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

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1. Introduction

Financial statements derive much of their usefulness from the association between the disclosed current period data and future economic outcomes. While the current period results in isolation may be useful for some purposes, the bulk of financial statement users are interested in predicting future outcomes that map into the value of equity or debt claims on the firm. Research in financial statement analysis examines how the mappings from current period data to future outcomes should be made. In this paper we model one of the most important mappings— the relation between the firm's current period disclosures and future sales—and examine how well our model works in the retail industry. While forecasting retail sales may seem like a rather narrow exercise, it is a direct test of the usefulness of the disclosures these firms make about their sales activity. In addition, we show that the relation between current period sales data and a logical forecast of future sales is significantly more complicated than one might think. By thinking carefully about how the mapping should be modeled and then estimating the model parameters and making forecasts, we illustrate a process that can be used for many financial statement items beyond just sales and across most industries.

Every financial statement forecast begins with a sales estimate. Typically the sales estimate is then combined with margin forecasts to estimate future income and combined with turnover forecasts to estimate future assets, but the entire process is predicated on a sales forecast. Prior models that forecast firm-level sales are typically based on estimated rates of mean reversion in total sales (most notably Nissim and Penman 2001 and Fairfield et al. 2009). We show that, by distinguishing between growth in sales-generating units (i.e., new stores) and growth in sales per unit (i.e., comparable store growth rates), our forecasts are significantly more accurate than the forecasts from these models. In particular, for a sample of retail firms between 1995 and 2010, the median in-sample error from our model is approximately 2 percent of sales whereas the median in-sample error from the mean reversion model is approximately 4 percent of sales. We go on to document that our model's out-of-sample forecasts, based on very few inputs, are almost as accurate as the consensus I/B/E/S analyst forecast. Importantly, our estimates can be used in conjunction with I/B/E/S forecasts to significantly improve overall forecast accuracy. This last result illustrates that analysts do not efficiently incorporate information available about different sources of sales growth into their forecasts.

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Our model illustrates a structured way to handle information about future sales-generating units and the future sales rates per unit and thus is applicable to virtually all industries. Further, the model estimates can distinguish between retail firms that enjoy "fad" status, so that their new stores earn considerably more than their more mature stores (e.g., Tiffany's), 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). We document that this distinction is useful and not fully appreciated by analysts. Thus our model is of practical use to analysts not only because it can improve their estimates, but also because it offers a clear structure for understanding a firm's sales process and provides a framework for organizing information they may collect about a firm's sales.

A considerable amount of accounting research has focused on how accounting data relate to equity value (labeled "capital markets research"). Financial statement analysis research explores the connections between current period accounting data, future economic outcomes, and the valuation of those expected outcomes. For instance, the literature on the time series of earnings, summarized in Brown (1993), focuses on the connection between current period earnings and future earnings. Relatedly, Freeman, Ohlson and Penman (1982) show that return on equity mean reverts, and Fairfield, Sweeney and Yohn (1996) show that the rate of mean reversion depends on the mix of income across the different line items. Other work has examined how specific financial statement ratios predict future profitability (see Ou and Penman 1989, Lev and Thiagarajan 1993, or Abarbanell and Bushee 1997).[1] Nissim and Penman (2001) fit these prior results into a comprehensive framework based on ratios that analyze growth and ratios that analyze profitability, showing that both components are necessary for valuation.

While much of the prior literature focuses on forecasting future profitability, much less work addresses how to forecast future growth. The benchmark result is in Nissim and Penman (2001) who study all publicly traded companies between 1962 and 1999 and show that percentage sales growth tends to mean revert very quickly. Fairfield et al. (2009) extend this result by showing that growth measures tend to mean revert to the industry mean while profitability measures tend to mean revert to the economy-wide mean. Neither paper conditions the predictions on the source of sales growth (new assets or existing assets). Cole and Jones (2004) take a "kitchen sink" approach to forecasting future sales in the retail industry, using up to 12 independent variables in a large pooled regression. This design suffers from two problems. First, pooling across firms in a single regression assumes that opening a new small store (e.g., a Starbucks) will create the same change in sales as opening a new large store (e.g., a Home Depot); we show later that firm-specific models yield very different regression coefficients. Second, the linear regression does not specify how comparable store growth rates and changes in the number of stores fit together in a logical way. By modeling how these variables are related to sales changes we gain power in the estimation and a meaningful interpretation of the results.

Another related literature uses nonfinancial metrics to predict future financial performance. Besides forecasting earnings rather than sales, these papers differ from our study in how closely related the nonfinancial 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

1. Other research that examines the specific evolution of an income statement line item include Anderson et al. (2003) and Anderson et al. (2006), who model economies of scale in selling, general, and administrative expenses.

Zhang (2001a, 2001b) study web traffic measures; and Nagar and Rajan (2001) study manufacturing quality measures. None of these measures distinguish between changes in financial performance due to changes in the performance of existing assets and changes due to the addition of new assets.[2] An exception is Bonacchi et al. (2012) who model nonfinancial metrics about subscription-based businesses. The model distinguishes between customers acquired at different points in time, with each cohort having its own evolution of profit margins and retention rates. Like our study of retail sales, they show how to integrate the nonfinancial inputs into a forecasted financial output and then use the model to forecast future earnings and predict analyst forecast errors.

Why study sales in the retail industry? From a practical perspective, we need to collect data from the management discussion and analysis (MD&A) on the number of sales-generating units and the growth in sales per unit, and these disclosures are very common and reasonably standardized in the retail industry. However, as we discuss later, many firms in many industries fit the general model that sales are generated by assets and the rate of sales generation changes in predictable ways. From a research design perspective, power in the tests comes from the homogeneity of our sample rather than from raw sample size. Further, by focusing on retail firms, our estimates have a natural interpretation as the sales rates for different vintages of stores, and we take advantage of this with many illustrations based on well-known retail firms. Finally, as the bellwether of personal consumption expenditures in the economy, the retail industry is of interest in its own right.

In the next section we develop a very general model of future sales and then introduce increasing levels of restrictions that allow the model to be estimated in different ways. We also present five ad hoc models based on prior literature or simple crass empiricism; these models serve as benchmarks for our model. In section 3 we describe our sample, giving the reader a snapshot of a typical retail firm. In section 4 we present a number of empirical results. Based on in-sample regressions, we show that all three of the variations on our model produce reasonable estimates, and all have lower residual errors than the five ad hoc models. We reach a similar conclusion using out-of-sample forecasts and provide evidence that the most significant source of forecasting error comes from the estimate of the next year's comparable store growth rate. Finally, we compare our out-of-sample forecast errors to I/B/E/S analyst forecast errors. While the I/B/E/S forecasts are slightly more accurate than our model forecasts, the analysts could lower their errors significantly if they adjusted their forecasts in the direction of our model. The relative performance of our model in out-of-sample tests is truly remarkable given the very short list of required inputs the model uses. We conclude in section 5.

