (2010) replicates our results for special price promotions using data from 2005-2006. This implies that the behaviors observed in our sample continue to be important today.[33] Unfortunately, Chapman's data do not contain information on feature and display promotions thus preventing a full replication of our results.

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[32] We estimate the following regression for each promotion activity (and also the price change specification of the same model) excluding observations from Campbell's products $\Lambda(Action_{ist}) = \alpha + \beta_1 QuarterEnd_{ist} + \beta_2 YearEnd_{ist} + \beta_3 MissedPriorQEPS_{ist} * QuarterEnd_{ist} + \beta_4 MissedPriorQEPS_{ist} * YearEnd_{ist} + \sum_{j=1}^{12} \gamma_j Month_{istj} + \epsilon_{ist}$ and, for the full sample, the following model $\Lambda(Action_{ist}) = \alpha + \beta_1 QuarterEnd_{ist} + \beta_2 YearEnd_{ist} + \beta_3 MissedPriorQEPS_{ist} * QuarterEnd_{ist} + \beta_4 MissedPriorQEPS_{ist} * YearEnd_{ist} + \beta_5 Campbell_{ist} + \beta_6 Campbell_{ist} * QuarterEnd_{ist} + \beta_7 Campbell_{ist} * YearEnd_{ist} + \beta_8 Campbell_{ist} * MissedPriorQEPS_{ist} * QuarterEnd_{ist} + \beta_{10} Campbell_{ist} * MissedPriorQEPS_{ist} * YearEnd_{ist} + \sum_{j=1}^{12} \gamma_j Month_{istj} + \epsilon_{ist}$ where *Campbell* is a dummy variable which equals one if the product is manufactured by Campbells Soup and zero otherwise. The coefficients of interest are not materially different from those presented in Table 2.

[33] Brown and Caylor (2005) suggest that, since the mid-1990s, managers seek to avoid negative quarterly earnings surprises more than to avoid either quarterly losses or earnings decreases.

4.2 Changes in Level of Support for Marketing Actions when Incentives to Manage Earnings are Higher

As discussed above, we observe special price promotions frequently supported by contemporaneous feature and/or display promotions. However, we also observe unsupported price promotions. In Section 4.5 below, we show evidence that these unsupported promotions are less effective (weighing the increase in sales against the subsequent decrease in sales) than the supported variety. To test whether the type of promotion changes in relation to a firm's earnings management incentive, we estimate the following regressions for the full and restricted samples including *Feature* and *Display* as additional control variables representing levels of support for special price promotions:

$$\Lambda(SpecialPrice_{ist}) = \alpha + \beta_1 QuarterEnd_{ist} + \beta_2 YearEnd_{ist} + \beta_3 MissedPriorQEPS_{ist} * QuarterEnd_{ist} + \beta_4 MissedPriorQEPS_{ist} * YearEnd_{ist} + \beta_5 Feature_{ist} + \beta_6 Display_{ist} + \sum_{j=1}^{12} \gamma_j Month_{istj} + \epsilon_{ist}$$

where *Special Price, Feature* and *Display* are three dummy variables which equal one if the sale is associated with a special price, feature or display promotion respectively, zero otherwise. *QuarterEnd* (*YearEnd)* is a dummy variable which equals one if the sale is during the last month of the manufacturer's fiscal quarter (year), zero otherwise. *MissedPriorQEPS* is a dummy variable which equals one if EPS for the previous quarter was 80-100% of the EPS for the same quarter in the previous year, zero otherwise. Calendar month fixed effects are included to control for seasonality.

Results are shown in table 4. Our data show that when controlling for the presence of feature and display promotions, there is no difference in the frequency of special price promotions at a regular fiscal quarter- or year-end compared to other months. However, the frequency of *unsupported* special price promotions (those without feature or display promotion support) increases at the fiscal quarter-end (but not at the fiscal year-end) when firms have incentive to increase earnings (β_3 is positive and significantly different from zero but $\beta_3 + \beta_4$ is not significantly different from zero in table 4).

This indicates that regular year-end promotions are generally *supported* and that the majority of the increase in quarter-end special price promotion associated with an increase in earnings management incentive is explained by an increase in the number of *unsupported* special price promotions.

4.3 Clearing Inventory

One potential alternative explanation for the findings relating to the increase in promotion activity and reductions in prices following poor performance is that firms respond to excess inventory levels rather than to manage earnings.[34] Inventory levels are likely to be correlated to historic performance, giving rise to a correlated omitted variable problem.

We therefore repeat the tests incorporating a firm-level proxy for the incentive to manage excess inventory as an additional control variable defined as the change in inventory days over the 12 months ending at the beginning of the quarter under observation.

$$InventoryChange_t = \left(\frac{Inventory_{t-1}}{Sales_{t-1}} - \frac{Inventory_{t-5}}{Sales_{t-5}}\right) \Big/ \frac{Inventory_{t-5}}{Sales_{t-5}}$$

[34] We thank Ross Watts and also seminar participants at the Harvard Business School for pointing out this possibility.

If promotion levels increase (prices are reduced) in quarters following upward spikes in inventory, we should observe a positive (negative) coefficient on this variable in the promotion frequency (price change) regressions.

Selected results of these analyses are shown in table 5. When considering the relevance of the inventory levels, table 5, column 1, shows that an increase in inventory of approximately 35% over the previous 12 months is associated with an increase in frequency of special prices of a similar magnitude to a level equivalent to a quarter-end following recent poor performance. Table 5, columns 2 and 3, shows no significant relationship between changes in inventory levels and price changes or frequency of feature promotions. Table 5, column 4, shows that an increase in inventory of approximately 35% is associated with an increase of 2% in the frequency of display promotion activity. Given the lack of any significant relation between recent financial performance and the frequency of display promotions, this result is more likely to be associated with inventory build-up ahead of promotion activity as opposed to promotion activity being the result of increased inventory.

All significant coefficients of interest from the prior tests shown in table 2 remain significant in table 5 at the 5% significance level with the exception of the likelihood of a quarter-end feature promotion following recent poor financial performance where the significance drops to the 10% level as shown in table 5, column 3. Overall, this suggests that although increases in inventory may be related to the level of promotional activities, the main results of this paper are robust to controls for changes in inventory.

4.4 Who is Behind the Earnings Management Behavior?

To ascertain who is responsible for the Earnings Management Behavior, we first test the two parts of hypothesis *H4*. Initially we check the results of the following two regressions:

$$PriceChange_{ist} = \alpha + \beta_1 YearEnd_{ist} + \beta_2 HiRevUB_{ist} + \beta_3 HiRevUB_{ist} * YearEnd_{ist} + \sum_4^{14} \beta_j \, Month_{istj} + \varepsilon_{ist}$$

$$PriceChange_{ist} = \alpha + \beta_1 YearEnd_{ist} + \beta_2 HiRevBM_{ist} + \beta_3 HiRevBM_{ist} * YearEnd_{ist} + \sum_{j=4}^{14} \beta_j \, Month_{istj} + \varepsilon_{ist}$$

where *HiRevUB* is a dummy variable which equals one if the UPC is one of the higher revenue UPC codes within the brand and *HiRevBM* is a dummy variable which equals one if the brand is one of the higher revenue brands within the manufacturer. If the coefficients on the interaction terms (β_3 *and* β_5) are negative and significantly different from zero, we can conclude that the year-end price reductions are focused on: a) the higher revenue UPC codes within each brand (First Regression) and; b) the higher revenue brands within each manufacturer (Second Regression).

The results of these regressions are shown in table 6. The significance of the interaction terms in table 6, columns 1 and 2 indicate that the year-end price reductions are 0.4% deeper for the higher revenue UPCs within each brand compared to the lower revenue UPCs within each brand (β_3 = -0.400 in table 6, column 1) and also 1.7% deeper for the higher revenue generating brands within each manufacturer (β_5 =-1.667 in table 6, column 2).

