Forecasting Sales: A Model and Some Evidence from the Retail Industry*

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Abstract
This paper presents a sales forecasting model and tests the model on a sample of firms in the retail industry. The model distinguishes between sales growth due to an increase in the number of sales-generating units (e.g. opening new stores) and growth due to an increase in the sales rate at the existing units (e.g. the comparable store growth rate). The model accommodates different trends in the sales rates, allowing new stores to earn more or less than existing stores, perhaps because new stores are different sizes than existing stores or may take either a long time to reach maturity or alternatively enjoy an early "fad" status. We show how to use the historical series of sales, stores and comparable store growth rates to estimate the sales rates on new stores and on existing stores. The model uses only a few years of firm-specific, publicly available information, yet generates in-sample forecast errors of less than two percent of sales, generates out-of-sample forecast errors that are comparable to analyst revenue forecasts, and when used with analyst forecasts, adds significant incremental information.

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Every financial statement forecast begins with an estimate of future sales. Typically the sales estimate is then combined with a margin forecast to estimate future income and combined with a turnover forecast to estimate future assets. Although the sales forecast is the starting point for the entire financial statement forecasting exercise, there is surprisingly little published guidance on how one should go about making this estimate with publicly available data. The purpose of this paper is to present a reasonably general sales forecasting model and to demonstrate its use in the retail sector. The model distinguishes between sales growth that arises from growth in the asset base (e.g. opening new stores) and sales growth that arises from increased sales from existing assets (e.g. comparable store sales growth). The model also accounts for the predictable change in sales that will result as the asset base matures. We document that our model, based solely on publicly available information, produces out-of-sample forecasts that add significant incremental information to the IBES analysts' revenue forecasts.

We develop and estimate our model in the retail sector for a number of reasons. First, the underlying sales-generating assets -- the stores -- are clearly identified for retail firms. Virtually every retail firm discloses the number of stores it operated during the year and most forecast the number of new stores they anticipate opening in the next year. Second, retail firms generally disclose the comparable store sales growth for the year, defined as the percentage growth in sales from stores that were open at the beginning of the prior fiscal year. This gives us the two main pieces of the puzzle in our model – the number of new sales-generating units and the growth in sales from existing units; our challenge is to weave these two drivers of future sales together. Finally, we focus on the retail sector because it is arguably the most closely watched barometer of consumer spending, and consumer spending makes up about two thirds of the US Gross Domestic Product.

While our model is developed with a retail firm in mind, sales forecasts for many other types of firms will have a similar flavor. Forecasting sales growth at a pharmaceutical company involves forecasting the sales growth from existing drugs and the sales growth from introducing new drugs to the market. Forecasting the sales growth for a cruise line company involves forecasting increases in fares or passenger counts on existing ships and forecasting the revenues from newly-launched ships. The retail industry offers us perhaps the best example of this type of problem because the sales-generating units are clearly identified and relatively homogeneous, but our forecasting model applies to a much broader set of firms.

There is a growing financial statement analysis literature that examines how profit margins and asset turnover ratios evolve over time. Nissim and Penman (2001) and Fairfield and Yohn (2001) document reversion in these ratios to an economy-wide mean, and Soliman (2003) shows that an industry statistic is a more predictive mean reversion target. Penman and Zhang (2002) and Fairfield and Yohn (2001) also consider how past changes in these ratios predict future changes. Collectively these results characterize the future profitability and asset investment necessary for a given level of sales activity. But to use these results for valuation, or to forecast actual income flows or asset balances, the user must also forecast the level of future sales activity. With respect to sales forecasting, Nissim and Penman (2001) show that percentage sales growth tends to mean revert very quickly, while Gaur, Osadchily and Seshadri (2008) document that the realized market return adds significant explanatory power when forecasting retail sales, as it proxies for demand.[1]

[1] The management accounting literature has focused on estimating future expenses by estimating the diminishing marginal returns to scale, paying particular attention to the "stickiness" of costs as sales decline (Anderson et al.

Another related literature uses non-financial metrics to predict future financial performance. Besides forecasting earnings rather than sales, these papers differ from our study in how closely related the non-financial measure is to the underlying sales-generating asset. For example, Amir and Lev (1996) study the product market size and market penetration in the wireless industry; Chandra, Procassini and Waymire (1999) and Fargher, Gorman and Wilkins (1998) study shipment data in the semiconductor industry; Rajgopal, Shevlin and Venkatachalam (2003) study order backlog, Ittner and Larcker (1998) and Banker, Potter and Srinivasan (2000) study customer satisfaction measures, Trueman, Wong and Zhang (2001a, 2001b) study web traffic measures, and Nagar and Rajan (2001) study manufacturing quality measures. None of these measures distinguish between changes in the financial performance due to changes in existing investments and changes due to new investment.[2]

Our purpose is to present a reasonably general model for forecasting sales growth and to test the validity of various restrictions on the model that might lead to more parsimonious representations. We also illustrate the model's flexibility to adapt to different types of environments. For instance, the model can distinguish between retail firms who enjoy "fad" status, so that their new stores earn considerably more than their more mature stores (e.g. Whole Foods), and retail firms that take a long time to reach maturity, so that their new stores earn considerably less than their more mature stores (e.g. JC Penney).

Our goal is to develop a model that can be used to forecast sales growth for a typical firm in a typical year based on publicly available data. One problem we must confront is the extreme limit on the number of observations in our regressions. The estimated sales-generating rates are unique to each firm, ruling out cross-sectional estimation, and the typical firm has only a limited time series of annual data. Moreover, stores change their strategies over time and so using a longer history many not aid in our forecasting exercise. Consequently, we estimate our model on relatively little data – in-sample results are based on a median of only 12 observations per firm and out-of-sample forecasts rely on estimates based on as few as five historical observations. For this reason we place heavy emphasis on developing a model with few estimated parameters. Another difficulty is that both the size of the asset base and the sales-generating rates per asset change each period. Our model shows how to use past comparable store growth rates to control for the sales rate changes so that the current sales-generating rates of new and existing stores can be estimated as stable parameters. In spite of these difficulties, the in-sample median absolute error is less than 2% of sales. In contrast, the estimate based on the mean reversion in sales growth (as in Nissim and Penman 2001) has an in-sample median absolute error that is 4.5% of sales.[3]

2003). Banker and Chen (2006) use this approach to estimate earnings, applying a simple autoregressive process to predict next year's sales (similar to Nissim and Penman 2001) but then estimate a sophisticated cost model given the sales forecast.

[2] Other accounting research using comparable store sales data includes Francis, Schipper and Vincent (2003) who show that comparable store sales in the restaurant industry provide information beyond contemporaneous earnings in a returns regression. There is an extensive literature in marketing addressing sales forecasts but this work relies on data that is internal to the firm (e.g. scanner data); this data is not available to outsiders such as analysts and investors.

[3] Improving the sales forecast by just a few percent can have enormous consequences. As an example, if a firm had an expected constant ROE of 20%, a cost of equity capital of 10% and an expected perpetual growth rate of 5%, its market-to-book ratio would be 3 (which is close to the current economy-wide value). If the growth rate was raised to 6% the firm's value would increase 17%; if the growth rate was lowered to 4% the firm's value would decrease 11%.

We next discuss how to use our model for out-of-sample prediction and examine its out-of-sample forecast errors. A common voluntary disclosure for a retail firm is to estimate the number of new stores it will open in the following fiscal year. Our model shows exactly how to incorporate this disclosure into a sales forecast. However, firms rarely forecast their comparable store growth rate and so we develop a simple forecast for this input based on mean reversion to the expected inflation rate. Putting these two forecasts together with the estimated sales-generating rates of new and existing stores from our model, we generate out-of-sample forecasts with a median absolute error of 3.8% of sales.[4]

THE MODEL

Our model is reasonably general and would apply to any sales-forecasting environment where the sales generated from specific assets can be identified (i.e. drugs, cruise ships, oil wells, airlines, apartment rental agencies). However, to make the model more concrete, we develop the notation with a retail firm in mind. The model requires that we distinguish between three classes of stores within a retail firm. The notation is as follows:

N_t = number of new stores opened in year t (i.e. 'new' stores)
$M_t = N_{t-1}$ = number of new stores opened in year t–1 (i.e. 'mid' stores)
D_t = number of stores closed in year t (i.e. 'dead' stores)
O_t = total number of stores that are open at the beginning of year t–1 and are still open at the end of year t (i.e. 'old' stores).

This notation implies two equalities concerning the numbers of different types of stores:[5]

1) O_t = total number of stores at year end – N_t – M_t and
2) $O_t = O_{t-1} + M_{t-1} - D_t$.

The average rate of sales in the fiscal year per store for each of the three classes of stores is denoted as

R_t^O = the average sales per store for the old stores in year t,
R_t^M = the average sales per store for the mid stores in year t, and
R_t^N = the average sales per store for the new stores in year t.

With this, total sales in year t are given by:

$$Sales_t = O_t R_t^O + M_t R_t^M + N_t R_t^N \quad (1)$$

[4] Our errors are larger when the firm undertakes a merger and acquisition (which mechanically raises realized sales) or a discontinued operation (which mechanically lowers realized sales). Using realized comparable store sales growth, our errors decline nearly a full percentage point to approximately 2.9% of sales; users of the model may be better-able to forecast a single firm's comp growth and may be aware of impending acquisitions or disposals.

[5] For the purpose of presenting the model, we assume that new stores are opened and dead stores are closed at the beginning of the year. In our empirical estimation, however, we divide each of these amounts by two, effectively assuming that the openings and closings happen half way through the year, on average.

Besides asserting that sales are generated by stores, (1) is a tautology because the sales-generating rate from each of the three classes of stores can change each period.[6] The purpose of the model is to show how these changing rates can be estimated.

