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Evidence on the Presence of Representativeness Bias in Investor Interpretation of Consistency in Sales Growth

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Abstract. We document that consistent patterns of high or low sales growth that are incongruent with underlying fundamentals are followed by significant stock price reversals. In contrast, no stock return reversals are found for firms that achieve the same level of sales growth in an inconsistent manner. Furthermore, future earnings announcement returns mimic the pattern of abnormal stock returns documented for the Consistent- and Inconsistent-Growth portfolios, respectively, corroborating our main findings. Our results are robust to controls for the magnitude of sales growth, fundamental strength, business cycle risk exposures, and standard risk factors. Our evidence is consistent with representativeness bias affecting investor interpretation of consistency in sales growth patterns.

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Keywords: representativeness • behavioral finance • asset pricing • fundamental analysis • stock return predictability

1. Introduction

A central issue in capital markets research is whether psychological biases affect investor processing of financial information. In a recent comprehensive study of behavioral finance theories, Chan et al. (2004) predict that under representativeness bias, firms with consistently high or low financial performance will experience greater price reversals than firms with inconsistent high or low performance. The potential bias arises if investors ignore base rates in extrapolating past patterns.[1] This idea has been discussed by prior research in a number of influential papers (De Bondt and Thaler 1985, 1987; Lakonishok et al. 1994; La Porta et al. 1997) but formally tested only in Chan et al. (2004). However, in contrast with earlier evidence supporting investor extrapolation of past financial performance, Chan et al. (2004) do not find evidence consistent with the presence of representativeness bias and conclude that their results "present a challenge to the entire class of theories that predict mispricing based on investors' representativeness or conservatism bias in processing firms' past performance" (p. 7).

We argue that the tests in Chan et al. (2004) may not be able to detect mispricing of consistent performance patterns under representative bias. This is because firms with consistently high (low) performance include both firms that correctly deserve high (low) valuations despite representativeness as well as firms that exhibit consistent performance though their growth rates are likely to revert to the mean. Combining the two groups of firms potentially reduces the ability of the Chan et al. (2004) tests to detect the effects of representativeness.

We reexamine the pricing of firms with consistent patterns of sales growth under the representativeness hypothesis tested in Chan et al. (2004) with an important design innovation developed by Piotroski and So (2012) that potentially addresses the above limitation of their tests. In particular, we expect that researchers are more likely to detect the errors in investor expectations generated by extrapolation of past consistent sales growth patterns when the patterns are inconsistent with underlying fundamental strength. In other words, we use fundamental strength to distinguish between firms where consistent past growth is sustainable from firms where consistent past growth is not sustainable.

Our tests are important for the following reasons. Should our tests fail to reveal evidence of mispricing, this is stronger evidence against the presence of biases such as representativeness. On the other hand, if our tests reveal evidence of representativeness bias, then this would suggest that the conclusion drawn by Chan et al. (2004) that market inefficiencies are unlikely to result from representativeness is unwarranted.

For the most part, our research design emulates that of Chan et al. (2004). We define consistency in sales growth (hereinafter SG) as in Chan et al. (2004); each year firms in the highest quintile of SG that outperform the median firm during each of the preceding five years are classified as Consistent-High SG firms.[2] Consistent-Low SG firms are defined analogously.

We then sort consistent-growth firms into two groups: firms with strong fundamentals and firms with weak fundamentals, respectively, using Piotroski's

(2000) *F*-score. The *F*-score is a composite measure of fundamentals based on nine financial signals relating to profitability, efficiency, and financial position. We then form a Consistent-Growth portfolio by going long in Consistent-Low SG firms with strong fundamentals and short in Consistent-High SG firms with weak fundamentals. We use the remaining firms in quintiles one and five of sales growth to create a portfolio long in Inconsistent-Low SG firms with strong fundamentals and short in Inconsistent-High SG firms with weak fundamentals. We refer to the difference in returns of the Consistent-Growth and Inconsistent-Growth portfolios as the Grand portfolio return. Note that to isolate the impact of consistency in sales growth, our design attempts to ensure that the Consistent-Growth and Inconsistent-Growth portfolios have both *similar* levels of sales growth as well as *similar* underlying fundamentals. If consistency in sales growth causes investors to misprice stocks because of representativeness bias, we expect future abnormal returns of the Grand portfolio to be positive.

We find a significant difference in the future stock returns of the Consistent-Growth portfolio relative to the Inconsistent-Growth portfolio. More specifically, the mean value-weighted and equally weighted monthly raw returns of the Consistent-Growth portfolio exceed that of the Inconsistent-Growth portfolio by 0.64% (t-statistic 1.99) and 0.81% (t-statistic 3.50) per month, respectively. The results are robust to controlling for book to market, size, and fundamentals by subtracting the returns of matching firms based on these characteristics. The results are also robust to adding controls for market risk and momentum. Furthermore, quarterly earnings announcement returns mimic these patterns during the four quarters following portfolio formation. The Consistent-Growth portfolio exhibits an average five-day market-adjusted announcement return of 0.61% (t-statistic 5.29), whereas the Inconsistent-Growth portfolio exhibits only 0.16% (t-statistic 1.25) for a difference of 0.45% (t-statistic 2.94) per announcement period. These results are also robust to controlling for the earnings announcement returns of matching firms with similar book to market, size, and fundamentals.