Further considering the year-end price reduction estimated in tests of *H1* above, we proceed to consider both within- and across-brand differences for firms with higher incentive to manage earnings upwards. We therefore estimate the following regressions:

$$PriceChange_{ist} = \alpha + \beta_1 YearEnd_{ist} + \beta_2 HiRevUB_{ist} + \beta_3 HiRevUB_{ist} * YearEnd_{ist} + \beta_6 Category_{ist} + \beta_7 YearEnd_{ist} * Category_{ist} + \beta_8 HiRevUB_{ist} * YearEnd_{ist} * Category_{ist} + \sum_{j=1}^{12} \gamma_j \, Month_{istj} + \varepsilon_{ist}$$

And

$$PriceChange_{ist} = \alpha + \beta_1 YearEnd_{ist} + \beta_4 HiRevBM_{ist} + \beta_5 HiRevBM_{ist} * YearEnd_{ist} + \beta_6 Category_{ist} + \beta_7 YearEnd_{ist} * Category_{ist} + \beta_9 HiRevBM_{ist} * YearEnd_{ist} * Category_{ist} + \sum_{j=1}^{12} \gamma_j \, Month_{istj} + \varepsilon_{ist}$$

The results of these regressions are shown in table 6, columns 3 and 4. Beginning with the distinction between lower and higher revenue UPCs, the sign and significance of β_7 in table 6, column 3 indicate that year-end prices are reduced by an average of 1.1% for the lower revenue UPC codes within brands and β_8 implies that year-end prices are reduced by an additional 1.6% for the higher revenue UPC codes within brands following a small decrease in quarterly EPS. Conversely, we cannot draw distinction between lower and higher revenue brands within a manufacture's suite because β_7 and β_9 in table 6, column 4 are both insignificant.

Overall, consistent with Hypothesis *H4*, part a, we find that price cuts are deeper for the higher revenue UPCs within a brand when manufacturers have incentives to manage earnings upwards. These results show that firms predictably alter their product line pricing when they have incentives to manage earnings upwards, but they do not suggest who is responsible for the price cuts. Two scenarios are possible because physical constraints on the depth of price cuts do not exist:

- Each brand manager might be acting independently by cutting prices on the higher revenue UPCs within their brand; or
- a higher level manager could be instructing every brand manager to act this way.

The same is not true for display promotions. As previously discussed, display promotions do not occur more frequently, as special prices and feature promotions do, following recent quarters of poor financial performance. Although limited shelf space may prevent manufacturers from adding additional aisle displays on short notice, it is still possible for firms to switch the products within their suite to be offered on display.

To investigate the prevalence of promotion switching behavior within each brand and within each company, we estimate the following logistic regressions.

$$\Lambda\left(Display_{ist}\right) = \alpha + \sum_{j=1}^{12}\gamma_j Month_{istj} + \beta_1 YearEnd_{ist} + \beta_2 HighRevUPC_{ist} + \beta_3 HighRevUPC_{ist} * YearEnd_{ist} + \varepsilon_{ist}$$

$$\Lambda\left(Display_{ist}\right) = \alpha + \sum_{j=1}^{12}\gamma_j Month_{istj} + \beta_1 YearEnd_{ist} + \beta_4 HighRevBM_{ist} + \beta_5 HighRevBM_{ist} * YearEnd_{ist} + \varepsilon_{ist}$$

$$\Lambda\left(Display_{ist}\right) = \alpha + \sum_{j=1}^{12}\gamma_j Month_{istj} + \beta_1 YearEnd_{ist} + \beta_2 HighRevUPC_{ist} + \beta_3 HighRevUPC_{ist} * YearEnd_{ist} +$$
$$\beta_6 MissedPriorQEPS_{ist} + \beta_7 MissedPriorQEPS * YearEnd_{ist} + \beta_8 HighRevUPC * MissedPriorQEPS * YearEnd_{ist} + \varepsilon_{ist}$$

$$\Lambda\left(Display_{ist}\right) = \alpha + \sum_{j=1}^{12}\gamma_j Month_{istj} + \beta_1 YearEnd_{ist} + \beta_4 HighRevBM_{ist} + \beta_5 HighRevBM_{ist} * YearEnd_{ist}$$
$$+\beta_6 MissedPriorQEPS_{ist} + \beta_7 MissedPriorQEPS * YearEnd_{ist} + \beta_9 HighRevBM * MissedPriorQEPS * YearEnd_{ist} + \varepsilon_{ist}$$

The results of the regressions are presented in table 7 and the magnitude of the effects can be seen graphically in figure 3.

We observe that display promotions occur more frequently:

- for higher revenue UPC codes within each brand. β_2, the coefficient on *HighRevUPC* is positive and significantly different from zero in table 7, columns 1 & 3. Display promotions occur almost three times more frequently for the higher revenue UPC codes within each brand compared to the lower revenue UPC codes within each brand at times other than the year-end;

- for lower revenue brands with no earnings management incentive within each manufacturer. β_4 is negative and significantly different from zero in table 7, columns 2 and 4. Display promotions almost never occur for the higher revenue brands within each manufacturer in non-year-ending months, but occur with a 1% frequency for lower revenue brands during these periods.

The β_3 and β_5 coefficients are insignificant in all four regressions and shows no evidence of any change in the frequency of aisle displays for higher revenue UPCs within the brand or for higher revenue brands within the manufacturer at a typical fiscal year-end.[35] However, our data imply that firms do switch which products are offered on display from the lower to the higher revenue brands in their suite. (β_7 is negative, β_9 is positive, and both are significant in table 7, column 4.) The probability of being offered on display falls to 2.5% for lower revenue brands and rises to 3.3% for higher revenue brands. The pattern of switching behavior can be seen graphically in figures 3.3 and 3.4, where figure 3.3 represents the firms' actions in at a typical year-end and figure 3.4 represents their actions at year-ends in which they have incentive to manage earnings upwards.

Overall, these results suggest that firms systematically alter the products which are promoted when the firm has incentive to manage earnings upwards and that managers senior to brand managers are making these decisions. Prices on the higher revenue UPCs within every brand fall when firms have incentives to manage earnings upwards. While

[35] Lack of significance on β_3 and β_4, the *MissedPriorQ.EPS * Q.End* and *MissedPriorQ.EPS * YearEnd* variables, in table 2, columns 9 and 10.

consistent with our earnings management hypothesis, this does not help us determine who is making the decision; every brand manager could be making these decisions independently or a senior manager could be directing them to do it. Nevertheless, we also find that firms switch display promotions from smaller to larger brands in their suite. This suggests that individuals senior to brand managers are making the decisions because individual brand managers would not volunteer to give up aisle displays for their brands.

Additional support to the argument that the promotions are motivated by the earnings management incentives and not by store level or regional managers is provided by additional analysis of the frequency of promotion (Special Prices, Feature and Display) in the Springfield[36] stores. This analysis shows that the probability of each type of promotion, by product, is significantly correlated to the contemporaneous frequency of the same type of promotion in the Sioux Falls market.[37] Nevertheless, we cannot completely rule out the idea that lower-level managers are also taking actions to manage earnings because we do not fully observe their behaviors or motivations in our data. We must therefore leave this question for future study.

4.5 Short-Run Gains vs. Income Shifting

We now turn to the question of whether taking these marketing actions result in short-term gains at the expense of long-term firm value. The answer to this question hinges on how consumers change their buying behavior over time. Past research has shown that consumers are willing to shift the timing of purchases in order to take advantage of price

[36] Similar results are found if we consider the Sioux Falls market

[37] Results not reported. Furthermore, this relationship is dominated by earnings management incentives. In a multivariate regression the coefficient on contemporaneous promotion in the Sioux Falls market becomes insignificant when proxies for earnings management incentives are included.

discounts for durable consumer packaged goods.[38] Consumers both delay purchases in anticipation of future price discounts, which leads to pre-discount dips in sales, and stockpile goods when discounts are offered, which leads to post-discount dips.

This strategic buying behavior can have a considerable impact on when sales occur. Averaged across multiple product categories, Van Heerde et al (2004) and Macé and Neslin (2004) estimate that approximately one-third of the growth in sales during a discount period can be attributed to consumers shifting the timing of purchases, with estimates ranging from 19% to 64%.