The model uses three different classes of stores for a few different reasons. First, for most retail firms new stores generate sales at very different rates than more mature stores. Consumers may take time to discover the new store and change their shopping habits, causing the new store sales to lag existing store sales. Alternatively, the new store may blitz the market with advertisements and promotions, or may be a retailing fad, causing new store sales to exceed existing store sales.[7]

The mid stores, which are last year's new stores, serve two purposes. First, as shown below, this category of store is necessary in order to precisely define comparable store sales growth. Second, by comparing the estimated mid store rate to the estimated old and new store rates, we learn something about the speed with which the firm's stores reach maturity or, alternatively, enjoy a new store "honeymoon period."

The comparable store sales growth rate—commonly referred to as the "comp rate"—is labeled C_t and defined as the percentage increase in sales from stores that were open at the beginning of the prior fiscal year and are currently still open. Expressing this in terms of our model gives

$$1 + C_t = \frac{O_t R_t^O}{(O_{t-1} - D_t) R_{t-1}^O + M_{t-1} R_{t-1}^M} . \tag{2}$$

The numerator $O_t R_t^O$ is the sales earned by the old stores in year t. The denominator is the sales these same stores earned a year earlier. To compute the sales from these stores in year t–1, recall that $O_t = O_{t-1} - D_t + M_{t-1}$ and consider the sales that each of these types of stores generated in year t–1. There were O_{t-1} old stores that were open a full year in t–1, but D_t of these stores were closed in the current year; the net of these stores generated sales at the old rate of R_{t-1}^O in year t–1. In addition, M_{t-1} of the stores in the O_t total are stores that moved from generating sales at the mid rate R_{t-1}^M in year t–1 to the old rate R_t^O in year t.

Note from (2) that, even if the old store rate isn't changing over time, if $R_{t-1}^M < R_t^O$ then a firm could show healthy same store growth rates as long as they keep opening new stores. As the young stores mature from earning R_{t-1}^M to earning R_t^O the comp rate will be positive. However, when new store openings slow there will be a precipitous drop in the observed comp rate.

We add the constraint that $R_t^M = R_t^O$ for much of our empirical work. That is, after the end of the fiscal year in which a store opens, it immediately generates sales at the old store rate.

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[6] We could insert a constant term in (1) to capture sales that are not related to stores, such as internet sales. Later, however, we will estimate the differenced version of this equation so a constant would simply cancel out.

[7] For parsimony we do not estimate a unique sales rate for closed stores; rather, they are assumed to earn at the old store rate until they close. This assumption is reasonable, as there are only 5 closed stores but 44 new stores for the median firm-year.

This, in turn implies that

$$1 + C_t = \frac{R_t^O}{R_{t-1}^O}. \tag{3}$$

Equation (3) is the most obvious expression of "same store sales growth" although it is clearly a simplification. The simplification is unreasonable for stores that require consumers to change their shopping habits; it may well take more than a year to reach maturity, so that $R_{t-1}^M < R_{t-1}^O$. Alternatively, some stores enjoy a fad status in the early months of existence, and this might extend beyond the end of the store's first partial year, making $R_{t-1}^M > R_{t-1}^O$. Later we document some examples of store types that fit each of these descriptions and use a more general model to accommodate this additional complexity. However, for much of our analysis we will use the simplifying assumption that $R_t^M = R_t^O$.

Because we estimate our sales model for each firm individually over time, the error term in a levels regression is unlikely to be stationary. For this reason we take first differences:

$$\Delta Sales_t = (O_t R_t^O - O_{t-1} R_{t-1}^O) + (M_t R_t^M - M_{t-1} R_{t-1}^M) + (N_t R_t^N - N_{t-1} R_{t-1}^N) \tag{4}$$

At this point our model is still a tautology: each sales-generating rate is allowed to change every period so that, by definition, equation (4) holds. In order to estimate the different sales rates, we need to impose some restrictions over time. A tempting restriction is simply to assume that the three rates are constant over time. Unfortunately this assumption is incompatible with the fact that firms rarely report comparable store growth rates that are zero each period. Ignoring the complications of mid store rates versus old store rates, (3) shows that the comp rate is the change in the sales-generating rate for old stores over time; the very thing we were tempted to assume was zero. The trick in the estimation will be to use the firm's historical comp rate to control for the known changes in the sales-generating rates over time so that we can estimate a "comp-adjusted" rate that is stable.

Denote by T the most recent year in the dataset for a particular firm. The necessary feature of any restriction we impose on the sales-generating rates is that it allows us to rewrite (4) for every period in terms of R_T^O, R_T^M and R_T^N. These rates are the estimated parameters in the regression. The independent variables in the regression are the changes in the number of stores of each type, adjusted for the historical comp rates and incorporating other assumed restrictions on the evolution of sales-generating rates.

We examine three different restrictions on the general model. Model 1 assumes that

1) $R_t^M = R_t^O$ for every period t and

2) $R_t^N = R_{t-1}^N(1+C_t)$ for every period t.

Assumption 1 says that after the fiscal year in which the store opens (when it is a new store), it immediately earns at the same rate as an old store. This in turn implies that $R_t^O = R_{t-1}^O(1+C_t)$, as in (3) above. Assumption 2 says that the sales-generating rate on new stores changes in the same way as the rate on the old stores; it too grows at the comparable store growth rate for the old stores. The idea behind assumption 2 is that the success of the new stores is probably related to the success of the old stores. If the products being sold in the old stores are generating increasing sales dollars then it is likely that the new stores will enjoy similar increases in their sales rate.[8] Using these two assumptions, we get the following sequence of sales changes:

In the final year T,

$$\Delta Sales_T = (O_T + M_T)R_T^O - (O_{T-1} + M_{T-1})R_{T-1}^O + N_T R_T^N - N_{T-1}R_{T-1}^N \tag{5}$$

which we can rewrite in terms of R_T^O and R_T^N as

$$\Delta Sales_T = \left[(O_T + M_T)(1+C_T) - (O_{T-1} + M_{T-1})\right]\frac{R_T^O}{(1+C_T)} + \left[N_T(1+C_T) - N_{T-1}\right]\frac{R_T^N}{(1+C_T)}. \tag{6}$$

Note the different sources of changes in sales in year T. Both terms are close to the change in the number of stores, either new stores in the second term or existing stores (i.e. old plus mid) in the first term. But for both terms the number of stores in year T–1 is "deflated" by one plus the comp rate for year T. By adjusting the beginning number of stores down using C_T like a deflator, the net change in brackets captures both the growth in the number of stores and the growth in the sales-generating rate of each store. It effectively treats 100 stores at the beginning of the year who grow same-store sales by 10% the same as growing from 91.91 to 100 stores with no change in the sales-generating rate.

More generally, for year T–τ, where τ counts back in time to the first year of data for an individual firm, we have

$$\Delta Sales_{T-\tau} = \left[\frac{(1+C_{T-\tau})(O_{T-\tau} + M_{T-\tau}) - (O_{T-\tau-1} + M_{T-\tau-1})}{\prod_{i=T-\tau}^{T}(1+C_i)}\right]R_T^O + \left[\frac{(1+C_{T-\tau})N_{T-\tau} - N_{T-\tau-1}}{\prod_{i=T-\tau}^{T}(1+C_i)}\right]R_T^N. \tag{7}$$

The numerator for each term captures the change in sales due to changes in the number of stores of each type and the comparable store growth rate for that year. The denominator of each term adjusts the data each year to be stated in terms of year T sales dollars. The two terms in square brackets are the independent variables in the regression. In this way we control for the known variation in the R_t^O and R_t^N series and can estimate R_T^O and R_T^N as fixed parameters. The first independent variable is labeled the "comp-adjusted" change in existing stores and the second independent variable is the "comp-adjusted" change in new stores.[9]

Model 2 generalizes model 1 slightly. Instead of fixing $R_t^M = R_t^O$, we assume $R_t^M = k R_t^O$. This modification allows the mid store rate to differ from the old store rate by a constant proportion, although the change in each rate over time is governed by the evolution of the comp rate. By allowing the mid store rate to differ from the old store rate we capture patterns of changing sales that are more complicated than in model 1. If *k* is greater than one, mid stores earn at a greater rate than old stores, which happens when a new store's "honeymoon period"

[8] In unreported results we estimate the model assuming the new store rate is constant rather than changing with C_t. The results are completely dominated by those reported with the new store rate adjusted by C_t.

[9] The reader may wonder why the second term in (7) is the change in new stores rather than just the number of new stores in year T–τ. Note that the prior year's number of new stores is also in the first term (i.e. $N_{T-\tau-1} = M_{T-\tau}$) which allows the sales generating rate on these stores to change between the years.

extends into the next fiscal year. In contrast, if *k* is less than one then a mid store earns at a lesser rate than an old store, which captures situations where stores take longer than the partial year in which they open to mature. In the results section we illustrate both of these situations.

To derive model 2, define $Q_t \equiv \dfrac{O_{t-1} - D_t + kM_{t-1}}{O_t}$ and note that Q_t is greater than or less than one as *k* is greater than or less than one. Now substitute kR_t^O in for R_t^M in (2) to get

$$(1+C_t)Q_t = \frac{R_t^O}{R_{t-1}^O}. \tag{8}$$

The variable Q_t isolates the influence of R_t^O not equal to R_t^M on the comp rate so that the RHS is a pure expression of growth in the old store rate. Without this adjustment, C_t is a mix of the change in the old store rate and the movement of stores from mid stores to old stores. The Q_t variable allows the independent variables to account for the known variation in sales due to stores maturing from mid to old and therefore allows the regression to estimate a fixed R_T^O.

For the new store rate we assume that $R_t^N = R_{t-1}^N(1+C_t)Q_t$. For the same reason that the Q_t adjustment cleans up C_t to reveal the evolution of the old store rate, we use it in model 2's second term to describe the evolution of the new store rate. That is, we want the new store rate to vary with growth in the old store rate and not because of the maturation of stores from mid to old. The two assumptions of model 2 are summarized as

1) $R_t^M = kR_t^O$ for every period t and
2) $R_t^N = R_{t-1}^N(1+C_t)Q_t$ for every period t.