2. The model

In this section we develop a general model for forecasting next year's sales. We then place increasingly restrictive constraints on the similarity between new and old assets, resulting in three variations on our model. We also describe five ad hoc models that we use as benchmarks for our model.

Our aim is to develop a model that can be used to forecast sales growth for a typical retail firm in a typical year based on publicly available data. One problem we must confront is the extreme limit on the number of observations available for 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, firms

2. Other 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 publicly available to outsiders such as financial analysts or competitors.

change their strategies over time, and using a longer history many not aid in our forecasting exercise. For these reasons we place heavy emphasis on developing a model with few estimated parameters. Consequently, we estimate our model on relatively little data; out-of-sample forecasts are estimated using only five historical observations.

We begin with the observation that the series of annual sales is the result of a number of different component forces. Further, it is valuable to decompose sales into its component forces because one of them—the number of new stores to be opened or closed in the next year—is often disclosed by management. 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:[3]

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

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

$$Sales_t = O_t R_t^O + M_t R_t^M + N_t R_t^N. \tag{1}$$

Besides asserting that sales are generated by stores, (1) is a tautology because the sales-generating rate from each of the three store maturity classes can change each period. 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. Second, as shown below, the mid stores are necessary in order to define precisely comparable store sales growth. In addition, 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

3. 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 halfway through the year, on average. This, in turn, implies that dead stores earned at the old store rate until they died.

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. 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.[4]

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 it keeps 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.

A useful special case is $R_t^M = R_t^O$. That is, after the end of the fiscal year in which a store opens, it immediately generates sales at the old store rate. 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.

As sales levels generally increase over time and we estimate our sales model over time, the error term in a levels regression is expected to be nonstationary. 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, (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" sales rate that is stable.

4. A numerical example of (2) is as follows: Suppose a firm started year t with 110 old stores and 25 mid stores, and during the year it closed 10 stores and opened 15 new ones, for a final total of 140 stores. Further, in year $t - 1$ there were 25 new stores (which is the mid store count for year t), 20 mid stores and 90 old stores, for a $t - 1$ total of 135 stores. As a check, note that the total store count increased by 5 in year t because 15 new stores opened and 10 stores died. If the sales per store rates are 6.7 for old stores in year t, 6.5 for old stores in year $t - 1$, and 6.3 for mid stores in $t-1$, then (2) says that $1 + C_t = 100{*}6.7/(80{*}6.5 + 20{*}6.3) = 1.037$.

Denote by T the most recent year in the dataset for a particular firm. The necessary condition of any restriction we impose on the sales-generating rates is that it allows us to rewrite (4) for a sample period in terms of R_T^O, R_T^M and R_T^N, allowing the parameters to be written in terms of year T dollars per store. Expressing the parameters in this fashion allows us to estimate them in a linear regression. We accomplish this by adjusting the independent variables for the historical comp rates, as seen below.

We examine the effect of three different restrictions on (4) in Models 1, 2, and 3 below. 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 comp 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.[5] 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 using assumption 2 as:

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

Note the different sources of changes in sales in year T. Both terms are close to the change in the number of stores, either existing stores (i.e., old plus mid) in the first term or new stores in the second 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 that grow same-store sales by 10 percent, the same as growing from 91.91 to 100 stores with no change in the sales-generating rate.

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

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

5. In unreported results we estimate the model assuming the new store rate is constant rather than changing with C_t. The median absolute errors from this alternative model are considerably higher than those reported with the new store rate adjusted by C_t.

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 due to comp growth 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.[6]

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" 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 $Q_t \equiv \frac{O_{t-1} - D_t + kM_{t-1}}{O_t}$ and note that Q_t is greater than or less than one as k is greater than or less than one. Now substitute $k\ R_t^O$ 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 right-hand side (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) $R_t^M = k\ R_t^O$ 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

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

6. 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 $T - \tau$. 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.

In addition to estimating the old store rate and the new store rate, model 2 requires an estimate of the proportionality factor k. For each value of k in the set {0.8, 0.9, 1.0, 1.1, 1.2}, we estimate the firm-level regression and retain the k that yields the lowest median absolute residual error. We limit k to this set because, while more extreme k values may result in a better in-sample fit, we do not expect extreme k values to be successful in out-of-sample prediction. 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.[7]

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
(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

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

Because there is only one rate in model 3 and it changes at a known rate, we can divide (10) by Sales at time $T - \tau - 1$ 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

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

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.

In summary, all three models illustrate how to weave together logically the changing numbers of stores with the comparable store growth rate. Model 1 distinguishes between new and old stores, model 2 further distinguishes between mid stores and old stores, and model 3 treats all three types of stores identically. All three models result in something very different from a linear regression of the change in sales on the change in the number of stores and the comp rate. While model 2 might appear the obvious winner because it is the most general, it also requires the most estimates and consequently may not be the best predictor out-of-sample. Practically speaking, model 2 is the most complicated model to understand and use, and there is evidence that humans often make better judgments in uncertain situations using simpler models (see Gigerenzer et al. 1999).

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 Nissim and Penman (2001).

7. 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 $T - \tau - 1$.

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 considers comp growth rates. This means that they effectively treat the estimated sales rates as constants.

Model 5 pools all types of stores together and estimates the average sales rate per store:

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

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 (i.e., the change in the number of stores). 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:

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

Model 7 assumes that changes in sales follow an autoregressive process, and does not require any information other than lagged sales.

$$\Delta Sales_{T-\tau} = \phi_1 \Delta Sales_{\tau-1}. \tag{15}$$

Model 8 is the "kitchen sink" model, combining models 6 and 7. It represents the pinnacle of ad hoc models insofar as it considers changes in the numbers of different store types and lagged sales but does not attempt to put these inputs into a logical framework:

$$\Delta Sales_{T-\tau} = \gamma_1[(O_{T-\tau} + M_{T-\tau}) - (O_{T-\tau-1} + M_{T-\tau-1})] + \gamma_2[N_{T-\tau} - N_{T-\tau-1}] + \phi_1 \Delta Sales_{\tau-1.} \tag{16}$$

3. The 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 10-K, are covered by COMPUSTAT, and did not have a change in their fiscal year during the six-year period.[8] A firm must have a minimum of

8. If the firm experiences a subsequent change in fiscal year, we eliminate firm-year observations in the year of and all years following the change.

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. 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 1,319 firm years) in the retail industry that have at least 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 average number of stores.

Firms disclosed the number of stores opening and closing separately 85 percent of the time. If this information is not disclosed separately, we compute the change in the ending number of stores and, if the difference is positive, we assume this was the number of stores opened and none were closed; if the difference is negative, we assume this was the number of stores closed and none were opened. If this assumption is incorrect it will understate the number of new stores opened and the number of old stores closed during the year, which in turn overstates the "comp-adjusted change in existing stores" term and understates the "comp-adjusted change in new stores" for that observation.