To establish how consumers in our sample shift the timing of purchases in response to price changes over time, we estimate the following regressions:

$$Ln\left(WeeklyUnitsSold_{ist}\right) = \alpha + \beta_1 Ln\left(\frac{Price_{is,t-1}}{MaxPrice_{is}}\right) + \beta_2 Ln\left(\frac{Price_{ist}}{MaxPrice_{is}}\right) + \beta_3 Ln\left(\frac{Price_{is,t+1}}{MaxPrice_{is}}\right) + \beta_4 Display_{ist} + \beta_6 Feature_{ist} + \sum_{j=1}^{12}\gamma_j Month_{istj} + \sum_i \delta_i UPC_i + \varepsilon_{ist}$$

$$Ln\left(WeeklyUnitsSold_{ist}\right) = \alpha + \beta_1 Ln\left(\frac{Price_{is,t-1}}{MaxPrice_{is}}\right) + \beta_2 Ln\left(\frac{Price_{ist}}{MaxPrice_{is}}\right) + \beta_3 Ln\left(\frac{Price_{is,t+1}}{MaxPrice_{is}}\right) + \beta_4 Display_{ist} + \beta_5 Display_{ist} * Ln\left(\frac{Price_{ist}}{MaxPrice_{is}}\right) + \beta_6 Feature_{ist} + \beta_7 Feature_{ist} * Ln\left(\frac{Price_{ist}}{MaxPrice_{is}}\right) + \sum_{j=1}^{12}\gamma_j Month_{istj} + \sum_i \delta_i UPC_i + \varepsilon_{ist}$$

where *Weekly Units Sold* is defined as the weekly number of units of product sold at a store, UPC_i are dummy variables for each UPC Code, $Price_{t-1}$ is the average price of the product in the store during month t-1, $Price_t$ is the average price of the product being sold in the store during month t, $Price_{t+1}$ is the average price of the product in the store during

[38] See Gupta (1988), van Heerde et al. (2000), van Heerde et al. (2004), and Macé and Neslin (2004).

month t+1, *MaxPrice* is the maximum price at which the product is sold in the store over the sample period.

Results are reported in table 8. The more general model, reported in table 8, column 2, allows for interactions between the marketing promotions and current prices. Here, the positive and significant coefficients in both regressions on β_1 and β_3 (the pre and post-prices) together with the negative coefficient on β_2 (current price) allow us to conclude that consumers both delay buying soup in anticipation of price discounts and also stockpile soup when it is offered on discounts. While current period sales are significantly higher when price discounts are offered, roughly one third of these sales are stolen from surrounding periods.

We estimate that for an *unsupported* 20% price discount, resulting sales volumes increase by 101% during the discount period, sales volumes decline by 27% in the period immediately before such a price discount because consumers delay purchases. Furthermore, sales volumes decline by 9% in the period immediately after a price discount because consumers have stockpiled goods. In contrast, for a 20% price discount supported with an aisle display promotion, we observe sales volumes increasing by over 300% during the promotion period.[39]

This pattern and the magnitude of the effect is consistent with prior research (Macé and Neslin, 2004; Van Heerde et al, 2004) and is clearly observable in figure 4 with sales volumes more than doubling in response to the price discount. Note that revenues do not spike quite as high as sales volumes because products are being sold at lower prices.

[39] Given the model specification, we do not attempt to model the pre-post promotion dip associated with the supporting aisle display promotion separately.

Using data on firms within the soup industry to estimate the contribution margin,[40] we conclude that such a short term boost in revenues may also boost quarterly net income. However, consistent with Stein's (1989) model of myopic behavior, there is a price to pay which is higher than the short-term boost in earnings at least for the unsupported promotion.

The impact of a temporary price cut on profits depends on a number of factors including the product's price elasticity of demand and the firm's cost structure. To assess these, consider the following example: Given a three week period of constant prices p, contribution is given by $3(p-c).v$ where c is the marginal cost and v is the sales volume assuming all prices equal p. If prices are reduced to $\underline{p}$ in the middle week, the total contribution over the three weeks is given by $(p-c).v|_{p_{t+1}=\underline{p}} + (\underline{p}-c).v|_{p_t=\underline{p}} + (p-c).v|_{p_{t-1}=\underline{p}}$.[41]

If price reductions are sufficient to boost short-term earnings through the end of a promotion, there will be a net increase in contribution before and during the price-cut evidenced by $(p-c).v|_{p_{t+1}=\underline{p}} + (\underline{p}-c).v|_{p_t=\underline{p}} > 2(p-c).v$. If earnings are reduced overall, then any increased contribution before and during a price cut will be offset by the lost sales resulting from the lag effects after the promotion relating to earlier prices. Therefore: $(p-c).v|_{p_{t+1}=\underline{p}} + (\underline{p}-c).v|_{p_t=\underline{p}} + (p-c).v|_{p_{t-1}=\underline{p}} < 3(p-c).v$. Using the marginal cost assumption

[40] An analysis of the financial statements of sample firms shows the mean Cost of Sales to Sales ratio is approximately 60% with raw materials estimated by one of the firms in the sample to be approximately 30% of Sales. We assume that the true variable part of Costs is therefore somewhere between these two and make our estimate of the effects based upon an assumption that variable costs are 40% of regular prices with fixed costs estimated to be 45% of regular prices at normal volumes. Effects on short-term profits can be boosted further if variable costs are lower and continue to be positive provided that variable costs are less than 45% of sales.

[41] The first component allows for anticipation of the price cut, the second component incorporates the effect of price changes when they occur and the third allows for demand changes in the period following reversion to 'normal' price.

mentioned above,[42] the regression model estimates presented in the previous section imply that a one week, one-third off price reduction would result in an increase in quarterly revenues of approximately 11% and quarterly EPS of 5.5% through the end of the promotion. Different effects on EPS may be achieved by discounting prices further depending on the operating and financial leverage of the firm. However, the presence of the post-promotion dip associated with the lag effects after of earlier prices means that the one-week one-third off price promotion will be costly overall. In this case, the overall effect of boosting this quarter's figures equates to a cost in the following period of approximately 7.5% of quarterly net income suggesting that unsupported promotions will, on average, be costly overall to the firm. In contrast, using the increases in sales volumes associated with supported promotions, it is feasible that the boost in earnings for *supported* promotions exceeds the cost of running the support.

Before concluding that the promotions observed in our data are negative overall to the promoting firms, however, we must also consider the possibility of long-term benefits in terms of customer retention and/or buying patterns.[43] In this regard, the overwhelming evidence presented in prior Marketing literature is clear; at best, sales promotions have no long-term positive impact either on consumer behavior or on sales;[44] at worst, sales promotions lead to some negative long-term consequences.[45] Such longer term effects might be considered comparable to the sacrifice of future profits associated with earnings management related reductions in research and development expenditure.

[42] Variable costs are assumed to be 40% of regular prices with fixed costs estimated to be 45% of regular prices at normal volumes. Higher variable cost assumptions result in lower estimates of increased earnings associated with price cuts and greater cost of promotion overall.
[43] We thank the anonymous referee for raising this possibility.
[44] See Pauwels, Hanssens and Siddarth (2002)
[45] See Mela, Gupta and Lehman (1997), Mela, Jedidi and Bowman (1998), Jedidi, Mela and Gupta (1999) or Kopalle, Mela and Marsh (1999) for examples.

In particular, Mela, Gupta and Lehmann (1997) find that when compared to the "good" effects of advertising, promotions have significantly larger "bad" effects on consumers' price and promotion sensitivities. They show that price promotions make both loyal and non-loyal consumers more price-sensitive and train consumers to look for deals in the marketplace. Similarly, Mela, Jedidi and Bowman (1998) show that promotions teach consumers to "lie in wait" for especially good deals so that they can stockpile goods. Finally, Kopalle, Mela and Marsh (1999) show that promotions can lead to a "triple jeopardy" in which: (1) baseline sales decrease as discounts become more endemic, (2) consumers become more price sensitive, making it more difficult to command higher margins, and (3) deals become a less effective tool for "stealing" sales from competing brands when they are frequently used.

These consensus results raise the question as to why firms may permit managers to run value-destroying promotions. Several hypotheses are possible. It may be beneficial in the short-run given the asymmetric response of stock prices to earnings which just beat or missed certain earnings targets. Current shareholders may seek to increase current value at the expense of future generations of shareholders.[46] Alternatively, as discussed by Arya, Glover and Sunder (1998), it may not be cost-effective to prevent or fully understand the real earnings management behavior.