Following the same method as in the derivation of model 1, we get

$$\Delta Sales_{T-\tau} = \left[\frac{(1+C_{T-\tau})Q_{t-\tau}(O_{T-\tau}+kM_{T-\tau})-(O_{T-\tau-1}+kM_{T-\tau-1})}{\prod_{i=T-\tau}^{T}(1+C_i)Q_i}\right]R_T^O + \left[\frac{(1+C_{T-\tau})Q_{t-\tau}N_{T-\tau}-N_{T-\tau-1}}{\prod_{i=T-\tau}^{T}(1+C_i)Q_i}\right]R_T^N. \tag{9}$$

In addition to estimating the old store rate and the new store rate, model 2 requires an estimate of the proportionality factor *k*. Because we have only 12 observations for the typical firm, we adopt a simple estimation procedure. For each value of *k* in the set {.8, .9, 1, 1.1, 1.2} we estimate the firm-level regression and retain the *k* that yields the lowest median absolute residual error. Finally, model 2 requires one more year of historical data than model 1 and is therefore estimated on a subset of the model 1 sample.[10]

Model 3 is a more restrictive version of model 1. It assumes

1) $R_t^N = R_t^M = R_t^O$ for every period t and

[10] Model 1 requires the variable $(O_{T-\tau-1} + M_{T-\tau-1})$ but this can be computed as $(O_{T-\tau} + D_{T-\tau})$, so only data from period $T-\tau$ is needed. However, model 2 requires the variable $(O_{T-\tau-1} + kM_{T-\tau-1})$, which cannot be computed from $(O_{T-\tau} + D_{T-\tau})$ and accordingly needs data from $T-\tau-1$.

2) $R_t^N = R_{t-1}^N(1+C_t)$ for every period t.

Model 3 assumes all stores are the same and experience the same comp growth rate. Substituting these assumptions into (7) gives

$$\Delta Sales_{T-\tau} = \left[\frac{(1+C_{T-\tau})(O_{T-\tau}+M_{T-\tau}+N_{T-\tau})-(O_{T-\tau-1}+M_{T-\tau-1}+N_{T-\tau-1})}{\prod_{i=T-\tau}^{T}(1+C_i)} \right] R_T^N \tag{10}$$

Because there is only one rate in model 3, and it changes at a known rate, we can divide (10) by Sales at time T-τ-1 and eliminate the sales-generating rate from the model altogether. Doing so gives

$$\%\Delta Sales_{T-\tau} = (1+C_{T-\tau})(1+G_{T-\tau})-1,$$

where $$G_{T-\tau} = \frac{(O_{T-\tau}+M_{T-\tau}+N_{T-\tau})-(O_{T-\tau-1}+M_{T-\tau-1}+N_{T-\tau-1})}{(O_{T-\tau-1}+M_{T-\tau-1}+N_{T-\tau-1})}. \tag{11}$$

In percentage terms, model 3 simply compounds the comparable-store growth rate with the percentage growth in the number of stores. Note that the model in this form does not require an estimate of any sales-generating rate.

Besides the models derived above, we measure the explanatory power and forecasting accuracy of a number of ad hoc approaches to sales forecasting. These models serve as benchmarks to measure the relative improvement that comes from modeling the effects of different types of stores and the comparable store growth rate. Model 4 estimates a rate of mean reversion in the percentage sales growth, based on our interpretation of Nissim and Penman (2001). We sort the entire pool of firm-years in our sample into deciles of percentage sales growth and then measure the median percentage sales growth in the next year for each decile, denoting it as SG_j, j=1 to 10. This gives

$$\Delta Sales_{T-\tau} = Sales_{T-\tau-1} SG_j. \tag{12}$$

The next two models represent the "crass empiricist" view. Each estimates a regression of the change in sales on the changes in the different types of stores and each is estimated firm by firm, much like models 1 and 2, but neither of the regressions take the comp rates into account. This means that they effectively treat the estimated sales rates as constants.

Model 5 lumps all types of stores together, estimating the average sales rate per store:[11]

$$\Delta Sales_{T-\tau} = \beta[(O_{T-\tau}+M_{T-\tau}+N_{T-\tau})-(O_{T-\tau-1}+M_{T-\tau-1}+N_{T-\tau-1})]. \tag{13}$$

Model 6 distinguishes between new stores and existing stores, much like model 1 above, but does not take the past comp rates into account in the estimation:

$$\Delta Sales_{T-\tau} = \gamma_1[(O_{T-\tau}+M_{T-\tau})-(O_{T-\tau-1}+M_{T-\tau-1})]+\gamma_2[N_{T-\tau}-N_{T-\tau-1}]. \tag{14}$$

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[11] Note that the independent variable in model 5 equals $N_{T-\tau} - D_{T-\tau}$; it is simply the number of new stores less the number of closed stores.

SAMPLE

To estimate our model for each fiscal year we need the number of stores at year end and the comparable store growth rate. Generally this information is available in the MD&A section of the 10-K, although this information is typically released to the public much sooner in the earnings announcement press release. To obtain this information we search each firm's 10-K filing for the following information:

1) number of stores at year end,
2) stores opened during the year,
3) stores closed during the year,
4) comparable store growth rate, and
5) expected number of store openings/closings for the following year.

We begin with 90 firms in the retail industry that have at least six sequential years of store-related information in their 10K, are covered by Compustat, and did not have a change in their fiscal year end from 1990-2006.[12] To generate out-of-sample forecasts we need a sample of firms that disclose their estimated number of store openings/closings for the next fiscal year. While this is a common disclosure in the retail industry, it is not a required disclosure, and of our 90 firms, three do not provide these forecasts in any of the years examined; we remove these firms from our sample. Thus, our sample consists of 87 firms (and 1,036 firm years) in the retail industry that have six sequential years of historical data (sales, stores and comparable store sales growth) and provide at least one number-of-stores forecast. Table 1 provides a list of the sample firms and their average sales and number of stores.

Firms disclosed the number of stores openings and closings separately 84% of the time. If this information was not disclosed separately we computed the change in the ending number of stores and, if the difference was positive, we assumed this was the number of stores opened and none were closed, if the difference was negative we assumed this was the number of stores closed and none were opened.

Table 2 provides descriptive statistics for the sample. The median firm has over $2.4 billion in total sales and annual sales growth of 10.6%. Median comparable store sales growth is 3.8%, meaning that a large component of annual sales growth is due to opening new stores. The distribution of industry sales growth is similar to the comparable store sales growth, where the industry sales are taken from the US Census Bureau's Advance Monthly Sales for Retail Trade (discussed in more detail later). In terms of number of stores, the median firm has 629 total stores, and in a typical year opens 44 new stores and closes 5 stores. There are a few very large firms in the sample, such as Walmart, that skew the sales and store count distributions. We estimate our model firm by firm, however, so the differences in firm size across our sample will not influence our statistics.

Table 3 gives the rank-order correlations between our main variables. As one might expect, total sales is positively correlated with the total number of stores and negatively correlated with the percentage sales growth—large firms have more total sales but grow at a slower rate. Sales growth is strongly related to comparable store sales growth and growth in the number of stores. The two main variables in our model, the comp-adjusted change in new stores and the comp-adjusted change in existing stores, are both strongly correlated with sales growth.

[12] A firm must have a minimum of six years of sequential annual data in order to estimate models 1 and 2. We require that the firm's fiscal year end remains constant to ensure equal time-periods in the sales figures in our model; this requirement eliminated four firms.

However, the two variables have a relatively low correlation with each other (0.081), implying that they are capturing different aspects of sales growth. The low correlation between the two variables allows us to interpret the regression coefficients as reasonably accurate estimates of the underlying sales-generating rates without worrying that multicollinearity is having an undue influence on the estimates.

RESULTS FROM IN-SAMPLE REGRESSIONS

We begin by estimating our three models (models 1–3) and three benchmark models (models 4–6) using the entire history of available data. Each model is estimated separately for each firm with a minimum of 6 and a median of 12 observations per firm. The empirical specifications for each model are exactly as given in the model section. In particular, the dependent variable is the change in sales (in millions) each year and the independent variables are the derived changes in the number of stores in each category, adjusted for the historical and current comp rates, and there is no intercept in the regressions. We use ordinary least squares to estimate our regressions, however, results are very similar using least absolute deviation regressions.

Table 4, panel A provides summary statistics from the in-sample regression estimates of models 1 and 2. Note that we divided the number of new stores by two because new stores are open only half of the fiscal year, on average, and thus the new store rate is comparable to the old store rate. Beginning with model 1, the median estimated sales rate for existing stores (i.e. old plus mid) is \$3.51 million per store and for new stores is \$3.73 million per store, suggesting that the rates for these two types of stores are not that different. Looking at the median rates across the sample is somewhat misleading; later we identify firms with radically different new store rates and old store rates and others with similar rates across new and old stores. The median p-values on the old store rate and the new store rate are .001 and .014 for model 1, respectively; impressive levels given the small sample used to estimate each regression. In addition, the estimated old stores sales rate is positive in 86 of the 87 regressions (98.9%), the estimated new store rate is positive in 80 of the 87 regressions (92.0%), and the median adjusted R^2 is 91.7%.[13]

Model 2 allows the rate of mid store sales to differ from the rate of old store sales by a constant proportion *k* (i.e. $R_t^M = kR_t^O$) and estimates the *k* that minimizes the median absolute residual error scaled by sales in each firm's regression. The median k is 1.0, suggesting that model 1's assumption that k=1 is reasonable, on average. However, allowing the *k* to vary from one is a meaningful generalization for a significant number of the firms in the sample. A noticeable difference between model 2 and model 1 is that the median estimated old store rate is higher in model 2. The higher old store rate is offset by *k* estimates that are less than one, so that mid stores earn less, and old stores earn more, than when *k* is fixed at one as in model 1. In the next section we give specific examples where allowing *k* to vary allows the model to better match the underlying sales-generating process.