Table 2 provides descriptive statistics for the sample. The median firm has over $2.8 billion in total sales, annual sales growth of 8.7 percent, and comparable store sales growth of 3.0 percent. The median retail firm on COMPUSTAT is much smaller, with approximately $500 million in total sales and has a slightly slower growth rate, at 7.7 percent. In terms of number of stores, the median firm has 692 total stores and in a typical year opens 39 new stores and closes six stores. There are a few very large firms in the sample, such as Wal-Mart, 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. However, the two variables have a relatively low correlation with each other (0.088), 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. In addition, we compute the variance inflation factors for each of the regressions that follow. In no case was this value greater than 10, which is the threshold for a serious multicollinearity problem (Kutner et al. 2004).

4. Results

In-sample regressions

We begin by estimating our three models (models 1–3) and five benchmark models (models 4–8) using the entire history of available data. Each model is estimated separately for each firm with a minimum of 6 and a median of 16 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

TABLE 1
Sample firms

Name	Average sales	Average stores	Name	Average sales	Average stores
7-Eleven	8,236	5,685	Michaels	2,903	905
Abercrombie	1,814	585	Neiman-Marcus	2,993	46
American Eagle	1,989	845	Nordstrom	6,771	148
Ann Taylor	1,332	548	O Reilly Auto	1,493	1,119
Autozone	4,897	3,160	Office Depot	11,676	944
Barnes	4,282	1,270	Officemax	3,897	757
Bed Bath And Beyond	4,006	549	Pacific Sunwear	869	755
Best Buy	21,855	544	Pathmark	3,880	139
Big Lots Inc	3,561	1,421	Penney, JC	23,778	2,291
BJ’s	6,707	142	Pep Boys	1,986	573
Bombay	471	440	Petsmart	3,468	766
Borders	3,201	1,116	Pier 1 Imports	1,382	957
Buckle	427	272	Radioshack	4,753	4,875
Caseys	2,176	1,167	Rite Aid	13,568	3,539
Charming	1,965	1,928	Ross Stores	3,349	514
Children’s Place	1,112	741	Ruddick	2,654	148
Circuit City	10,098	903	Safeway	28,687	1,497
Claires	1,025	2,682	Saks	4,854	259
Cost Plus	666	184	Sears	37,609	833
Costco	44,229	383	Sharper	426	122
CVS	43,540	5,252	Smart & Final	1,689	203
Dillards	7,460	314	Sports Authority	1,405	192
Dollar General	6,667	6,118	Staples	13,402	1,481
Dress Barn	990	1,070	Starbucks	5,104	5,001
Family	4,359	4,575	Talbots	1,558	832
Fred’s	1,168	458	Target	39,024	1,263
Gap Inc	12,631	2,772	Tiffany & Co	2,026	148
Great A&P Tea Co	9,708	733	TJX	13,645	1,971
Group 1 Automotive	5,081	126	Toys	10,769	1,286
Guitar Center	1,073	106	Trans World	937	720
Gymboree	618	641	Tween Brands	656	555
Hancock Fabrics	368	404	Tweeter	552	124
Haverty	694	112	Urban	985	171
Home Depot	54,887	1,502	Wal-Mart	235,098	2,881
Hot Topic	418	461	Walgreen	27,817	3,752
Intimate Brands	3,536	1,720	Weis	2,102	190
Jo-Ann	1,577	884	West Marine	567	292
Kohl’s	10,959	616	Wet Seal	455	431
Limited Brands	9,392	4,159	Whole Foods	3,823	160
Linens ‘n Things	2,131	408	Wild Oats	841	97
Long’s Drug Stores	4,137	437	Williams	1,991	408
Lowe’s	30,953	1,030	Wolohan	359	50
May	13,403	645	Zale	1,920	1,887
Men’s Wearhouse	1,314	718			

variables are the derived changes in the number of stores in each category, adjusted for the historical and current comp rates; the regressions are estimated without an intercept because the model has no constant term.

TABLE 2
Descriptive statistics

Variables	Mean	Median	Std. dev.	First quartile	Third quartile
Sales	11,122	2,824	32,626	1,066	8,998
Sales Growth	10.8%	8.7%	15.8%	2.5%	16.6%
Comparable Store Sales Growth	2.9%	3.0%	6.6%	−0.1%	6.3%
Total Stores	1,236	692	1,531	272	1,389
Store Growth	7.9%	5.1%	16.3%	0.4%	11.6%
Change in Stores	60	23	217	2	76
New Stores	95	39	193	13	97
Mid Stores	95	40	191	13	98
Closed Stores	35	6	117	1	34
Old Stores	1,046	568	1,344	207	1,176
Comp-adjusted change in # of existing stores	71	31	211	5	101
Comp-adjusted change in # of new stores	1	1	87	−5	7

Notes:

There are 1,319 firm-year observations and 87 individual firms. Sales is Annual Net Sales for fiscal year t (COMPUSTAT SALE), 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 (7); new and closed stores are assumed to occur halfway through the year.

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; this makes the new store rate comparable to the old store rate. The median p-values on the old store rate and the new store rate are 0.0001 and 0.0079 for model 1, respectively. In addition, the estimated old stores sales rate is positive in 86 of the 87 regressions (98.9 percent), the estimated new store rate is positive in 82 of the 87 regressions (94.3 percent), and the median adjusted R^2 is 89.6 percent.[9]

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 0.90, suggesting that the median firm's mid stores generate less than the old stores and allowing the k to vary from one is a meaningful generalization for a significant number of the firms

9. 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 $(n-1)/(n-p)$.

TABLE 3
Spearman correlation table

	Sales	Sales growth	Comp. store sales growth	Total stores	Store growth	Change in stores	Comp-adjusted change in # of existing stores	Comp-adjusted change in # of new stores
Sales	1.000	−0.150	−0.034	0.542	−0.157	0.163	0.250	−0.025
		(0.0001)	*(0.2199)*	*(0.0001)*	*(0.0001)*	*(0.0001)*	*(0.0001)*	*(0.3674)*
Sales Growth		1.000	0.674	−0.097	0.689	0.524	0.524	0.326
			(0.0001)	*(0.0004)*	*(0.0001)*	*(0.0001)*	*(0.0001)*	*(0.0001)*
Comp. Store Sales Growth			1.000	−0.035	0.271	0.203	0.454	0.269
				(0.2035)	*(0.0001)*	*(0.0001)*	*(0.0001)*	*(0.0001)*
Total Stores				1.000	−0.155	0.341	0.488	0.015
					(0.0001)	*(0.0001)*	*(0.0001)*	*(0.5979)*
Store Growth					1.000	0.777	0.395	0.468
						(0.0001)	*(0.0001)*	*(0.0001)*
Change in Stores						1.000	0.657	0.431
							(0.0001)	*(0.0001)*
Comp-adjusted Δ in # of exis. stores							1.000	0.088
								(0.0013)
Comp-adjusted Δ in # of new stores								1.000

Notes:

There are 1,319 firm-year observations and 87 individual firms. Sales is Annual Net Sales for fiscal year t (COMPUSTAT SALE), 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 (7); new and closed stores are assumed to occur halfway through the year.

in the sample.[10] In the next section we give specific examples where allowing k to vary allows the model to match better the underlying sales-generating process. The significance of the coefficient estimates for model 2 are very similar to those of model 1 and the R^2 is marginally higher.