Overall, this evidence permits us to conclude the effects of increased promotions in our sample, especially the unsupported ones, have a negative effect on the firms concerned.

[46] See Skinner and Sloan (2002) or Brown and Caylor (2005) for further discussion of the asymmetry or Dye (1988) for a discussion of a model of overlapping generations.

5. Conclusion

We have shown that the timing of marketing actions (price, feature and display promotions) observed at the retail level is closely related to the fiscal calendar of product manufacturers. In contrast to prior literature that suggests firms reduce discretionary expenditures in order to boost reported earnings, we show that soup manufacturers roughly double the frequency of all marketing promotions at the fiscal year-end and when earnings management incentives are stronger. Further, this increase is focused more heavily on less attractive, unsupported price promotions.

Our results imply that an important distinction needs to be made among different types of marketing expenditures. Television advertising, which has been the focus of prior work, produces long-run effects. We might expect firms to reduce this type of discretionary expense prior to reporting deadlines because much of its benefit would be realized after the deadline has passed; prior literature shows this does happen.[47] Conversely, price, feature and display promotions, which are the focus of our study, produce short-run effects. Firms might be expected to invest more in these types of actions prior to reporting deadlines, and we show that this also does happen.

Our study also provides observational evidence in support of previous survey work that suggests managers are willing to sacrifice long-term value in order to smooth earnings and prefer to use real actions over accounting actions to meet earnings benchmarks (Graham, Harvey and Rajgopal, 2005). We estimate that soup manufacturers use price reductions to legally boost sales revenues and quarterly earnings by almost 5% at the

[47] See for example Mizik and Jacobson, (2007).

fiscal year-end. Nevertheless, there is a price to pay, as we estimate that quarterly EPS falls by almost 7.5% in the subsequent reporting period, resulting in a net loss of 2.5% of quarterly EPS to the manufacturer.

Finally, we show that firms systematically alter their pricing and promotion strategies both within and across brands when incentive to manage earnings upwards are stronger. Within brands, we show that firms make deeper price reductions for higher revenue UPCs following periods of poor financial performance. More interestingly, across brands we find that firms shift display promotions away from smaller revenue brands and towards larger ones following periods of poor financial performance. This is consistent with the actions being directed, at least in part, by parties higher in the organization than the brand managers, as no individual brand manager would voluntarily give up aisle displays in support for his or her brand. Together, these results imply that firms make systematic decisions across their product lines to manage earnings.

Our results will be of interest to practitioners negotiating with suppliers as well as those responsible for setting price and promotion strategy in response to competitor actions; we show that a firm's internal desire to meet or beat earnings benchmarks can help determine when it will take marketing actions. The final results relating to the level of those responsible for the actions may also be of interest to those designing incentive-based compensation as well as regulators monitoring reporting of fiscal period-ending promotion.

Variable Definitions

Display is a dummy variable which equals one if there is any display promotion for the product within the store at the time of the sale, zero otherwise.

Feature is a dummy variable which equals one if the sale is associated with a feature promotion, zero otherwise.

HiRevBM or *HighRevBrand/Manu* is a dummy variable which equals one if the brand is one of the larger revenue generating brands within the owning group.

HiRevUB or *HighRevUPC/Brand* is a dummy variable which equals one if the UPC is one of the larger revenue generating UPC codes within the Brand.

Inventory Change is the change in firm level inventory over the previous 12 months $\left(\frac{Inventory_{t-1}}{Sales_{t-1}} - \frac{Inventory_{t-5}}{Sales_{t-5}}\right) \Big/ \frac{Inventory_{t-5}}{Sales_{t-5}}$

JustAbove is a dummy variable which equals one if EPS for the current quarter is 100-120% of the EPS for the same quarter in the previous year, zero otherwise.

JustBeat is a dummy variable which equals one if the manufacturer reports (ex-post) earnings for the quarter which are between zero and 10% above the mean analyst forecast at the beginning of the quarter and zero otherwise

JustBelow is a dummy variable which equals one if EPS for the current quarter is 80-100% of the EPS for the same quarter in the previous year, zero otherwise.

MaxPrice is the maximum price at which the product is sold in the store over the sample period.

MissedPriorQEPS is a dummy variable which equals one if EPS for the previous quarter was 80-100% of the EPS for the same quarter in the previous year, zero otherwise.

$Price_t$ is the average price of the product being sold in the store during month t.

Price Change is the mean price change (in %) for the product over the previous month.

QuarterEnd is a dummy variable which equals one if the sale is during the last month of the manufacturer's fiscal quarter, zero otherwise.

Special Price is a dummy variable which equals one if the sale is associated with a special price, zero otherwise.

Weekly Units Sold is defined as the number of units of product sold at a store in a week

YearEnd is a dummy variable which equals one if the sale is during the last month of the manufacturer's fiscal year, zero otherwise.

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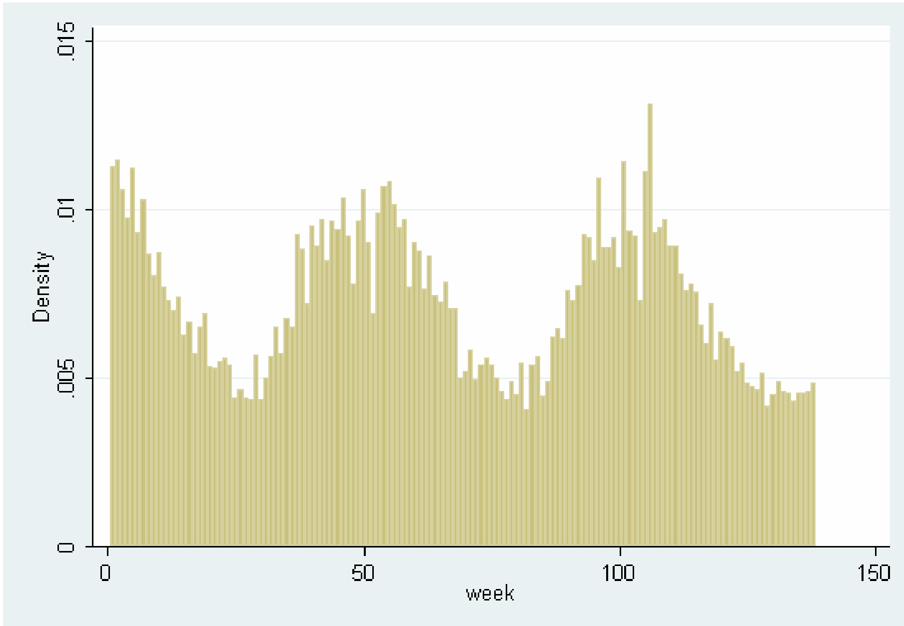
Figure 1: Sales Frequency by Week in the Sample.



Week one is the beginning of the calendar year.