Table 4, panel B compares the in-sample fit of models 1 and 2 with the simplified model 3 and the three ad hoc models. Our accuracy measure computes each firm's median absolute residual error, where each regression residual has been scaled by sales to allow for aggregation across firms. We report the median of this statistic across firms.

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[13] The adjusted R^2 for a model without an intercept is slightly different from the standard statistic. It is computed using the sum of the squared dependent variable rather than the sum of the squared difference between the dependent variable and its mean, and it adjusts for the number of estimated parameters p with the factor n/(n–p) rather than (n–1)/(n–p).

Model 1 has a median forecast error of 2.49% of sales, while allowing k to vary results in a median forecast error of 1.99%.[14] The median error for model 3 is much higher at 3.24%, however, this estimation requires only one year of historical data and does not require the estimation of sales-generating rates.

The final three columns of Table 4, Panel B provide the in-sample fit of models 4–6, our ad hoc benchmark models. Model 4, which uses the sample-wide level of mean reversion to estimate the sales change (in a similar vein to Nissim and Penman 2001), has a median residual error of 4.5% of sales. Model 5 estimates a coefficient on the changes in total stores, but ignores both the effect of comparable store sales growth and the store types, resulting in a median residual error of 4.61% of sales, and model 6 estimates coefficients on the changes in new stores and changes in existing stores, resulting in a median residual error of 4.04% of sales. Model 6 posts the lowest median residual error of the benchmark models, but is still significantly larger than the errors for model 1 and model 2.

In sum, models 1–3 produce uniformly lower median absolute errors than any of the ad hoc benchmark models. As we incorporate the comparable store growth rates and changes in the numbers of different types of stores, our model explains significantly more of the in-sample variation in sales changes, with the best performance coming from model 2.

The median absolute residual errors are useful statistics for assessing the overall accuracy of the different models but they give little insight into the nuances of the model at the individual firm level. Table 5 provides the individual firm estimates of the new store rate and the old store rate for model 1. Both estimates are usually significant at the .10 level, suggesting that the model is sufficiently flexible to work well for most firms, despite the fact that the typical regression has only 12 observations. We also test the hypothesis that the new store rate equals the old store rate and reject this hypothesis at the .10 level in 19 of the 87 companies. For these firms it is particularly important to estimate separate sales rates for the different types of stores. Consider a few examples. As a benchmark, American Eagle Outfitters earns an estimated $3.09 million per existing store and $3.00 million per new store. This implies that American Eagle has neither a sales frenzy when they first open nor a long maturity period before their stores reach steady state, nor have they systematically changed their store size over time.

In contrast to American Eagle, grocery stores typically open with heavy advertising and promotions, causing the annualized new store rate to far exceed the old store rate. Safeway, Whole Foods and Wild Oats all show this effect in our sample. For example, Safeway's estimated new store rate of $38.11 million per store is approximately twice that of the estimated old rate of $19.84 million per store. Another example of a "honeymoon" effect is Target. Target has an old store rate of $30.84 and a new store rate of $146.59 million.[15]

At the other extreme, companies whose old store rate is significantly higher than the new store rate are slow to mature, possibly because they require changes in customer loyalty or shopping habits. In our sample AutoZone and Tweeters (they sell high-end stereo equipment) are good examples of stores that might require a shift in trust regarding the help with purchases or the quality of the equipment, while JC Penney and Rite Aid are good examples of stores that are slow to mature because of the need to change shopping habits (such as visiting the new

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[14] Note that model 2 fits better than model 1 by construction because the *k* in model 2 is optimized and model 1 is a special case of model 2.

[15] This honeymoon effect can also be driven by increasing store sizes over time. In 1995 the average Target store was 106,000 square feet and in 2006 it was just under 130,000 feet. This is an additional reason to keep the estimation period relatively short; over time the stores become less comparable.

shopping center that opened with these stores). At Tweeters the estimated new store rate of \$1.05 million is only about one fourth of the estimated old store rate of \$4.37 million.[16]

For a few firms, the added flexibility of model 2 captures a significant difference between the sales-generating rates of the different types of stores. For instance, with k set equal to one, the model 1 results in Table 5 show Wal-mart as having an old store rate of \$111.65 million and a new store rate of \$322.74 million, with an adjusted R^2 of 93.5%. The estimated k ($k \in$ .8, 1.2) in model 2 is 1.2, which means that the mid store rates is 120% of the old store rate. When this is added to the model the old store rate becomes \$105.55 million and the new store rate increases to \$335.34 million, the implied mid store rate is 1.2×105.55 = \$126.66 million, and the adjusted R^2 increases slightly to 94%. Model 2 reveals that the "honeymoon" effect of opening a new store takes more than the partial year in which a Wal-mart store opens to dissipate and reach maturity (as noted in footnote 15, this could also be a function of Wal-mart increasing the square footage of their new stores).

While model 2 is more general than model 1 and has a better fit in-sample, it is possible that model 2's superior in-sample results are caused by over-fitting the data.[17] If so, out-of-sample forecasts will reveal this. In the next section we discuss how to use these models to make out-of-sample forecasts and examine the resulting out-of-sample forecast accuracy.

OUT-OF-SAMPLE FORECASTS

To use the models to forecast next year's change in sales, we need three things. We need a forecast of the number of stores the firm will open and/or close in the next year, we need a forecast of the comparable store growth rate for the next year, and, for models 1 and 2, we need to estimate the old and new store sales-generating rates from a subset of the data prior to the year being forecasted.

We obtain the expected number of store openings/closing from the MD&A section of the firm's 10-K, as previously discussed. In our preliminary analysis, we will use prior year comp growth as an estimate of comp growth, though in later analyses we will forecast comp growth more carefully. Finally, to estimate the old and new store sales-generating rates, we estimate the coefficients on *actual* stores using five years of historical data, and then apply these coefficients to the *forecasted* store variables.[18] For example, realized data from 1995-1999 is used to estimate the sales-generating rates and these forecasts are applied to the comp-adjusted number of stores forecast for 2000.[19] The comp-adjusted number of each store type is constructed from the estimated comp growth, the number of each type of store at the prior fiscal year end, and the

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[16] A handful of firms in Table 5 have negative estimated rates or negative adjusted R^2s. Cases like these where the model has clearly failed are typically caused by one of the following: 1) the firm has two or more radically different types of stores that are being forced in the estimation to have the same sales rate (e.g. Sears has large department stores and small tire centers), 2) the firm undertook a large restructuring, closing many stores and opening different types of new stores (The Great A&P underwent such a change in 1998), and 3) the firm has a significant non-store revenue source (e.g. Ruddick operates grocery stores but also sells commercial sewing thread).

[17] In terms of estimation requirements, model 2 requires an additional year of data; in our paper we restrict our analysis to this limited dataset.

[18] A more traditional out-of-sample forecasting approach might be to estimate the regression coefficients using forecasted stores rather than actual store counts. However, this would require six consecutive years of store forecasts, severely limiting the sample. Nonetheless, applying this approach on the limited sample with the necessary data yields similar results to those reported.

[19] We have also considered an estimation period of seven, rather than five, years. The models are no more accurate under this alternative, and therefore, we present a five year estimation period to maximize the number of forecasts.

firm's disclosed estimate of the number of store openings N_{T+1} and/or closings D_{T+1} for the next year.

We present preliminary analyses in Table 6. There are two forecasted inputs to our model: the forecasted number of new and/or closed stores and the forecasted comp growth rate. The first row is the forecast of each of our models using perfect foresight of these two inputs. In other words, if we knew exactly how many stores would be opened or closed, and the realized comp growth in year T+1, this is how our model would perform out-of-sample. With perfect foresight for comp growth and the number of stores, model 1 outperforms both model 2 and 3, with a median error of 2.39% of sales.[20] To assess the relative contribution of perfect foresight of the comp growth versus perfect foresight of the number of new and/or closed stores, we next examine the changes in the median absolute residual error when only one of these inputs is known with certainty. These results are presented in the second and third row of results for stores and comp growth, respectively. This disaggregation allows us to determine where additional effort in forecasting provides the most benefit.

The second row has perfect-foresight comp growth, but uses the store forecasts provided by managers in the 10-K. Consistent with Cole and Jones (2004), the manager's forecasts in the 10-K appear to be very accurate; perfect foresight of the number of new and/or closed stores adds very little. In fact, the actual values have larger outliers and thus, for model 3, the error is actually smaller when using the smoother estimated variable than the actual variable.

The final row provides perfect foresight with respect to stores, but replaces realized comp growth with prior year comp growth. The differences are startling for all three models; the errors nearly double when perfect foresight of next year's comp growth is removed. In sum, the main source of the forecast error is realized comp growth rates that differ from forecasted comp growth rates. In the next section, we focus on providing a better forecast of comp growth.

Estimating comparable store sales growth

While firms will sometimes predict comp growth for the next month or next quarter, it is rare for them to make such a prediction for a full year into the future. As such, we cannot rely on management forecasts of comp growth and must forecast this input ourselves. We bring three sources of data to bear on the problem of predicting future comp rates: the company's own comp rate history and two different sources of industry sales growth rates.[21] Roughly two weeks after each month end the US Census Bureau releases the Advance Monthly Sales Report for Retail Trade documenting the seasonally adjusted (but not price adjusted) sales figures for the month for each NAICS code within the Retail sector. The advantage of this source of industry data is that we can match it to the specific NAICS code of the firm; the disadvantage is that it covers both private and public firms in the retail industry, not just the public firms in our sample, so it may not be representative. For this reason we also collect comparable monthly sales data from Wal-Mart, the largest retailer in the industry. Approximately one week after each month end Wal-Mart discloses their comparable store growth rate for the month.[22] We compute both

[20] Note that the out-of-sample error for model 3 is actually lower than the in-sample error presented in Table 4. The difference is the sample, as the in-sample estimations include data from the initial five years of data used to estimate the coefficients for models 1 and 2, while the results reported in Table 6 do not. If we do not require data for models 1 and 2, the perfect foresight error for model 3 is 3.24, exactly the same as the in-sample results in Table 4.