Table 4, panel B compares the in-sample fit of the three theoretically-derived models with the five 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.

Model 1 has a median forecast error of 2.43 percent of sales. Allowing k to vary, as in model 2, lowers the median forecast error to 1.84 percent. The median error for model

10. Note that the optimal k differs across time. In the earlier years of our study, the median is 1.1, but recent recession years are associated with lower rates for new and mid stores. Our out-of-sample forecasts rely on the five most recent historical years, allowing the optimal k to change over economic time periods.

TABLE 4
In-sample comparison of models

Panel A: In-sample estimation results for model 1 and model 2

Models	Median p-values from estimated sales rates: Old rate	Median p-values from estimated sales rates: New rate	Percent positive sales rates: Old	Percent positive sales rates: New	Mean (Median) $k \in (.8, 1.2)$	Median Adjusted R^2
Model 1: New/Old, $k = 1$	0.0001	0.0079	98.9%	94.3%	$k = 1$	89.6%
Model 2: New/Old, $k \in (.8, 1.2)$	0.0001	0.0086	98.9%	94.3%	0.98 (0.90)	91.0%

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	Model 7 chgsales	Model 8 (Model 6+Model 7)
Median of Median [|Residual| / Sales]	2.43%	1.84%	3.16%	4.08%	4.74%	4.23%	5.77%	3.47%

Notes:

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 SALE). There are 1,319 firm-year observations and 87 individual firms. Regressions are estimated by firm with a median of 16 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 9). Descriptions of the six models follow.

(The table is continued on the next page.)

TABLE 4 (continued)

Derived 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 is in the set {0.8, 0.9, 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: $\Delta Sales_{T-\tau} = \gamma_1[(O_{T-\tau}+M_{T-\tau})-(O_{T-\tau-1}+M_{T-\tau-1})]+\gamma_2[N_{T-\tau}-N_{T-\tau-1}]$.

Model 7: $\Delta Sales_{T-\tau} = \phi_1\Delta Sales_{\tau-1}$.

Model 8: $\Delta Sales_{T-\tau} = \gamma_1[(O_{T-\tau}+M_{T-\tau})-(O_{T-\tau-1}+M_{T-\tau-1})]+\gamma_2[N_{T-\tau}-N_{T-\tau-1}]+\phi_1\Delta Sales_{\tau-1}$.

much higher at 3.16 percent; however, this model requires only one year of historical data and does not require the estimation of sales-generating rates.

The final five columns of Table 4, Panel B provide the in-sample fit of the ad hoc models 4–8. Model 4, which uses the sample-wide level of mean reversion to estimate the sales change (as in Nissim and Penman 2001), has a median residual error of 4.08 percent of sales, dominating model 7, which treats mean-reversion as a firm-specific feature and has a median error of 5.77 percent 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 4.74 percent 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 4.23 percent of sales. Model 8 posts the lowest median residual error of the benchmark models, but the error is almost twice as large as the error on model 2. Even model 3, which does not require estimates of the sales rates but uses the logical structure of the model, has a substantially lower median residual error rate than the ad hoc models.

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 generally significant at the 0.10 level, suggesting that the model is sufficiently flexible to work well for most firms.

Consider a few examples from Table 5. As a benchmark, American Eagle Outfitters earns an estimated \$2.67 million per existing store and \$2.83 million per new store, and the estimated k in model 2 is 1.0 (not tabulated). 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 often open with heavy advertising and promotions, causing the annualized new store rate to far exceed the old store rate. Safeway and Costco clearly show this effect in our sample. For example, Safeway's estimated new store rate of \$39.67 million per store is approximately twice that of the estimated old rate of \$20.91 million per store.[11]

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 Starbucks are good examples of stores that are slow to mature because of the need to change shopping habits (such as visiting the new shopping center that opened with these stores or changing their morning commute).

For some 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 Petsmart as having an old store rate of \$4.00 million and a new store rate of \$5.74 million, with an adjusted R^2 of 95.9 percent. However, the estimated k in model 2 is 1.2, which means that the mid store rate is 120 percent of the old store rate. When this is added to the model, the old store rate decreases to \$3.676 million and the new store rate increases to \$7.46 million, with the implied mid store rate being $1.2 \times 3.676 =$ \$4.41 million. Model 2 reveals that the "honeymoon"

11. The honeymoon effect can also be driven by increasing store sizes over time. The estimated new store sales rate at Target is twice the old store rate partly because in 1995 the average Target store was 106,000 square feet but had grown to almost 134,000 feet in 2010. This is an additional reason to keep the estimation period relatively short; over time the stores become less comparable.