Figure 2: Fiscal Year-End Frequency Distribution for Companies in Sample

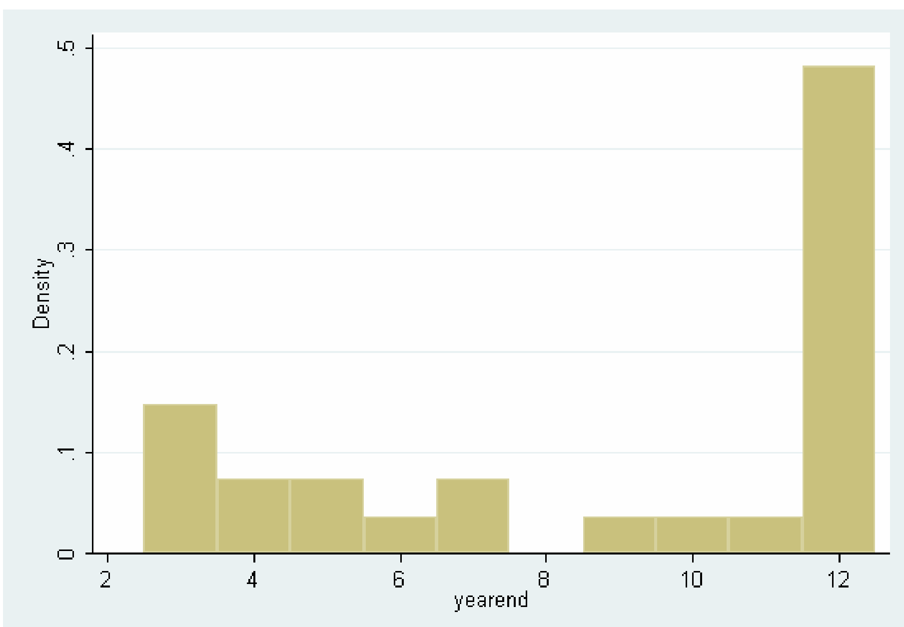


Figure 3: Frequency of Display Promotions around the Year-end

Figure 3.1

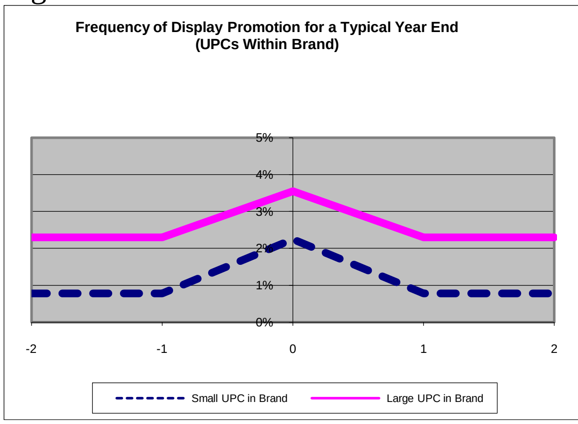


Figure 3.2

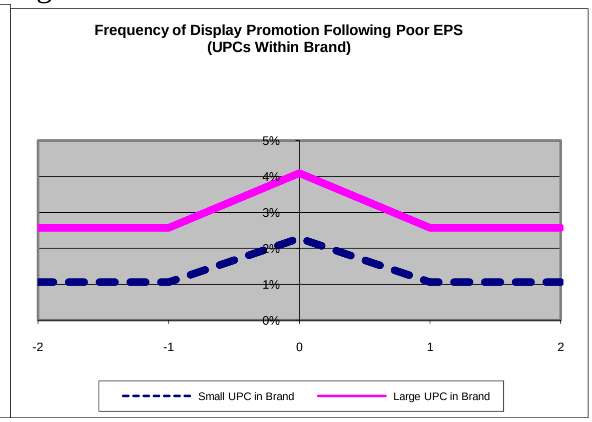


Figure 3.3

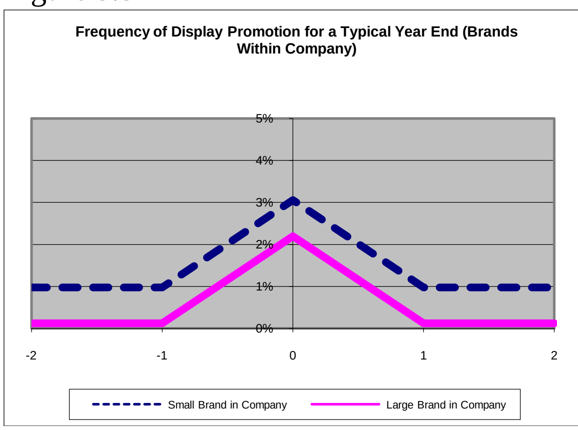


Figure 3.4

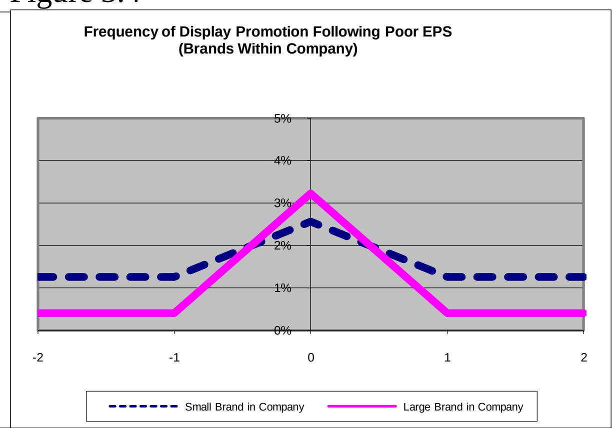


Figure 4: The Effect of a 20% Price Reduction on Volume and Revenues

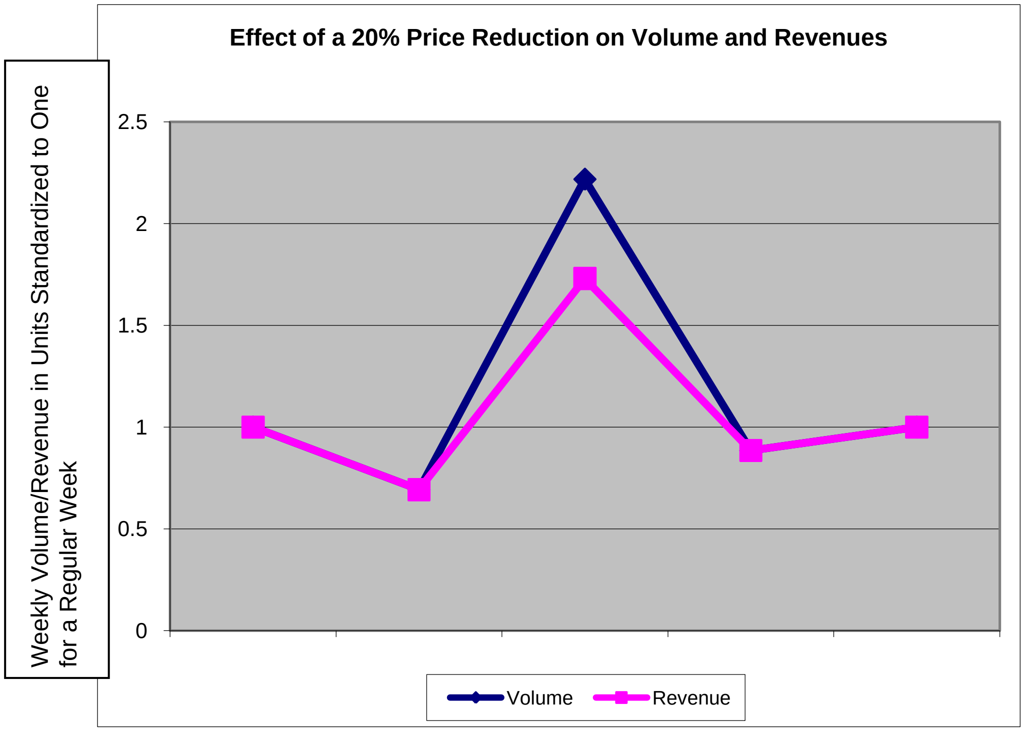


Table 1: Summary Statistics

Number of Individual Purchases Contained in Database	33,820	
Number for which Manufacturer is Known	200,491	
Number for which Fiscal Year-end is Known	197,564	
Distinct store/UPC/week triplets	114,870	
With multiple UPC/Brand (and historic prices)	104,750	(70,876) (Table 5)
With multiple Brand/Manufacturer (and historic prices)	109,348	(68,687) (Table 5)

	Distinct Store/UPC/ Week		Sometimes Discounted Distinct Store/UPC/ Week		With Historic Price Data		Sometimes Discounted With Historic Prices	
Campbells Products	96,297	83.8%	32,534	85.0%	62,438	88.1%	24,552	85.0%
Other	18,573	16.2%	5,728	15.0%	8,470	11.9%	4,316	15.0%
Total Observations	114,870		38,262		70,898		28,868	
# of Special Prices	2,243	2.0%	2,243	5.9%	1,524	2.2%	1,524	5.3%
# of Feature Promotions	1,773	1.5%	1,739	4.5%	1,172	1.7%	1,155	4.0%
# of Display Promotions	1,469	1.3%	1,260	3.3%	982	1.4%	874	3.0%
# With at least 1 promotion	3,157	2.7%	2,914	7.6%	2,172	3.1%	2,048	7.1%
# Unique UPC Codes	433		159		344		141	
# Unique Stores	36		35		36		35	
# Unique Brands	38		16		31		14	
# Unique Manufacturers	27		14		22		12	