[21] These industry growth rates are effectively our proxy for changes in market demand, similar to ex post realized returns examined in Gaul et al. (2008).

[22] Monthly comparable store growth rates are growth in the sales at stores open for the same full month in the previous fiscal year. Consequently, they are naturally seasonally adjusted.

industry sales growth variables using the third month after the prior fiscal year end (i.e. nine months before the fiscal year end being forecasted).

In Table 7 we provide a correlation matrix with the firm's realized comp rates, prior year comp rates and our two industry sales growth measures. The strongest relation is between current and prior year comps, which are correlated at .509, however, recall that we used prior year comps as our estimate of current year comp growth in Table 6 and this variable performed poorly. Industry growth is significantly correlated with current year comps at 0.220, while Wal-Mart's prior year monthly comps exhibit a lower correlation at 0.136.

In Table 8 we investigate how well various combinations of the Table 7 variables predict future comparable store growth rates. Each model is estimated using the 891 firm-years that have sufficient data to estimate all four models. The first three models include an intercept, prior year comp rates and either the industry growth or Wal-Mart comp rates. All three yield very similar results with an adjusted R^2 of between 16.2% and 17.8%. The fourth model estimates mean reversion to an expected inflation rate of 2%, which is approximately the long term forecasted inflation rate given by the Congressional Budget Office. In particular, we estimate the model

$$C_t - .02 = \beta(C_{t-1} - .02). \quad (15)$$

By fixing the "target" of the mean reversion, we eliminate the need to estimate an intercept. As seen in the table, this last model works as well as any of the others and, because it requires one less parameter estimate, we consider it our lead model of comp rates for out-of-sample forecasts.

Using the estimations of comparable store sales growth

Table 9 provides the out-of-sample median absolute sales forecast error (scaled by sales) for each of our three models using four different methods of forecasting future comp rates. Median errors are presented for each model-comp growth estimate combination. Errors range from 3.79% to 4.29% and are generally lower than the errors from Table 6 where we simply used the prior year comp growth (e.g., 4.34% for model 1). The mean reversion to 2% comp forecast shown in the fourth row of Table 9 appears to produce the lowest forecast errors across each of the models, never exceeding a median error of 3.9% of sales. The differences in errors across the three models are not statistically different from one another; it seems that estimating new and old rates (model 1), and mid store rate that differs from the old store rate by a factor *k* (model 2) captures just enough meaningful variation in sales changes over the entire sample to balance out the additional estimation error they create.

As previously noted, the greatest proportion of the error in the model (relative to a perfect foresight model) is the comp growth input, and the difficulty of accurately forecasting comp growth is the biggest weakness of our model. Firms often give guidance on this figure, however, as the year unfolds. Consider Ross stores in 2006. Using the last model in Table 9 and a prior year comp rate of 6%, we would estimate a comp rate for 2006 of $.02 + .90\times(.06-.02) = .056$. Ross also disclosed in their 2005 10-K that they would open 66 new stores, resulting in 797 stores at the end of 2006, and that 2006 would be a 53 week fiscal year. Combining these estimates with the estimated sales rates for Ross Stores in Table 5 gives a 2006 sales forecast of

731 old stores × \$6.67/old store × **1.056 ×** (53/52)
+ 66 new stores × 7.88/new store × **1.056** × (53/52) = \$5,808 million.[23]

[23] Sales are higher in 53 week years relative to 52 week years (see for example, Johnston et al. 2009). As such, because the information is provided in the press release, we incorporate this information into our forecast.

The actual 2006 sales is $5,570 million, so the forecast error -.0426 of the actual result. However, in a press release issued on May 17, 2006 (approximately a month after the issuance of their 2005 10-K) management estimated that the 52-week annual comp rate would be between 3% and 4%. Applying these two facts to the store counts and estimated rates above gives an updated forecast of

731 old stores × $6.67/old store × **1.035** × (53/52)
+ 66 new stores × 7.88/new store × **1.035** × (53/52) = $5,692 million.

This forecast is twice as accurate, with an error of only -.0219. Thus, while on average our model is subject to the weakness of the comp growth input, this can be remedied if the firm provides additional disclosures.

Shocks to the sales generating process

As we noted in footnote 16, our models are unlikely to perform well in certain situations, such as when there has been a rapid store expansion due to a merger or a rapid contraction due to a restructuring. In these settings, because we are using information that was issued in the prior fiscal year, we expect our sales forecasts to have larger errors. We identify 181 firm-year observations from the 522 firm-year observations examined in Table 9 that had either a merger or acquisition (106 firm-years), a discontinued operation (62 firm-years) or both (13 firm-years).[24] We partition firm-year observations with and without these large shocks in Table 10. The errors for firm-years without a large shock are 3.56% of sales, while those firm-years with a large shock are 5.03% of sales. Those firms with mergers have larger positive errors (actual sales exceed forecasted sales) while those firms with discontinued operations have larger negative errors (actual sales fall short of forecasted sales), on average. While our model does not attempt to forecast these large shocks to sales, users of this model could temper their reliance on the model estimate if they had additional information about impending shocks (such as merger announcements).[25]

Comparison to IBES analysts' revenue forecasts

To put our models' out-of-sample error rates in perspective, we compare them to the error of the consensus IBES analysts' sales forecast. The data for our forecast model is typically available at the prior year's earnings announcement date, although may sometimes not be available until the 10-K is filed; that is, it becomes available somewhere between 9 and 12 months prior to end of the forecasted fiscal year end. Model 1, combined with a mean reversion comp growth estimate, yielded an out-of-sample median forecast error in Table 9 of 3.79% of sales. As a comparison, the IBES consensus analysts' sales forecast has a median error of 3.2% twelve months prior to

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[24] We identify firms who underwent a merger or acquisition in the forecasted year as those with non-zero "AQC" in Compustat Xpressfeed. We proxy for rapid contractions with the existence of a discontinued operation ("DO" in Xpressfeed). Focusing on discontinued operations understates the effects of rapid contractions, as many firms restructure their operations, including the closure of a large number of stores, but this does not quality for reporting under discontinued operations. Compustat has only recently begun separately tracking restructuring charges from all other special items. As such, we focus on discontinued operations to reduce noise. Results are similar if we also include large special items (income-decreasing special items of 2% or 5% of sales).

[25] Shocks can also occur during the estimation period and this is also expected to weaken our model's ability to forecast accurately; users of the model should consider manually adjusting the stores in the estimation period to take these shocks into account.

the fiscal year end (not tabulated). We illustrate the errors graphically in Figure 1. We partition 1997–2003 and 2004–2007 for two reasons. First, analysts have issued more accurate sales forecasts over time (not tabulated). Second, analysts may have adapted their forecasts using the model presented in this paper as early as 2004 (the year it was first made publicly available). Referring to the first time period, it is clear from the graph that using only five years of history, the firm's public disclosure about next year's store openings and closing, and a simple heuristic for forecasting comp growth, our model does almost as well as the consensus analyst sales forecast. This is noteworthy, as analysts are able to take many additional factors into account when forming their forecasts, such as management guidance, the economy, and announced plans relating to large acquisitions or dispositions.

Finally, we regress realized change in sales on the IBES forecast and our forecast of the change in sales using model 1, and present this estimation in Table 11. Consistent with analysts having a much larger information set, the coefficient on the IBES change in sales forecast issued four months after the prior fiscal year end is significant, with a coefficient of 0.743. However, even with the larger information set used by the IBES analysts, our forecast of the change in sales is positive and significant, with a coefficient of 0.069. Thus, the model forecast has significant explanatory power for realized change in sales, after controlling for the IBES forecast. Interestingly, when we partition this test over a similar time period to Figure 1 (1997–2003 and 2004–2007), model 1 has greater explanatory power for future change in sales in the earlier time period. Thus, especially in the earlier time period, IBES analysts do not appear to be fully incorporating the implications of forecasted stores and comparable store sales growth.[26] Though they appear to be adding in more of this information in the more recent time period, model 1 continues to provide marginally significant explanatory power for change in sales, suggesting that not all analysts have adopted the implications of forecasted store changes into their forecasting models.

CONCLUSION

We present a model of the sales-generating process that logically combines information about the number of sales-generating units and changes in the sales rates on those units. The model is reasonably flexible, accommodating different sales rates for different maturities of units, and it specifies how these rates can be estimated from past data. The model produces sales forecasts for a sample of retail firms that are as accurate as analyst revenue forecasts and, when used in conjunction with analyst forecasts, add significant incremental information.

The model and empirical work can be extended in a number of ways. First, while the model was developed with a retail firm in mind, it could be applied to any situation with reasonably homogeneous sales-generating units given data on past changes in the sales-generating rates (that is, something analogous to the comparable store sales growth rate). Further, the model would certainly generate more accurate forecasts if the user applied it at the segment level. For instance, Wal-Mart discloses sales, store counts and comps separately for Wal-Mart stores and Sams Clubs. The model could be estimated separately on each of these store-types to produce more accurate predictions. Finally, the model does not take into account the endogenous nature of store openings and closings. It is likely that retail firms open or close stores based in part on the sales-generating rates observed at new versus old stores. Our coefficient estimates simply reflect the net effect of these decisions, but a more complete model could use the estimates to anticipate future store openings and closings.