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
7-Eleven	2.54	−3.67 ns	44.0%	Michaels	3.24	5.17	97.3%
Abercrombie	2.53	2.39 ns	84.0%	Neiman-Mar	63.79	65.52	92.0%
American Eagle	2.67	2.83	91.6%	Nordstrom	22.95	33.60	44.7%
Ann Taylor	1.99	2.36	97.1%	O'Reilly Auto	1.46	1.40	98.4%
Autozone	1.46	0.59	91.8%	Office Depot	7.16	11.70	72.6%
Barnes	0.72	0.77 ns	58.7%	Officemax	4.65	7.16	96.9%
Bed Bath Bey	7.13	16.06	96.8%	Pacific Sunwear	0.80	0.89	97.2%
Best Buy	45.82	12.27 ns	94.4%	Pathmark	14.56	9.50 ns	37.4%
Big Lots Inc	2.31	3.40	86.0%	Penney, JC	5.54	1.91	95.4%
BJs	54.87	62.75	96.9%	Pep Boys	3.02	−3.31 ns	80.8%
Bombay	0.77	1.51	73.6%	Petsmart	4.00	5.74	95.9%
Borders	1.56	4.27 ns	63.3%	Pier 1 Imports	1.17	1.68	95.4%
Buckle	2.28	3.45	98.9%	Radioshack	0.18 ns	7.10	-2.7%
Caseys	3.41	6.92	98.2%	Rite Aid	5.46	7.76	89.0%
Charming	1.00	0.63	55.4%	Ross Stores	7.04	7.42	97.6%
Children's Place	1.89	1.41	98.6%	Ruddick	16.84	37.65	63.1%
Circuit City	2.30	2.09	28.1%	Safeway	20.91	39.67	66.8%
Claire's	0.50	0.34	90.6%	Saks	6.72	−12.36 ns	2.9%
Cost Plus	3.14	4.02	97.7%	Sears	−78.48	94.78 ns	28.2%
Costco	131.94	251.03	97.4%	Sharper	2.43	5.17	94.3%
CVS	14.45	11.03	47.4%	Smart & Final	7.95	14.16	40.4%
Dillards	16.31	20.75	92.6%	Sports Auth	6.19	6.34	96.4%
Dollar General	1.35	2.17	99.2%	Staples	7.85	10.74 ns	49.1%
Dress Barn	1.11	1.48	97.3%	Starbucks	1.22	0.65	84.0%
Family	1.14	1.55	98.1%	Talbots	0.64	1.38	89.6%
Fred's	2.29	3.55	88.4%	Target	32.45	65.87	88.1%
Gap Inc	3.28	4.26	70.0%	Tiffany & Co	11.72	27.13	83.7%
Great A&P	7.60	−29.18 ns	36.0%	TJX	7.98	6.25 ns	79.9%
Group 1 Auto	30.23	30.28	74.0%	Toys	5.90	12.68	52.6%
Guitar Center	10.52	4.44 ns	91.7%	Trans World	0.79	1.50	85.7%
Gymboree	1.00	1.40	94.5%	Tween Brands	1.13	1.24	96.0%
Hancock Fabrics	0.92	1.32	71.8%	Tweeter	4.37	1.05 ns	90.9%
Haverty	4.35	6.83	87.5%	Urban	5.62	13.22	98.1%
Home Depot	31.58	55.87 ns	72.2%	Wal-Mart	125.10	136.91	93.0%
Hot Topic	0.75	0.86	94.9%	Walgreen	7.17	7.62 ns	91.5%
Intimate Brands	1.92	1.68 ns	91.7%	Weis	7.14	2.39 ns	31.5%
Jo-Ann	2.16	2.99	55.0%	West Marine	1.35	2.44	83.7%
Kohl's	15.67	32.53	94.7%	Wet Seal	0.90	1.16	94.7%
Limited Brands	1.28	2.30 ns	45.9%	Whole Foods	26.89	29.89	93.8%
Linens 'n Things	4.51	8.95	95.7%	Wild Oats	10.30	11.27	88.5%
Long's Drug	8.92	13.87	88.6%	Williams	6.33	7.54	92.3%
Lowe's	26.36	57.64	96.8%	Wolohan	5.21	6.22	94.9%
May	1.06 ns	−0.57 ns	−20.3%	Zale	0.54	0.64	67.2%
Mens Warehse	0.94	1.51	45.7%				

(The table is continued on the next page.)

TABLE 5 (continued)

Notes:

All coefficients are statistically significant at $p < .10$ (one-tailed) unless marked "ns."

The median firm has 16 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 9). See Table 4 for model 1 and related definitions.

effect of opening a new store takes more than the partial year in which a Petsmart store opens to dissipate and reach maturity. 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. If so, the out-of-sample forecasts discussed in the next section will reveal this.

The model is by no means perfect for every firm, as evidenced by the occasional negative estimated rates (e.g., Great A&P Tea Co.) or negative adjusted R^2s (e.g., May Co.). Cases 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., Weis Markets operates large supermarkets and much smaller pet supply stores), (2) the firm undertakes a large restructuring, closing many stores and opening different types of new stores (in 2005 Sears merged with Kmart causing the store count to jump from 873 to 3,843 and mixing together two different types of stores), and (3) the firm has a significant nonstore revenue source (e.g., Staples only generates 39 percent of its sales from stores with the rest coming from online and direct business contracts). While our model does not automatically adapt to these special circumstances, it is not uncommon for firms to disclose sufficient details about the different sources of revenue to allow our model to be applied to each source separately. In addition, we later show that removing observations with mergers, acquisitions, or discontinued operations in the period significantly improves our out-of-sample forecast accuracy.

Out-of-sample forecasts

To use the models to forecast next year's change in sales, we need three inputs. 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.

As we show below, the forecast accuracy is very sensitive to the accuracy of the comparable store growth rate estimate. We considered many different sources of information to guide this estimate, including the changes in firm advertising expenditures, the U.S. Census Bureau's Advance Monthly Sales Report for Retail Trade, Wal-Mart's monthly comp disclosure, and estimating a firm-specific rate based on a firm's own history of comps. In the end, however, the most parsimonious model simply assumes that the firm's comp rate mean-reverts to 2 percent, which is approximately the Congressional Budget Office's long-run expected rate of inflation for our sample period. Finally, we consider various estimation periods (five years, ten years, or all available data). Overall the most robust comp-growth model simply estimates a single mean reversion rate for rolling 10 year periods for the pooled sample at the beginning of each year:

$$C_t - .02 = \gamma_{t-1}(C_{t-1} - .02). \tag{17}$$

Because the mean reversion coefficient γ_{t-1} is estimated over the 10 year pool of historical data preceding the forecast year, it varies slightly each year. For the entire pooled sample the coefficient is 0.469, and the model's adjusted R^2 is 22.3 percent (not tabulated).

We obtain the forecasted number of store openings/closing from the MD&A section of the firm's 10-K, as previously discussed. 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.[12] 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. The comp-adjusted number of each store type is constructed from the estimated comp growth from (17), the number of each type of store at the prior fiscal year end, and the 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 the out-of-sample results 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 in panel A of Table 6 is the forecast for 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 $T + 1$, but still estimated the sales-generating rates from five years of historical data, this is how our model would perform out-of-sample. With perfect foresight for comp growth and the number of stores, model 2 outperforms models 1 and 3, with a median error of 2.59 percent of sales.[13] As in the in-sample forecasting exercise, model 3 performs the worst among our three models. 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 median absolute residual error when only one of these inputs is known with certainty.

The second row has perfect foresight of comp growth, but uses the actual store forecasts provided by managers in the 10-K. Consistent with Cole and Jones (2004), the manager's forecasts for new stores in the 10-K appear to be very accurate; removing perfect foresight for the number of new and/or closed stores does not change the forecast error much (untabulated tests show that the differences are all insignificant).

The third row in Table 6 provides perfect foresight with respect to stores but replaces realized comp growth with our estimate based on mean reversion model in (17). The differences are startling for all three models when perfect foresight of next year's comp growth is removed. Clearly a key source of the forecast error is realized comp growth rates that differ from forecasted comp growth rates.