Table 2: The Relation of Promotional Activity to EPS Growth

Dependent Variable	*Special Price*		*Price Change*	
Regression Type	Logit		OLS (Newey)	
Column #	1	2	3	4
Sample	Full	Restricted	Full	Restricted
QuarterEnd β_1	-0.017	-0.035	-0.631	-1.153
	(-0.11)	(-0.19)	(-3.65)**	(-3.33)**
YearEnd β_2	0.909	1.067	0.054	-0.509
	(1.72)$^{+}$	(3.33)**	(0.20)	(-0.90)
*MissedPriorQEPS*Q.End* β_3	1.028	0.980	1.093	1.190
	(3.04)**	(3.12)**	(4.85)**	(2.44)*
*MissedPriorQEPS*YearEnd* β_4[48]	-0.946	-0.826	-1.988	-2.551
	(-1.56)	(-1.44)	(-6.38)**	(-3.86)**
Constant	-3.890	-2.640	1.744	2.973
	(-24.92)**	(-14.12)**	(6.93)**	(15.25)**
Monthly Fixed Effects	Yes	Yes	Yes	Yes
N	114,870	38,262	70,898	28,868
Pseudo-R^2 (Adj-R^2 if OLS)	0.063	0.077	0.012	0.016

Dependent Variable	*Feature*		*Display*	
Regression Type	Logit		Logit	
Column #	5	6	7	8
Sample	Full	Restricted	Full	Restricted
QuarterEnd β_1	0.006	-0.041	-0.115	-0.195
	(0.03)	(-0.16)	(-0.37)	(-0.74)
YearEnd β_2	0.840	1.047	1.278	1.294
	(1.62)	(3.33)**	(1.73)$^{+}$	(2.15)*
*MissedPriorQEPS*Q.End* β_3	1.019	1.071	0.271	0.313
	(2.19)*	(2.43)*	(0.75)	(0.97)
*MissedPriorQEPS*YearEnd* β_4	-0.868	-0.886	-0.341	-0.193
	(-1.09)	(-1.18)	(-0.65)	(-0.38)
Constant	-4.017	-2.760	-4.054	-2.948
	(-21.09)**	(-12.17)**	(-12.59)**	(-11.94)**
Monthly Fixed Effects	Yes	Yes	Yes	Yes
N	114,870	38,262	114,870	38,262
Pseudo-R^2 (Adj-R^2 if OLS)	0.065	0.082	0.147	0.177

$^{+, *, **}$ Significant at the 10%, 5%, 1% level (two tail)

$$\Lambda\left(Action_{ist}\right) = \alpha + \beta_1 QuarterEnd_{ist} + \beta_2 YearEnd_{ist} + \beta_3 MissedPriorQEPS * QuarterEnd_{ist} + \beta_4 MissedPriorQEPS_{ist} * YearEnd_{ist} + \sum_{j=1}^{12} \gamma_j Month_{istj} + \varepsilon_{ist}$$

$$PriceChange_{ist} = \alpha + \beta_1 QuarterEnd_{ist} + \beta_2 YearEnd_{ist} + \beta_3 MissedPriorQEPS * QuarterEnd_{ist} + \beta_4 MissedPriorQEPS_{ist} * YearEnd_{ist} + \sum_{j=1}^{12} \gamma_j Month_{istj} + \varepsilon_{ist}$$

Display is a dummy variable which equals one if there is any display promotion for the product within the

[48] To estimate the difference in probability of promotion between a non fiscal-quarter-ending month with low earnings management incentive and the last month of the fiscal year with high earnings management incentive, readers must aggregate the effects of β_1, β_2, β_3 and β_4.

store at the time of the sale, zero otherwise. *Feature* is a dummy variable which equals one if the sale is associated with a feature promotion, zero otherwise. *MissedPriorQEPS* is a dummy variable which equals one if EPS for the previous quarter was 80-100% of the EPS for the same quarter in the previous year, zero otherwise. *Price Change* is the mean price change (in %) for the product over the previous month. *QuarterEnd* is a dummy variable which equals one if the sale is during the last month of the manufacturer's fiscal quarter, zero otherwise. *Special Price* is a dummy variable which equals one if the sale is associated with a special price, zero otherwise. *YearEnd* is a dummy variable which equals one if the sale is during the last month of the manufacturer's fiscal year, zero otherwise.

Table 3: The Relation of Promotional Activity to Analyst Forecasts

Dependent Variable	*Special Price*		*Price Change*	
Regression Type	Logit		OLS (Newey)	
Column #	1	2	3	4
Sample	Full	Restricted	Full	Restricted
QuarterEnd β_1	0.134	0.138	-0.772	-1.641
	(0.38)	(0.38)	(-5.24)**	(-5.45)**
JustBeat β_2	-0.896	-0.967	0.332	0.609
	(-3.96)**	(-4.87)**	(4.18)**	(3.35)**
*JustBeat*QuarterEnd* β_3	1.186	1.208	0.287	0.290
	(4.99)**	(5.03)**	(1.81)$^{+}$	(0.81)
Constant	-4.031	-2.791	0.571	-1.593
	(-14.18)**	(-8.46)**	(3.16)**	(-8.01)**
Monthly Fixed Effects	Yes	Yes	Yes	Yes
N	112,247	37,136	69,775	28,221
Pseudo-R^2 (Adj-R^2 if OLS)	0.088	0.104	0.0138	0.0198

Dependent Variable	*Feature*		*Display*	
Regression Type	Logit		OLS (Newey)	
Column #	5	6	7	8
Sample	Full	Restricted	Full	Restricted
QuarterEnd β_1	0.183	0.170	0.158	0.035
	(0.52)	(0.43)	(1.75)$^{+}$	(0.27)
JustBeat β_2	-0.759	-0.818	-0.440	-0.503
	(-3.77)**	(-4.82)**	(-1.48)	(-1.80)$^{+}$
*JustBeat*QuarterEnd* β_3	1.044	1.066	0.638	0.702
	(4.16)**	(4.12)**	(2.32)*	(2.38)*
Constant	-4.173	-2.935	-4.283	-3.122
	(-13.60)**	(-8.30)**	(-21.92)**	(-20.07)**
Monthly Fixed Effects	Yes	Yes	Yes	Yes
N	112,247	37,136	112,247	37,136
Pseudo-R^2	0.075	0.091	0.147	0.179

$^{+, *, **}$ Significant at the 10%, 5%, 1% level (two tail)

$$\Lambda(Action_{ist}) = \alpha + \beta_1 QuarterEnd_{ist} + \beta_2 JustBeat_{ist} + \beta_3 JustBeat_{ist} * QuarterEnd_{ist} + \sum_{j=1}^{12} \gamma_j Month_{istj} + \epsilon_{ist}$$

$$PriceChange_{ist} = \alpha + \beta_1 QuarterEnd_{ist} + \beta_2 JustBeat_{ist} + \beta_3 JustBeat_{ist} * QuarterEnd_{ist} + \sum_{j=1}^{12} \gamma_j Month_{istj} + \epsilon_{ist}$$

Display is a dummy variable which equals one if there is any display promotion for the product within the store at the time of the sale, zero otherwise. *Feature* is a dummy variable which equals one if the sale is associated with a feature promotion, zero otherwise. JustBeat is a dummy variable which equals one if the manufacturer reports (ex-post) earnings for the quarter are between zero and 10% above the consensus analyst forecast at the beginning of the quarter and zero otherwise. Price Change is the mean price change (in %) for the product over the previous month. *QuarterEnd* is a dummy variable which equals one if the sale is during the last month of the manufacturer's fiscal quarter, zero otherwise. *Special Price* is a dummy variable which equals one if the sale is associated with a special price, zero otherwise.