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[26] The incremental association extends to model 2 and model 3 (not tabulated).

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Figure 1: Comparison of IBES and Model 1 (1999-2003 and 2004-2007)

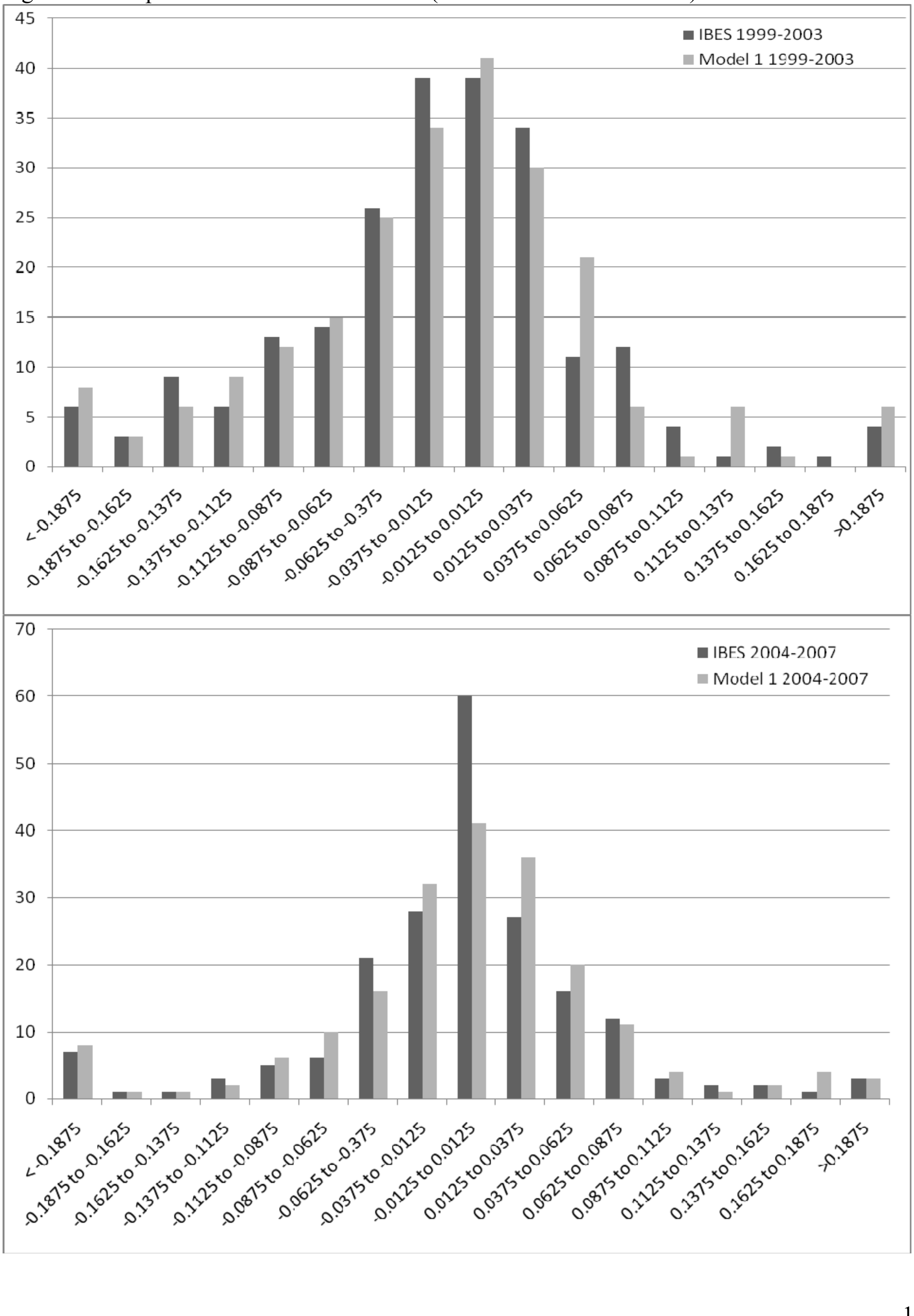

Table 1: Sample Firms

Name	Average Sales	Average Stores	Name	Average Sales	Average Stores
Abercrombie	1,319	432	Neiman-Marcus	3,099	47
American Eagle	1,539	746	Nordstrom	6,026	138
Ann Taylor	1,139	456	Office Depot	11,527	882
Autozone	4,516	2,917	Officemax	3,897	757
BJS	5,759	132	O Reilly	845	642
Barnes and Noble	4,118	1,350	Pacific Sunwear	761	686
Bed, Bath and Beyond	2,865	392	Pathmark	3,880	139
Best Buy	15,350	743	Penney, JC	25,311	2,634
Big Lots	3,245	1,437	Pep Boys	2,044	586
Bombay	471	440	Petsmart	2,778	627
Borders	3,256	1,214	Pier 1 Imports	1,382	920
Buckle	339	250	Radioshack	4,915	5,024
CVS	25,062	4,595	Rite Aid	10,789	3,227
Caseys	1,627	1,103	Ross Stores	2,518	406
Charming Shoppes	1,818	1,830	Ruddick	2,331	140
Childrens Place	846	628	Safeway	26,204	1,464
Circuit City	9,949	851	Saks	5,623	321
Claires	1,025	2,677	Sears	39,745	851
Cost Plus	570	151	7-Eleven	8,236	5,685
Costco	35,073	338	Sharper Image	426	122
Dillards	7,727	313	Smart and Final	1,689	203
Dollar General	5,158	5,261	Sports Authority	1,405	192
Dress Barn	795	876	Staples	10,263	1,243
Family	3,632	4,093	Starbucks	3,299	3,527
Freds	1,007	408	TJX	11,345	1,731
Gap, The	11,912	2,656	Talbots	1,543	848
Great A & P	10,082	788	Target	32,850	1,162
Group 1 Automotive	5,036	126	Tiffany	1,788	130
Guitar Center	1,073	106	Toys R Us	10,986	1,305
Gymboree	519	577	Trans World	938	741
Hancock Fabrics	401	454	Tween Brands	586	491
Haverty Furniture	703	109	Tweeter	552	124
Home Depot	49,634	1,253	Urban Outfitters	583	109
Hot Topic	320	347	Wal-Mart	178,897	2,604
Intimate Apparel	3,536	1,720	Walgreen	21,909	3,128
Jo-Ann Stores	1,448	925	Weis Markets	1,979	193
Kohls	8,499	454	West Marine	544	273
Limited	9,409	4,594	Wet Seal	420	411
Linens N Things	2,058	388	Whole Foods	2,466	118
Longs Drug	4,035	430	Wild Oats	841	97
Lowes	24,704	801	Williams-Sonoma	1,619	359
May Department	13,403	645	Wolohan	365	50
Mens Wearhouse	1,095	553	Zale	1,894	1,826
Michaels	2,540	811			

Table 2: Descriptive Statistics

Variables	Mean	Median	Std Dev	First Quartile	Third Quartile
Sales	9,295.5	2,415.4	25,714.8	929.1	8,177.8
Sales Growth	12.9%	10.6%	15.4%	4.2%	18.4%
Comparable Store Sales Growth	3.8%	3.8%	6.2%	0.9%	7.0%
Industry Sales Growth	4.3%	4.1%	4.7%	1.4%	7.1%
Total Stores	1,131	629	1,365	231	1,333
Store Growth	9.7%	6.5%	20.8%	0.9%	13.2%
Change in Stores	64	27	217	4	81
New Stores	99	44	187	14	104
Mid Stores	96	42	182	14	100
Closed Stores	35	5	128	1	33
Old Stores	936	494	1,187	186	1,093
Comp-adjusted change in # of existing stores	77	34	195	8	102
Comp-adjusted change in # of new stores	3	1	72	-3	7

There are 1,036 firm-year observations and 87 individual firms. Sales is Annual Net Sales for fiscal year t (Compustat #12), Sales Growth is [($Sales_t$– $Sales_{t–1}$)/$Sales_{t–1}$]. Comparable Store Sales Growth is equal to Sales Growth for stores that were open for the entire current year and the entire prior year (see Old Stores below). Total Stores is equal to the total number of stores open at the end of fiscal year t. Store Growth is [(Total $Stores_t$ – Total $Stores_{t–1}$)/Total $Stores_{t–1}$]. Change in Stores is Total $Stores_t$ – Total $Stores_{t-1}$. New Stores is equal to the number of stores opened during fiscal year t. Mid Stores is equal to the number of New Stores opened in year t–1. Closed Stores is equal to the number of stores closed during fiscal year t. Old Stores is equal to the number of stores that were open for all of year t and t–1, so that Old Stores = Total Stores – New Stores – Mid Stores. The comp-adjusted changes in the number of existing and new stores are the independent variables from equation 7; new and closed stores are assumed to occur halfway through the year.