The last row of panel A, Table 6 gives the fully implementable, out-of-sample forecast errors for the three models. The store forecasts are taken from the 10-K disclosures, and the comp growth forecast is for the mean reversion model in (17). The most accurate model is model 2 with an error rate of 4.03 percent. Summarizing the results for model 2, the full strength of in-sample estimation yields a median absolute error of 1.84 percent of sales; this becomes 2.59 percent for out-of-sample forecasts with perfect foresight of inputs and 4.03 percent using estimates of the inputs.

12. 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.

13. Note that the out-of-sample errors for models 1 and 3 with perfect foresight of the two inputs are actually lower than the in-sample errors presented in Table 4. The differences are that Table 6 uses five-year rolling periods to estimate the 739 out-of-sample sales forecasts and does not have a sales forecast for the first five years, while Table 4 uses all available data and has 1,319 firm-year residuals.

TABLE 6
Out-of-sample forecast errors using a five-year estimation period

Panel A: Forecast models

Foresight assumption	Model 1: $k = 1$ Median error	Model 2: $k \in (0.8, 1.2)$ Median error	Model 3: $(1 + g)(1 + c) - 1$ Median error
Perfect Foresight for both Comp Growth and Change in Stores	2.77%	2.59%	3.25%
Perfect Foresight for Comp Growth but not Change in Stores (using store forecasts provided by firm)	2.82%	2.71%	2.98%
Perfect Foresight for Change in Stores but not Comp Growth [using $C_t - .02 = \gamma_{t-1}(C_{t-1} - .02)$ estimate]	4.22%	4.09%	4.54%
No Perfect Foresight [using store forecasts provided by firm and Comp Growth $C_t - .02 = \gamma_{t-1}(C_{t-1} - .02)$ estimate]	4.17%	4.03%	4.38%

Panel B: Median errors of ad hoc models

Model 4 Mean reversion	Model 5 Chgstores	Model 6 Chg new/old stores	Model 7 Chgsales	Model 8 (Model 6+Model 7)
5.01%	4.45%	5.20%	4.57%	5.92%

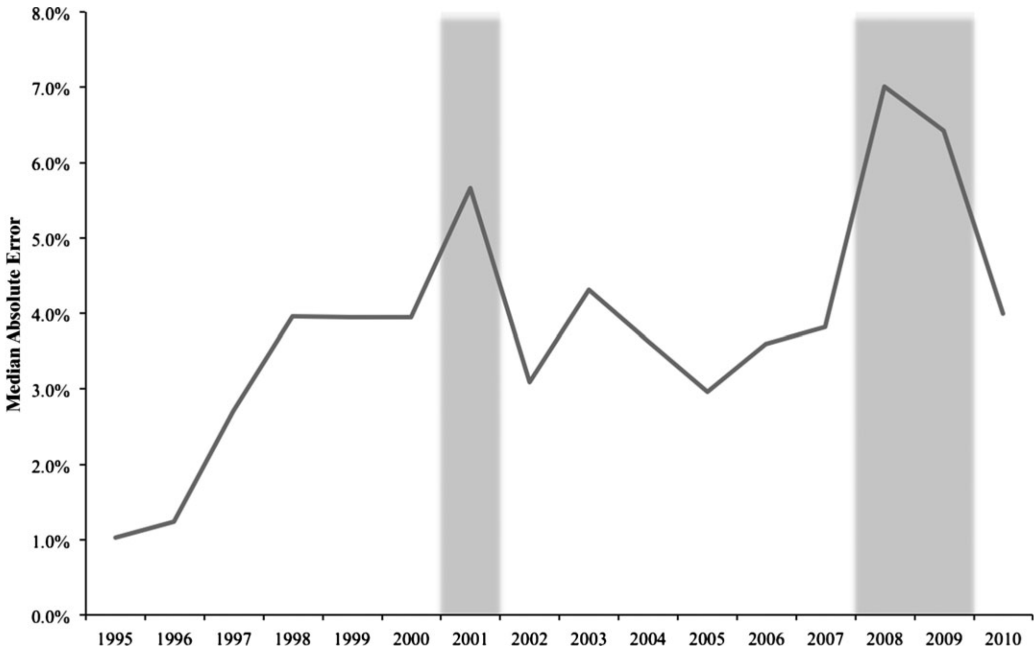
Notes:

The dependent variable $\Delta SALES_{T+1}$, is the change in sales, where Sales is Annual Net Sales (COMPUSTAT SALE). There are 87 individual firms and 739 out-of-sample firm-year sales forecasts. Estimation periods are exactly five observations per firm. Firm-specific 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]). See Table 4 for model descriptions and additional variable definitions.

We report the out-of-sample forecast errors for the ad hoc models in Panel B of Table 6. All of the ad hoc models have larger out-of-sample errors than the fully implementable out-of-sample forecast models presented in panel A. While model 8, which uses information on both prior changes in sales and changes in stores, performs best in-sample, it is the least accurate out-of-sample. It appears as though model 8's in-sample success is due to over-fitting the data.

In Figure 1, we display the time-series variation in the median accuracy of the fully implementable, out-of-sample forecast errors for model 2. The figure plots the annual median error as a percent of total sales for model 2 along with vertical bars, which highlight years with recessions using the National Bureau of Economic Research (NBER) recession indicator. The figure shows that the forecast errors have increased through time, although this is largely due to the expanding sample over time. In the early years the only firms that provided store forecasts were the larger firms in our sample. The figure also shows that the median errors of model 2 are larger in recession years. In the years without

Figure 1 Model 2 out-of-sample absolute forecast errors by year



recessions, the error is always less than or equal to 4.3 percent, whereas in the three years with recessions (2001, 2008, and 2009), the errors are always higher, at 5.7 percent, 7.0 percent, and 6.4 percent, respectively.

Table 7 examines the sources of error in the out-of-sample forecasts for models 1 and 2 in recession and nonrecession years. As seen at the bottom of the table, firms' disclosures on the number of new stores they intend to open are almost always correct, with a median error of zero. In fact, in 14 of the 16 years the median error on forecasted new store openings is either zero or one store. However, the forecasted number of old stores to be closed is much less accurate, with a median error of five stores in nonrecession years and six stores in recession years. And the error is generally due to an understatement of the number of closures. In 15 of the 16 years the median number of store closures was at least four more stores than forecast. This bias will systematically lower the estimated old store sales rate compared to the actual rate. But as table 7 shows, the error in the number of stores contributes relatively little to the overall median forecast error. For model 2 in nonrecession years, moving from perfect foresight to using the firm's disclosed future store counts only increases the error from 2.55 percent to 2.65 percent; the change in recession years is from 3.42 percent to 3.62 percent.[14]

Table 7 also clearly shows that the increase in the median error during recession years is driven by the error in the comp rate rather than the error in the number of stores. As

14. The consistency of the understated store closures over time can sometimes cause the model with perfect foresight actually to underperform relative to the model using the estimated number of stores, as is the case for model 1 in Table 7. This occurs because, without perfect foresight, both the estimated old store sales rate and the forecast are based on the slightly understated store counts. Consequently, combining estimated sales rates based on the biased data with the true number of stores can result in higher forecast errors.