Table 4: The Relation of Promotional Support to EPS Growth

Dependent Variable	*Special Price*	
Regression Type	Logit	
Column #	1	2
Sample	Full	Restricted
QuarterEnd β_1	0.035	0.167
	(0.18)	(0.83)
YearEnd β_2	-0.003	0.054
	(-0.01)	(0.18)
*MissedPriorQEPS*Q.End* β_3	0.769	0.587
	(2.79)**	(3.05)**
*MissedPriorQEPS*YearEnd* β_4[49]	-0.815	-0.599
	(-2.22)*	(-1.57)
Feature β_5	5.380	4.552
	(22.17)**	(23.70)**
Display β_6	7.901	6.914
	(17.53)**	(16.17)**
Constant	-6.413	-5.278
	(-27.08)**	(-20.41)**
Monthly Fixed Effects	Yes	Yes
N	114,870	38,262
Pseudo-R^2 (Adj-R^2 if OLS)	0.346	0.510

+, *, ** Significant at the 10%, 5%, 1% level (two tail)

$$\Lambda(SpecialPrice_{ist}) = \alpha + \beta_1 QuarterEnd_{ist} + \beta_2 YearEnd_{ist} + \beta_3 MissedPriorQEPS_{ist} * QuarterEnd_{ist} + \beta_4 MissedPriorQEPS_{ist} * YearEnd_{ist} + \beta_5 MissedPriorQEPS_{ist} + \beta_6 MissedPriorQEPS_{ist} + \sum_{j=1}^{12} \gamma_j Month_{istj} + \epsilon_{ist}$$

Display is a dummy variable which equals one if there is any display promotion for the product within the store at the time of the sale, zero otherwise. *Feature* is a dummy variable which equals one if the sale is associated with a feature promotion, zero otherwise. *MissedPriorQEPS* is a dummy variable which equals one if EPS for the previous quarter was 80-100% of the EPS for the same quarter in the previous year, zero otherwise. *QuarterEnd* is a dummy variable which equals one if the sale is during the last month of the manufacturer's fiscal quarter, zero otherwise. *Special Price* is a dummy variable which equals one if the sale is associated with a special price, zero otherwise. *YearEnd* is a dummy variable which equals one if the sale is during the last month of the manufacturer's fiscal year, zero otherwise.

[49] To estimate the difference in probability of promotion between a non fiscal-quarter-ending month with low earnings management incentive and the last month of the fiscal year with high earnings management incentive, readers must aggregate the effects of β_1, β_2, β_3 and β_4.

Table 5: The Relation of Promotional Activity to EPS Growth with Inventory Controls

Dependent Variable	*Special Price*	*Price Change*	*Feature*	*Display*
Regression Type	Logit	OLS (Newey)	Logit	Logit
Column #	1	2	3	4
Sample	Full	Full	Full	Full
YearEnd β_1	-0.367	0.349	-0.243	-0.832
	(-1.58)	(0.90)	(-1.00)	(-3.55)**
*MissedPriorQEPS*Q.End* β_2	-0.575	-2.157	-0.382	-0.758
	(-0.93)	(-6.76)**	(-0.53)	(-1.17)
*MissedPriorQEPS*YearEnd* β_3	0.660	1.228	0.681	0.104
	(2.14)*	(4.98)**	(1.71)+	(0.32)
InventoryChange β_4	2.387	0.739	0.984	6.765
	(1.90)+	(0.41)	(0.80)	(2.42)*
Constant	-3.955	-2.327	-4.106	-3.686
	(-20.95)**	(-1.62)	(-17.19)**	(-15.11)**
Monthly Fixed Effects	Yes	Yes	Yes	Yes
N	33,232	15,445	32,386	32,945
Pseudo-R^2	0.040	0.042	0.044	0.080

+, *, ** Significant at the 10%, 5%, 1% level (two tail)

$$\Lambda(SpecialPrice_{ist}) = \alpha + \beta_1 YearEnd_{ist} + \beta_2 MissedPriorQEPS_{ist} * QuarterEnd_{ist} + \beta_3 MissedPriorQEPS_{ist} * YearEnd_{ist} + \beta_4 InventoryChange_{ist} + \sum_{j=1}^{12} \gamma_j Month_{istj} + \epsilon_{ist}$$

$$PriceChange_{ist} = \alpha + \beta_1 YearEnd_{ist} + \beta_2 MissedPriorQEPS_{ist} * QuarterEnd_{ist} + \beta_3 MissedPriorQEPS_{ist} * YearEnd_{ist} + \beta_4 InventoryChange_{ist} + \sum_{j=1}^{12} \gamma_j Month_{istj} + \epsilon_{ist}$$

Display is a dummy variable which equals one if there is any display promotion for the product within the store at the time of the sale, zero otherwise. *Feature* is a dummy variable which equals one if the sale is associated with a feature promotion, zero otherwise. *Inventory Change* is the change in firm level inventory over the previous 12 months $\left(\frac{Inventory_{t-1}}{Sales_{t-1}} - \frac{Inventory_{t-5}}{Sales_{t-5}}\right) \Big/ \frac{Inventory_{t-5}}{Sales_{t-5}}$. *MissedPriorQEPS* is a dummy variable which equals one if EPS for the previous quarter was 80-100% of the EPS for the same quarter in the previous year, zero otherwise. *Price Change* is the mean price change (in %) for the product over the previous month. *Special Price* is a dummy variable which equals one if the sale is associated with a special price, zero otherwise. *YearEnd* is a dummy variable which equals one if the sale is during the last month of the manufacturer's fiscal year, zero otherwise.

Table 6: Relation of Marketing Action and Revenue Contribution (Prices)

	OLS Regressions (Newey)			
Dependent Variable	*Price Change*	*Price Change*	*Price Change*	*Price Change*
Column #	1	2	3	4
YearEnd[a] β_1	-0.433	0.879	-0.599	0.758
	(-1.57)	(1.71)[+]	(-2.01)[*]	(1.41)
HiRevUB[b] β_2	0.259		0.260	
	(3.14)[**]		(3.15)[**]	
YearEnd HiRevUB*[c] β_3	-0.400		0.062	
	(-1.84)[+]		(0.25)	
HiRevBM[b] β_4		0.379		0.374
		(1.35)		(1.34)
YearEnd HiRevBM*[c] β_5		-1.667		-1.367
		(-3.27)[**]		(-2.51)[*]
MissedPriorQEPS β_6			0.965	0.874
			(4.24)[**]	(3.90)[**]
*MissedPriorQEPS * YearEnd* β_7			-1.121	-0.319
			(-3.49)[**]	(-0.29)
*MissedPriorQEPS *YE*HiRevUB* β_8			-1.572	
			(-3.57)[**]	
*MissedPriorQEPS *YE*HiRevBM* β_9				-1.521
				(-1.37)
Constant	1.365	1.291	1.601	1.439
	(5.37)[**]	(4.42)[**]	(5.44)[**]	(4.93)[**]
N	70,876	68,687	70,876	68,687
Adj-R^2	0.011	0.012	0.012	0.013
Test 1 *a+c=0*	p=0.001	p=0.006		
Test 2 *b+c=0*	p=0.476	p=0.002		
Test 3 *a=0 & c=0*	p=0.002	p=0.001		
Test 4 *b=0 & c=0*	p=0.006	p=0.004		
Fixed Effects for Calendar Month				

+, *, ** Significant at the 10%, 5%, 1% level (two tail)

Column 1 $$PriceChange_{ist} = \alpha + \beta_1 YearEnd_{ist} + \beta_2 HighRevUPC_{ist} + \beta_3 HighRevUPC_{ist} * YearEnd_{ist} + \sum_{j=1}^{12} \gamma_j Month_{istj} + \varepsilon_{ist}$$

Column 2 $$PriceChange_{ist} = \alpha + \beta_1 YearEnd_{ist} + \beta_4 HighRevBM_{ist} + \beta_5 HighRevBM_{ist} * YearEnd_{ist} + \sum_{j=1}^{12} \gamma_j Month_{istj} + \varepsilon_{ist}$$

Column 3 $$PriceChange_{ist} = \alpha + \beta_1 YearEnd_{ist} + \beta_2 HighRevUPC_{ist} + \beta_3 HighRevUPC_{ist} * YearEnd_{ist} + \beta_6 MissedPriorQEPS_{ist} + \beta_7 YearEnd * MissedPriorQEPS_{ist} + \beta_8 HighRevUPC * MissedPriorQEPS * YearEnd_{ist} + \sum_{j=1}^{12} \gamma_j Month_{istj} + \varepsilon_{ist}$$

Column 4 $$PriceChange_{ist} = \alpha + \beta_1 YearEnd_{ist} + \beta_2 HighRevBM_{ist} + \beta_3 HighRevBM_{ist} * YearEnd_{ist} + \beta_6 MissedPriorQEPS_{ist} + \beta_7 YearEnd * MissedPriorQEPS_{ist} + \beta_8 HighRevBM * MissedPriorQEPS * YearEnd_{ist} + \sum_{j=1}^{12} \gamma_j Month_{istj} + \varepsilon_{ist}$$

HiRevBM is a dummy variable which equals one if the brand is one of the larger revenue generating brands within the owning group. *HiRevUB* is a dummy variable which equals one if the UPC is one of the larger revenue generating UPC codes within the Brand.*MissedPriorQEPS* is a dummy variable which equals one if EPS for the previous quarter was 80-100% of the EPS for the same quarter in the previous year, zero otherwise. *Price Change* is the mean price change (in %) for the product over the previous month. *YearEnd* (*YE*) is a dummy variable which equals one if the sale is during the last month of the manufacturer's fiscal year, zero otherwise.