Table 3: Spearman Correlation Table

	Sales Growth	Comp. Store Sales Growth	Industry Sales Growth	Total Stores	Store Growth	Change in Stores	Comp-adjusted change in # of existing stores	Comp-adjusted change in # of new stores
Sales	-0.170	0.001	0.006	0.550	-0.193	0.158	0.295	0.013
	(0.0001)	*(0.9688)*	*(0.8391)*	*(0.0001)*	*(0.0001)*	*(0.0001)*	*(0.0001)*	*(0.6692)*
Sales Growth		0.627	0.207	-0.066	0.692	0.520	0.469	0.303
		(0.0001)	*(0.0001)*	*(0.0348)*	*(0.0001)*	*(0.0001)*	*(0.0001)*	*(0.0001)*
Comparable Store Sales Growth			0.221	0.014	0.221	0.173	0.404	0.235
			(0.0001)	*(0.6578)*	*(0.0001)*	*(0.0001)*	*(0.0001)*	*(0.0001)*
Industry Sales Growth				0.009	0.128	0.118	0.143	0.101
				(0.7840)	*(0.0001)*	*(0.0002)*	*(0.0001)*	*(0.0015)*
Total Stores					-0.155	0.385	0.582	0.071
					(0.0001)	*(0.0001)*	*(0.0001)*	*(0.0219)*
Store Growth						0.749	0.333	0.466
						(0.0001)	*(0.0001)*	*(0.0001)*
Change in Stores							0.664	0.453
							(0.0001)	*(0.0001)*
Comp-adjusted change in # of existing stores								0.081
								0.0088

There are 1,036 firm-year observations and 87 individual firms. Sales is Annual Net Sales for fiscal year t (Compustat #12), Sales Growth is [($Sales_t$– $Sales_{t–1}$)/$Sales_{t–1}$]. Comparable Store Sales Growth is equal to Sales Growth for stores that were open for the entire current year and the entire prior year (see Old Stores below). Total Stores is equal to the total number of stores open at the end of fiscal year t. Store Growth is [(Total $Stores_t$ – Total $Stores_{t–1}$)/Total $Stores_{t–1}$]. Change in Stores is Total $Stores_t$ – Total $Stores_{t-1}$. The comp-adjusted changes in the number of existing and new stores are the independent variables from equation 7; new and closed stores are assumed to occur halfway through the year.

Table 4: In Sample Comparison of Models

Panel A - In Sample Estimation Results for Model 1 and Model 2

Models	Median Estimated Sales Rates (p-values)		Percent Positive Sales Rates		Mean (Median) $k \in (.8, 1.2)$	Median Adjusted R^2
	Old Rate	NewRate	Old	New		
Model 1: New/Old, k = 1	3.51 (0.001)	3.73 (0.014)	98.9%	92.0%	n/a	91.7%
Model 2: New/Old, $k \in (.8, 1.2)$	3.70 (0.001)	3.98 (0.012)	98.9%	92.0%	1.0 (1.0)	92.8%

Panel B – In Sample Regression Errors for Models 1 – 6

	Model 1 k=1	Model 2 $k \in (.8, 1.2)$	Model 3 (1+G)(1+C)–1	Model 4 Mean Reversion	Model 5 ChgStores	Model 6 ChgNew/ Old Stores
Median of Median [|Residual|/Sales]	2.49%	1.99%	3.24%	4.50%	4.61%	4.04%

The dependent variable is the change in sales from year t–1 to year t ($\Delta SALES_t$), where sales is Annual Net Sales for fiscal year t (Compustat #12). There are 1,036 firm-year observations and 87 individual firms. Regressions are estimated by firm with a minimum of 6 and a median of 12 observations per regression. Regressions are estimated without intercepts using ordinary least squares. All p-values are for one-tailed tests. The adjusted R^2 has been modified to reflect the absence of a constant term (see footnote 13). Descriptions of the six models follow.

Table 4, Continued

LMR Models

Model 1:

$$\Delta Sales_{T-\tau} = \left[\frac{(1+C_{T-\tau})(O_{T-\tau}+M_{T-\tau})-(O_{T-\tau-1}+M_{T-\tau-1})}{\prod_{i=T-\tau}^{T}(1+C_i)} \right] R_T^O + \left[\frac{(1+C_{T-\tau})N_{T-\tau}-N_{T-\tau-1}}{\prod_{i=T-\tau}^{T}(1+C_i)} \right] R_T^N$$

Model 2:

$$\Delta Sales_{T-\tau} = \left[\frac{(1+C_{T-\tau})Q_{t-\tau}(O_{T-\tau}+kM_{T-\tau})-(O_{T-\tau-1}+kM_{T-\tau-1})}{\prod_{i=T-\tau}^{T}(1+C_i)Q_i} \right] R_T^O + \left[\frac{(1+C_{T-\tau})Q_{t-\tau}N_{T-\tau}-N_{T-\tau-1}}{\prod_{i=T-\tau}^{T}(1+C_i)Q_i} \right] R_T^N$$

Model 3: $\Delta Sales_{T-\tau} = ([([(O_{T-\tau} + M_{T-\tau} + N_{T-\tau}) - (O_{T-\tau-1} + M_{T-\tau-1} + N_{T-\tau-1})]$
$/ (O_{T-\tau-1} + M_{T-\tau-1} + N_{T-\tau-1})) \times (1 + C_t)] - 1) \times Sales_{t-1}$

where
N_t = number of new stores opened in year t (i.e. 'new' stores)
$M_t = N_{t-1}$ = number of new stores opened in year t–1 (i.e. 'mid' stores)
D_t = number of stores closed in year t (i.e. 'dead' stores)
O_t = number of stores open for at least 2 years and open at the end of year t (i.e. 'old' stores)
C_t = comparable store sales growth, where comparable stores have been open two full years and are open at the end of year t, and
$Q_t \equiv \frac{O_{t-1} - D_t + kM_{t-1}}{O_t}$, where *k* in the set {.8, .9, 1, 1.1, 1.2}.
Models 1 and 2 estimate the sales-generating rates R_T^O and R_T^N.

Ad hoc Models
Model 4: $\Delta Sales_{T-\tau} = Sales_{T-\tau-1} SG_j$. where SG_j is the median sales growth in year t for each decile j, and j is formed in year t–1 based upon the sales growth in year t–1.

Model 5: $\Delta Sales_{T-\tau} = \beta[(O_{T-\tau} + M_{T-\tau} + N_{T-\tau}) - (O_{T-\tau-1} + M_{T-\tau-1} + N_{T-\tau-1})]$.

Model 6: $\Delta Sales_{T-\tau} = \gamma_1[(O_{T-\tau} + M_{T-\tau}) - (O_{T-\tau-1} + M_{T-\tau-1})] + \gamma_2[N_{T-\tau} - N_{T-\tau-1}]$.

Notes: Model 4 estimates the growth rates SG_j, model 5 estimates the parameter β and model 6 estimates the parameters γ_1 and γ_2.

Table 5: In-Sample Firm Specific Estimates for Model 1

Name	Old Rate	New Rate	Adjusted R^2	Name	Old Rate	New Rate	Adjusted R^2
Abercrombie	3.52	5.25	93.4	Neiman-Marcus	58.73	39.93♦	88.4
American Eagle	3.09	3.00	91.1	Nordstrom	33.31	42.84	78.9
Ann Taylor	2.78	3.00	97.5	Office Depot	9.12	20.01	57.8
Autozone	1.40	0.57	92.7[F]	Officemax	4.65	7.16	96.9
BJS	46.48	40.54	96.1	O Reilly	1.25	2.40	92.9[F]
Barnes & Noble	0.75	0.81♦	58.8	Pacific Sunwear	1.20	1.80	99.0
Bed, Bath, Beyond	6.57	15.65	96.7[F]	Pathmark	14.56	9.50♦	37.4
Best Buy	2.19♦	1.87♦	-7.5	Penney, JC	6.29	2.14	95.9[F]
Big Lots	2.22	3.24	85.6	Pep Boys	3.31	-3.68	76.3[F]
Bombay	0.77	1.51	73.6	Petsmart	3.95	3.45	96.8
Borders	2.74	5.88♦	28.6	Pier 1 Imports	1.09	1.92	95.5
Buckle	1.47	2.58	97.3	Radioshack	0.03♦	7.35♦	-8.8
CVS	6.91	9.22	92.3[F]	Rite Aid	6.11	2.75	83.8[F]
Caseys	2.64	3.99	98.7	Ross Stores	6.67	7.88	97.8
Charming Shop.	1.09	0.65	56.7	Ruddick	12.37	36.42	42.1
Childrens Place	1.78	1.27	98.7[F]	Safeway	19.84	38.11	65.0[F]
Circuit City	2.40	2.18♦	24.7	Saks	8.45♦	-8.13♦	-2.9
Claires	0.50	0.34	90.0	Sears	-25.35♦	-488.10♦	-13.6
Cost Plus	3.47	3.73	97.3	7-Eleven	2.54	-3.67♦	44.0
Costco	120.77	206.59	98.4	Sharper Image	2.43	5.17	94.3
Dillards	20.20	25.33	94.4[F]	Smart and Final	7.95	14.16	40.4
Dollar General	1.08	2.23	99.3[F]	Sports Authority	6.19	6.34	96.4
Dress Barn	0.90	0.95	94.0	Staples	9.25	14.89	91.0
Family	1.02	1.19	98.7	Starbucks	1.18	0.66♦	98.9
Freds	2.33	3.40	95.5	TJX	6.74	-2.01♦	76.3
Gap, The	4.03	5.23	67.5	Talbots	1.49	2.94	91.8[F]
Great A & P	6.55	3.79♦	30.2	Target	30.84	146.59	88.2
Group 1 Auto.	58.71	62.31	47.1	Tiffany	15.30	13.02	94.2
Guitar Center	10.52	4.44♦	91.7	Toys R Us	5.91	12.68	47.9
Gymboree	1.12	1.10	96.5	Trans World	1.03	2.10	84.5
Hancock Fabrics	0.37	0.82	12.4	Tween Brands	1.24	2.50	97.1
Haverty Furniture	5.50	8.48	74.7	Tweeters	4.37	1.05♦	90.9[F]
Home Depot	39.30	-29.18♦	88.7	Urban Outfitters	5.98	7.87	99.2
Hot Topic	0.89	1.04	97.9	Wal-Mart	111.65	322.74	93.5
Intimate Apparel	1.92	1.68♦	91.7	Walgreen	7.86	20.78	98.1
Jo-Ann Stores	1.91	2.63	54.6	Weis Markets	7.85	10.68	60.9
Kohls	16.48	62.38	98.9[F]	West Marine	1.47	2.66	84.4[F]
Limited	1.42	4.05	57.3	Wet Seal	1.06	1.38	94.2[F]
Linens N Things	4.68	8.90	95.7	Whole Foods	29.85	43.33	97.5
Longs Drug	8.72	14.01	89.9	Wild Oats	10.30	11.27	88.5
Lowes	31.19	88.70	97.6[F]	Williams-Son.	6.87	8.05	91.9
May Dept	1.06♦	-0.57♦	-20.3	Wolohan	5.17	6.54	94.9
Mens Wearhouse	2.48	3.64	96.6[F]	Zale	0.62	0.76	60.5
Michaels	3.33	5.52	98.2[F]				

All coefficients are statistically significant at $p < .10$ (one-tailed) unless denoted with a "♦".