TABLE 7

Out-of-sample forecast errors using a five-year estimation period, for years with no recessions versus years with recessions

	No recession years		Recession years only	
Foresight assumption	Model 1: $k = 1$ Median error	Model 2: $k \in (0.8, 1.2)$ Median error	Model 1: $k = 1$ Median error	Model 2: $k \in (0.8, 1.2)$ Median error
Perfect Foresight for both Comp Growth and Change in Stores	2.55%	2.55%	2.90%	3.42%
Perfect Foresight for Comp Growth but not Change in Stores (using store forecasts provided by firm)	2.30%	2.65%	3.73%	3.62%
Perfect Foresight for Change in Stores but not Comp Growth [using $C_t - .02 = \gamma_{t-1}(C_{t-1} - .02)$ estimate]	3.69%	3.73%	4.86%	4.57%
No Perfect Foresight [using store forecasts provided by firm and Comp Growth $C_t - .02 = \gamma_{t-1}(C_{t-1} - .02)$ estimate]	3.72%	3.82%	6.72%	7.01%
Median forecast error of store openings	0		0	
Median forecast error of store closures	5		6	
Median forecast error of comp. store sales growth	0.28%		−2.37%	

Notes:

The dependent variable $\Delta SALES_{T+1}$, is the change in sales, where Sales is Annual Net Sales (COMPUSTAT SALE). There are 87 individual firms in recession years and 73 firms in the no recession years, with a total of 739 out-of-sample firm-year sales forecasts. Estimation periods are exactly five observations per firm. Firm-specific 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]). See Table 4 for model descriptions and additional variable definitions. Recession years are 2001, 2008 and 2009 according to the NBER.

seen at the bottom of the table, our model for comp growth has a median error of only 0.28 percent in nonrecession years, but overestimates the actual growth by 2.37 percent during recession years. To see how this flows through into the error in model 2, note that in nonrecession years moving from "perfect foresight for comp growth but not change in stores" shown in the second row to "no perfect foresight" shown in the fourth row only increases the median from 2.65 percent to 3.82 percent. However, the same contrast during recession years increases the error from 3.62 percent to 7.01 percent.

Shocks to the sales-generating process

As we noted earlier, our models perform poorly 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 our estimates are based on historical data, we expect the sales forecasts to have larger errors. We identify 72 firm-year observations from the 739 out-of-sample predictions in Table 6 that have a merger or acquisition (52 firm-years), a

TABLE 8
Out-of-sample forecast errors using a five-year estimation period conditioning on realized shocks to sales for model 2 [$k \in (0.8, 1.2)$]

Sales shock	Median error (absolute value)	Positive errors (percent positive values)	Negative errors (percent negative values)
No Merger and Acquisition or Discontinued Operation (667 firm-years)	3.92%	280/667 (42.0%)	387/667 (58.0%)
Merger and Acquisition or Discontinued Operation (72 firm-years)	5.88%	50/72 (69.4%)	22/72 (30.3%)
Merger and Acquisition (and no Discontinued Operation) (52 firm-years)	4.98%	42/52 (80.76%)	11/52 (21.1%)
Discontinued Operation (and no Merger and Acquisition) (18 firm-years)	9.04%	8/18 (44.4%)	10/18 (65.4%)

Notes:

The dependent variable $\Delta SALES_{T+1}$, is the change in sales, where Sales is Annual Net Sales (COMPUSTAT SALE). There are 87 individual firms and 739 firm-year observations. Estimation periods are exactly five observations per firm. Firm-specific 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]). See Table 4 for model descriptions and additional variable definitions.

discontinued operation (18 firm-years), or both (2 firm-years).[15] We partition the out-of-sample sales forecasts for firm-years with and without these large shocks in Table 8. There is a significant difference between the forecast errors of model 2 for observations with and without a shock in the period. The median absolute forecast error for firm-years without a large shock is 3.92 percent of sales, while those firm-years with a large shock have a median error of 5.88 percent of sales. The third and fourth rows of the table show that mergers cause larger positive errors (actual sales exceed forecasted sales) while discontinued operations cause 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 mergers or discontinued operations.

A specific implementation

As seen in Table 6, the greatest proportion of the error in the model (relative to a perfect foresight model) comes from the comp growth input. While our model of comp growth is based on mean reversion, other information about this input often arises as the year unfolds. Consider how we might develop an estimate for comp growth and sales at Ross

15. We identify firms that 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 qualify 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 percent or 5 percent of sales; not tabulated).

Stores in 2006. First, instead of using the cross-sectional estimate of mean reversion in comp growth, we could estimate a firm-specific rate. If we estimate the rate of mean reversion for Ross Stores on the prior five years of data, we get a coefficient of only 0.008. Combining this rate with the prior year's comp of 6 percent gives an estimated comp rate for 2006 of 0.02 + 0.008 × (0.06 – 0.02) = 0.021. In their 2005 10-K Ross disclosed that they would open 66 new stores in 2006, resulting in a total of 797 stores. If we combine these inputs with the estimated sales rates for Ross Stores in Table 5, we estimate 2006 sales as

$$731 \text{ old stores} \times \$6.67\ /\ \text{old store} \times \mathbf{1.021} + 66 \text{ new stores} \times 7.88\ /\ \text{new store} \times \mathbf{1.021} \\ = \$5,509 \text{ million.}$$

The actual 2006 sales is $5,570 million, so the forecast error is 1.09 percent of actual sales. But we can improve on this. Ross also disclosed in their 2005 10-K that 2006 would be a 53-week fiscal year, and this would logically increase the comp growth estimate to 1.021 × (53/52) – 1 = 4.1 percent. Using this new comp rate would increase the sales forecast to $5,615 million and lower the forecast error to –0.81 percent of sales. Finally, on May 17, 2006, approximately a month after the issuance of their 2005 10-K, management revealed in a press release that they expected the comp rate to be between 3 percent and 4 percent. Using 3.5 percent as the new comp estimate gives a sales forecast of $5,584 million and reduces the forecast error to –0.26 percent, almost five times lower than our first estimate's error.