Table 7: Relation of Marketing Action and Revenue Contribution (Display)

	Logistic Regressions			
Dependent Variable	*Display*	*Display*	*Display*	*Display*
Column #	1	2	3	4
YearEnd[a] β_1	1.064	1.259	1.183	1.329
	(2.93)**	(3.60)**	(3.18)**	(4.01)**
HiRevUB[b] β_2	1.337		1.338	
	(5.49)**		(5.51)**	
*YearEnd*HiRevUB*[c] β_3	-0.369		-0.512	
	(-0.98)		(-1.25)	
HiRevBM[b] β_4		-0.618		-0.620
		(-1.72)+		(-1.73)+
*YearEnd*HiRevBM*[c] β_5		-0.038		-0.107
		(-0.07)		(-0.19)
MissedPriorQEPS β_6			0.349	0.265
			(0.95)	(0.71)
*MissedPriorQEPS*YE* β_7			-0.961	-1.145
			(-1.07)	(-1.86)+
*MissedPriorQEPS*YE*HiRevUB* β_8			0.794	
			(0.98)	
*MissedPriorQEPS *YE*HiRevBM* β_9				0.869
				(1.83)+
Constant	-4.810	-3.556	-4.811	-3.554
	(-23.24)**	(-11.58)**	(-23.26)**	(-11.59)**
N	104,750	109,348	104,750	109,348
Pseudo- R^2	0.074	0.152	0.074	0.152
Test 1 *a+c=0*	p=0.134	p=0.053		
Test 2 *b+c=0*	p=0.015	p=0.015		
Test 3 *a=0 & c=0*	p=0.013	p=0.226		
Test 4 *b=0 & c=0*	p=0.000	p=0.188		
Fixed Effects for Calendar Month				

+, *, ** Significant at the 10%, 5%, 1% level (two tail)

Column 1 $$\Lambda\left(Display_{ist}\right)=\alpha+\beta_1 YearEnd_{ist}+\beta_2 HighRevUPC_{ist}+\beta_3 HighRevUPC_{ist}*YearEnd_{ist}+\sum_{j=1}^{12}\gamma_j Month_{istj}+\varepsilon_{ist}$$

Column 2 $$\Lambda\left(Display_{ist}\right)=\alpha+\beta_1 YearEnd_{ist}+\beta_4 HighRevBM_{ist}+\beta_5 HighRevBM_{ist}*YearEnd_{ist}+\sum_{j=1}^{12}\gamma_j Month_{istj}+\varepsilon_{ist}$$

Column 3 $$\Lambda\left(Display_{ist}\right)=\alpha+\beta_1 YearEnd_{ist}+\beta_2 HighRevUPC_{ist}+\beta_3 HighRevUPC_{ist}*YearEnd_{ist}+\beta_6 MissedPriorQEPS_{ist}$$
$$+\beta_7 YearEnd*MissedPriorQEPS_{ist}+\beta_8 HighRevUPC*MissedPriorQEPS*YearEnd_{ist}+\sum_{j=1}^{12}\gamma_j Month_{istj}+\varepsilon_{ist}$$

Column 4 $$\Lambda\left(Display_{ist}\right)=\alpha+\beta_1 YearEnd_{ist}+\beta_4 HighRevBM_{ist}+\beta_5 HighRevBM_{ist}*YearEnd_{ist}+\beta_6 MissedPriorQEPS_{ist}$$
$$+\beta_7 YearEnd*MissedPriorQEPS_{ist}+\beta_9 HighRevBM*MissedPriorQEPS*YearEnd_{ist}+\sum_{j=1}^{12}\gamma_j Month_{istj}+\varepsilon_{ist}$$

Display is a dummy variable which equals one if there is any display promotion for the product within the store at the time of the sale, zero otherwise. *HiRevBM* is a dummy variable which equals one if the brand is one of the larger revenue generating brands within the owning group. *HiRevUB* is a dummy variable which equals one if the UPC is one of the larger revenue generating UPC codes within the Brand.*MissedPriorQEPS* is a dummy variable which equals one if EPS for the previous quarter was 80-

100% of the EPS for the same quarter in the previous year, zero otherwise. *YearEnd* (*YE*) is a dummy variable which equals one if the sale is during the last month of the manufacturer's fiscal year, zero otherwise.

Table 8: Impact of Marketing Actions on the Timing of Consumers' Purchases

Dependent Variable	*Ln(Weekly Units Sold)*	
Regression Type	OLS (Newey)	
Column #	*1*	*2*
Ln(Price$_{t-1}$/MaxPrice) β_1	0.606	0.423
	(3.00)**	(2.48)*
Ln(Price$_t$/MaxPrice) β_2	-3.378	-3.126
	(-9.88)**	(-8.63)**
Ln(Price$_{t+1}$/MaxPrice) β_3	1.418	1.392
	(4.80)**	(4.67)**
Display β_4	1.023	0.638
	(7.48)**	(2.51)*
*Display * Ln(Price$_t$/MaxPrice)* β_5		-0.520
		(-1.92)$^{+}$
Feature β_6	2.070	1.454
	(10.94)**	(6.81)**
*Feature * Ln(Price$_t$/MaxPrice)* β_7		-0.672
		(-3.18)**
Constant	6.250	6.255
	(73.85)**	(73.21)**
Fixed Effects for UPC as well as Calendar Month		
N	27,008	27,008
Adj-R^2	0.428	0.430

$^{+, *, **}$ Significant at the 10%, 5%, 1% level (two tail)

Column 1
$$Ln\left(WeeklyUnitsSold_{ist}\right) = \alpha + \beta_1 Ln\left(\frac{Price_{is,t-1}}{MaxPrice_{is}}\right) + \beta_2 Ln\left(\frac{Price_{ist}}{MaxPrice_{is}}\right) + \beta_3 Ln\left(\frac{Price_{is,t+1}}{MaxPrice_{is}}\right) + \beta_4 Display_{ist} + \beta_6 Feature_{ist} + \sum_{j=1}^{12}\gamma_j Month_{istj} + \sum_i \delta_i UPC_i + \varepsilon_{ist}$$

Column 2
$$Ln\left(WeeklyUnitsSold_{ist}\right) = \alpha + \beta_1 Ln\left(\frac{Price_{is,t-1}}{MaxPrice_{is}}\right) + \beta_2 Ln\left(\frac{Price_{ist}}{MaxPrice_{is}}\right) + \beta_3 Ln\left(\frac{Price_{is,t+1}}{MaxPrice_{is}}\right) + \beta_4 Display_{ist} + \beta_5 Display_{ist} * Ln\left(\frac{Price_{ist}}{MaxPrice_{is}}\right) + \beta_6 Feature_{ist} + \beta_7 Feature_{ist} * Ln\left(\frac{Price_{ist}}{MaxPrice_{is}}\right) + \sum_{j=1}^{12}\gamma_j Month_{istj} + \sum_i \delta_i UPC_i + \varepsilon_{ist}$$

Display is a dummy variable which equals one if there is any display promotion for the product within the store at the time of the sale, zero otherwise. *Feature* is a dummy variable which equals one if the sale is associated with a feature promotion, zero otherwise. *MaxPrice* is the maximum price at which the product is sold in the store over the sample period. *Price$_t$* is the average price of the product being sold in the store during month t. *Weekly Units Sold* is defined as the number of units of product sold at a store in a week.