[F] The null that Old Rate is equal to the New Rate is rejected at $p < .10$ (two-tailed).

The median firm has 12 observations. Regressions are estimated without intercepts using ordinary least squares. The adjusted R^2s have been modified to reflect the absence of a constant term (see footnote 13). See Table 4 for model 1 and related definitions.

Table 6: Out-of-Sample Forecast Errors Using a Five-Year Estimation Period with Perfect Foresight of Inputs

	Model 1: $k = 1$	Model 2: $k \in (.8, 1.2)$	Model 3: $(1+g)(1+c)-1$
Foresight Assumption	Median Error	Median Error	Median Error
Perfect Foresight for both Comp Growth and Change in Stores	2.39%	2.80%	2.95%
Perfect Foresight for Comp Growth but not Change in Stores (using store forecasts provided by firm)	2.87%	2.65%	2.73%
Perfect Foresight for Change in Stores but not Comp Growth (using prior year comp growth)	4.34%	4.15%	4.63%

The dependent variable $\Delta SALES_{T+1}$, is the change in sales, where Sales is Annual Net Sales (Compustat #12). There are 87 individual firms and 1,036 firm-year observations. Estimation periods are exactly five observations per firm. Regressions are estimated without intercepts using ordinary least squares. The models require an estimate of comparable store sales growth for the year being forecasted and an estimate of the change in the number of stores. Median Error is equal to the median of each firm's individual median absolute residual scaled by sales (i.e. Median of Median [|Residual|/Sales]). The out-of-sample residual is $\Delta SALES_{HAT} - \Delta SALES_t$ where $\Delta SALES_{HAT}$ is estimated by multiplying the coefficients generated from the estimation period to forecasted values of stores and comparable store sales growth. See Table 4 for model descriptions and additional variable definitions.

Table 7: Spearman Correlation Table for Comparable Store Sales Growth Estimation

Variables	Comparable Store Sales Growth	Prior Year Comparable Store Sales Growth	Industry Sales Growth	Walmart Comparable Store Sales Growth
Comparable Store Sales Growth	1.000	0.509 *(0.0001)*	0.215 *(0.0001)*	0.127 *(0.0001)*
Prior Year Comparable Store Sales Growth		1.000	0.220 *(0.0001)*	0.136 *(0.0001)*
Industry Sales Growth			1.000	0.095 *(0.0045)*
Walmart Comparable Store Sales Growth				1.000

There are 891 firm-year observations. Comparable Store Sales Growth is the growth in sales attributable to stores that have been open for two full years and remain open at the end of fiscal year t. Industry Sales Growth is the monthly sales growth for the firm's NAICS code taken from the Advance Monthly Retail Sales Report provided by the US Census Bureau. Both the Industry Sales Growth and the Walmart Comparable Store Sales Growth are obtained in the third month of fiscal year t.

Table 8: In-Sample Estimation of Comparable Store Sales Growth

	Dependent Variable: Comparable Store Sales Growth			
Variables	Coefficient (t-statistic)	Coefficient (t-statistic)	Coefficient (t-statistic)	Coefficient (t-statistic)
Intercept	0.021 (9.31)	0.014 (5.17)	0.008 (1.55)	0.02 (n.a.)[27]
Prior Year Comparable Store Sales Growth	0.412 (13.15)	0.383 (12.05)	0.402 (12.79)	0.457 (15.14)
Industry Sales Growth		0.182 (4.30)		
Walmart Comparable Store Sales Growth			0.245 (3.05)	
Adjusted R^2	16.2%	17.8%	17.0%	20.4%[28]
Median [Median_i $\lvert \text{Residual}_i \rvert$]	2.54%	2.67%	2.59%	2.63%

There are 859 firm-year observations with available data to estimate all four regressions. Models are estimated with pooled regressions, as follows:

Comparable Store Sales Growth = $\alpha_0 + \alpha_1$Prior Year Comparable Store Sales Growth + ε

Comparable Store Sales Growth = $\alpha_0 + \alpha_1$Prior Year Comparable Store Sales Growth + α_2Industry Sales Growth +ε

Comparable Store Sales Growth = $\alpha_0 + \alpha_1$Prior Year Comparable Store Sales Growth + α_2Walmart Sales Growth +ε

Comparable Store Sales Growth = .02 + α_1(Prior Year Comparable Store Sales Growth–.02) + ε

where Comparable Store Sales Growth is the growth in sales attributable to stores that have been open for two full years and remain open at the end of fiscal year t. Industry Sales Growth is the monthly sales growth for the firm's NAICS code taken from the Advance Monthly Retail Sales Report provided by the US Census Bureau. Walmart Sales Growth is the average comparable store sales growth reported by Walmart for the first three months of each firm's fiscal year.

27 The intercept is restricted to .02 in this model.

28 The adjusted R^2 in this model is not comparable to that of the other models because it is estimated with a restricted intercept.

Table 9: Out-of-Sample Forecast Errors Using a Five Year Estimation Period

Comparable Stores Sales Forecasts	Model 1: k = 1	Model 2: k ∈ (.8, 1.2)	Model 3: (1+C)(1+G)-1
	Median Error	Median Error	Median Error
$\hat{\alpha}_0 + \hat{\alpha}_1$Prior Year Comparable Store Sales Growth	3.98%	4.29%	3.86%
$\hat{\beta}_0 + \hat{\beta}_1$Prior Year Comparable Store Sales Growth + $\hat{\beta}_2$Industry Sales Growth + ε	4.16%	4.26%	4.09%
$\hat{\beta}_0 + \hat{\beta}_1$Prior Year Comparable Store Sales Growth + $\hat{\beta}_2$WalMart Sales Growth + ε	4.06%	4.38%	4.12%
.02 + $\hat{\gamma}_1$(Prior Year Comparable Store Sales Growth – .02)	3.79%	3.88%	3.81%

The dependent variable $\Delta SALES_{T+1}$, is the change in sales, where Sales is Annual Net Sales (Compustat #12). There are 87 individual firms and 522 firm-year observations. Estimation periods are exactly five observations per firm. Regressions are estimated without intercepts using ordinary least squares. Each of the models requires an estimate of the change in stores and comparable store sales growth for the year being forecasted. We use the store forecasts provided in each firm's 10-K for the former, and estimate the latter in a variety of ways. The four rows provide estimates of comparable store sales growth in year T+1 that are estimated via out-of-sample forecasts based on the regression models of comparable store sales growth outlined in Table 8. Median Error is equal to the median of each firm's individual median absolute residual scaled by sales (i.e. Median of Median [|Residual|/Sales]). The out-of-sample residual is $\Delta SALES_{HAT}$ – $\Delta SALES_t$ where $\Delta SALES_{HAT}$ is estimated by multiplying the coefficients generated from the estimation period to forecasted values of stores and comparable store sales growth. See Table 4 for model descriptions and additional variable definitions.

Table 10: Out-of-Sample Forecast Errors Using a Five-Year Estimation Period Conditioning on Realized Shocks to Sales for Model 1 (k=1)

Sales Shock	Median Error (Absolute Value)	Median Error (Positive Values)	Median Error (Negative Values)
No Merger and Acquisition or Discontinued Operation (354 firm-years)	3.56%	3.27%	-4.78%
Merger and Acquisition or Discontinued Operation (181 firm-years)	5.03%	4.23%	-6.51%
Merger and Acquisition (and no Discontinued Operation) (106 firm-years)	3.64%	4.79%	-2.71%
Discontinued Operation (and no Merger and Acquisition) (62 firm-years)	6.90%	3.67%	-8.98%
Merger and Acquisition and Discontinued Operation (13 firm-years)	6.55%	4.78%	-17.35%

The dependent variable $\Delta SALES_{T+1}$, is the change in sales, where Sales is Annual Net Sales (Compustat #12). There are 87 individual firms and 522 firm-year observations. Estimation periods are exactly five observations per firm. Regressions are estimated without intercepts using ordinary least squares. The models require an estimate of comparable store sales growth for the year being forecasted and an estimate of the change in the number of stores. Median Error is equal to the median of each firm's individual median absolute residual scaled by sales (i.e. Median of Median [|Residual|/Sales]). The out-of-sample residual is $\Delta SALES_{HAT} - \Delta SALES_t$ where $\Delta SALES_{HAT}$ is estimated by multiplying the coefficients generated from the estimation period to forecasted values of stores and comparable store sales growth. See Table 4 for model descriptions and additional variable definitions.

Table 11: Regression of Realized Change in Sales on Sales Estimates

	Dependent Variable: ΔSales		
	Full Sample	1999–2003	2004–2007
Variables	Coefficient (t-statistic)	Coefficient (t-statistic)	Coefficient (t-statistic)
Intercept	68.02 (1.50)	46.88 (0.71)	95.56 (1.86)
Model 1 Change in Sales Estimate	0.069 (6.09)	0.091 (6.71)	0.042[a] (1.84)
I/B/E/S Change in Sales Estimate	0.743 (45.34)	0.663 (29.19)	0.832 (33.19)
Adjusted R^2	94.34%	92.89%	96.95%
Number of firm-year observations	439	241	198

There are 439 firm-year observations. Models are estimated with pooled OLS regressions.
[a] Lower than the coefficient estimated from 1999–2003 with a p-value of 0.11.