Comparison to I/B/E/S analysts' revenue forecasts

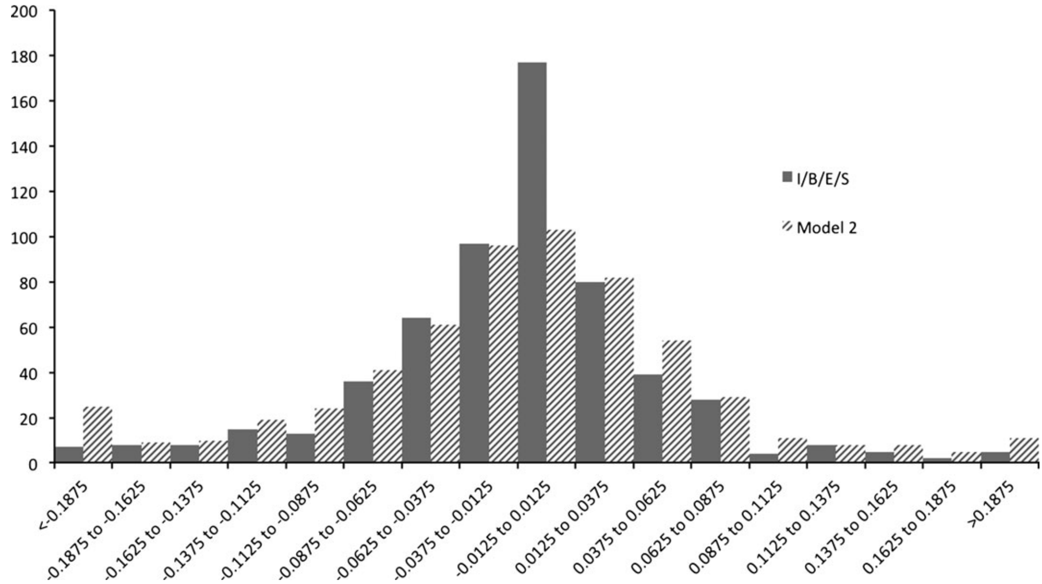
To put our models' out-of-sample error rates in perspective, we compare them to the error of the consensus I/B/E/S analysts' sales forecast. Prior research suggests that analyst forecasts will be difficult to beat with an econometric model such as ours (see Brown et al. 1987 or the review by Ramnath et al. 2008).

The data for our forecast model is typically available at the prior year's earnings announcement date, although sometimes may 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. In Table 6 we found that model 2, combined with a mean reversion comp growth estimate, yielded an out-of-sample median absolute forecast error of 4.03 percent of sales. As a comparison, the I/B/E/S consensus analysts' sales forecast has a median absolute error of 3.15 percent 11 months prior to the fiscal year end (not tabulated). We illustrate the signed forecast errors graphically in Figure 2. The first observation from the graph is that the I/B/E/S forecasts have considerably more forecast errors in the narrowest range, –0.0125 to 0.0125, than model 2.[16] Outside of this region, the two models deliver similar forecasts errors until the most extreme tails, where model 2 produces larger errors than the I/B/E/S forecasts. The second observation from Figure 2 is that the I/B/E/S forecasts are optimistic, resulting in more negative forecast errors than positive forecast errors. As we show next, an advantage of model 2 over an I/B/E/S analyst forecast is that it is much less biased.

Our final tests examine whether our model can provide incremental forecasting power beyond the I/B/E/S forecast. We regress the signed I/B/E/S forecast error on the difference between the model 2 estimate and the I/B/E/S estimate (scaled by sales) and present the results in Table 9. The full sample results are in the first column. The negative intercept

16. The frequency of I/B/E/S and model 2 forecasts errors in the narrowest region are almost the same prior to 2007, but analyst forecasts adapted to the 2008–2009 recession years more quickly than our model did. However, as the Ross Stores example illustrates, our model easily accommodates new information, and users could have adapted their forecasts accordingly.

Figure 2 Comparison of I/B/E/S and model 2 forecast error distributions



shows that I/B/E/S forecasts are optimistic, on average. More interesting, however, is the positive and significant coefficient on the difference between the model 2 forecast and the I/B/E/S forecast. The more the model 2 forecast exceeds the I/B/E/S forecast, the more the actual result will exceed the I/B/E/S forecast, and vice versa. In other words, the analyst could lower her forecast error if she increased her forecast when the model 2 estimate was greater than her own forecast and lowered her forecast when the model 2 estimate was lower than her own. The results in the second and third columns show that incremental benefit from model 2 is mostly due to years without mergers, acquisitions, or discontinued operations. Finally, we divide the sample based on whether the model 2 estimate is greater or less than the I/B/E/S estimate, shown in columns 4 and 5 of Table 9, respectively. The biggest incremental contribution of using model 2 along with the I/B/E/S forecast occurs when the model 2 estimate is less than the I/B/E/S estimate. In this case, the analyst would do better to reduce her forecast by almost a third of the difference in the two models' estimates. The R^2 of 8.38 percent in this case is four times larger than for the full sample.

5. Conclusion

The model presented here is a simple and yet powerful way to forecast a firm's future sales based on publicly available data. This task is ubiquitous in financial analysis. It is the starting point for the earnings forecast and has a significant impact on estimates of a firm's value. As an example, if a firm had an expected constant return on equity (ROE) of 20 percent, a cost of equity capital of 10 percent and an expected perpetual growth rate of 5 percent, its market-to-book ratio would be 3. If the growth rate is raised to 6 percent the firm's market-to-book ratio increases by 17 percent; if the growth rate is lowered to 4 percent the ratio decreases by 11 percent (see Lundholm and Sloan 2006 for a derivation of the theoretical market-to-book ratio). Even a small improvement in forecast accuracy can consequently have large implications in the accuracy of value estimates.

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 is applicable to any situation with reasonably homogeneous sales-generating units given data on past changes in the

TABLE 9
Regression of I/B/E/S forecast error on model 2 [$k \in (0.8, 1.2)$] sales estimate

	Dependent variable: I/B/E/S forecast error									
	Full sample		Firm years with no shocks		Firm years with shocks		Model 2 estimate < I/B/E/S estimate		I/B/E/S estimate < Model 2 estimate	
Variables	Coefficient	(*t*-statistic)	Coefficient	(*t*-statistic)	Coefficient	(*t*-statistic)	Coefficient	(*t*-statistic)	Coefficient	(*t*-statistic)
Intercept	–0.012	(–4.17)	–0.012	(–4.68)	–0.019	(–1.10)	–0.002	(–0.23)	–0.010	(–2.17)
Model 2 Sales Estimate less I/B/E/S Estimate	0.116	(3.64)	0.101	(3.12)	0.172	(1.51)	0.304	(5.25)	0.034	(0.70)
Adjusted R^2	2.02%		1.61%		2.04%		8.38%		–0.002%	
Number of firm-year observations	596		534		62		291		305	

Notes:

There are 596 firm-year observations. A firm has a shock if it experiences a merger and acquisition or discontinued operation greater than or equal to 1 percent of sales. I/B/E/S Forecast Error is (Sales – I/B/E/S Estimate) / Sales, Model 2 Sales Estimate less I/B/E/S Estimate is (Model 2 Estimate – I/B/E/S Estimate)/Sales.

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 Sam's 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 estimated sales-generating rates to anticipate future store openings and closings.

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