Our primary findings regarding how investors interpret consistency in sales growth do not change when we use unexpected shocks to business cycle variables as control variables for business cycle risk (Chen et al. 1986). Thus, our results cannot be attributed to either aggregate asset pricing risk exposures or to several established return predictors.

We also test two other potential alternative explanations for our results that consistency in performance may simply proxy for variation in sales growth (Lakonishok et al. 1994) or the value-glamour effect in prior studies such as Piotroski and So (2012). We perform several tests to rule out these alternative explanations. First, our research design controls for the returns of matching firms selected based on similar book to market and fundamentals. Second, we use Fama and MacBeth (1973) type regressions to control for book to market and sales growth. If our measure of consistency in growth merely captures extreme sales growth levels or variation in book-to-market ratios, our regression controls should capture such variation. We find that returns to our Consistent-Growth portfolio remain significantly higher than the Inconsistent-Growth portfolio after controlling for sales growth, book-to-market ratios, or the value-glamour effects as in Piotroski and So (2012), suggesting that the effects we document are distinct from the effects documented in prior work.

An important limitation of our study as well as prior studies investigating the effects of representativeness bias on investor behavior is that the underlying theory is not yet sufficiently developed to identify specific characteristics that investors may focus on in deciding which categories firms belong to.[3] We use one potential characteristic, sales growth, which we believe is both salient and likely to lead to mispricing because it does not incorporate any information on underlying fundamentals such as profit margins. Furthermore, current theory also does not tell us how the behavioral bias underlying representativeness might interact with the behavioral biases underlying mispricing of fundamentals. However, as noted before, our research design controls for fundamentals in several ways and thus mitigates concerns that our results may be driven by the biases underlying mispricing of fundamentals.

Notwithstanding the above limitations, we contribute to the literature by documenting robust evidence on mispricing of consistent past patterns of sales growth as implied by representativeness bias. To our knowledge, the only other archival study that formally investigates whether investors misprice consistent patterns of long-term financial performance is Chan et al. (2004). They find no evidence of such mispricing contrary to the predicted effects under representativeness bias and conclude that it is unlikely that market inefficiencies result from representativeness. In contrast, our evidence suggests that their conclusion that representativeness does not affect stock prices may be unwarranted and that more research is needed on how psychological biases affect investor behavior. Our study is of potential use to investment professionals as well as to researchers interested in further developing, refining, and testing behavioral finance theories.

The remainder of the paper proceeds as follows. We discuss prior work and hypothesis development in §2. We discuss the construction of our empirical tests in §3 and present our results in §4. We conclude in §5.

2. Prior Work and Hypothesis Development

2.1. Evidence on Use of the Representativeness Heuristic in Psychology

A heuristic is a strategy for making decisions that ignores information that is costly to process with the goal of making decisions more efficiently, though sometimes it can lead to serious errors of judgment.[4] Representativeness is a particular heuristic often used in behavioral finance theories to explain investor overreaction to past growth patterns. Kahneman and Tversky (1972) define it as a way of assessing subjective probability of an event, or a sample, by "the degree to which it is similar in essential characteristics to its parent population; and reflects the salient features of the process by which it is generated" (p. 430). Kahneman and Tversky (1973) summarize experiments that demonstrate that representativeness is used in assessing subjective probabilities.

Grether (1980) points out that the experiments conducted by Kahneman and Tversky (1973) do not take into account the experience or incentives of subjects. He repeats their experiments to see whether experience or financial incentives affect subjects' use of the representativeness heuristic. His experiments confirm the findings in Kahneman and Tversky (1973) for inexperienced or financially unmotivated subjects. However, he finds that the evidence is less clear for experienced and financially motivated subjects.[5]

2.2. Use of Representativeness in Explaining Investor Mispricing

Lakonishok et al. (1994) suggest that contrarian strategies work by exploiting investor biases including underweighting of base rates, which is one manifestation of representativeness. They document that stocks with high past growth and high expected future growth are overpriced and stocks with low past growth and low expected future growth are underpriced, consistent with representativeness bias affecting investor behavior. Barberis et al. (1998) describe a formal mechanism via which a sequence of publicly released financial performance signals can lead to mispricing because of representativeness. In their model, investors overreact if a firm consistently exhibits high or low performance because they irrationally consider consistent performance as representative of extreme valuations. In other words, investors might classify some stocks as "growth" stocks based on a history of consistent growth ignoring the likelihood that few firms just keep growing.

Chan et al. (2004) provide comprehensive empirical tests of the Barberis et al. (1998) theory. They find that contrary to the model's predictions, stocks do not become mispriced after long consistent sequences of good or bad earnings or sales growth. Chan et al. (2004) interpret this as evidence that investors' beliefs are not affected by representativeness, whereas Daniel (2004) takes their results to mean that publicly available signals of financial performance are not the principal drivers of stock mispricing. Thus, whether representativeness bias affects investor processing of accounting information is an open question.

2.3. Hypothesis Development

Our central hypothesis is essentially the same as the hypothesis about consistency of growth patterns in Chan et al. (2004). They note that if investor processing of consistent growth patterns is affected by representativeness bias then firms that exhibit consistently high (or consistently low) financial performance will be classified as high growth (or declining growth) firms. In other words, investors will likely overextrapolate the consistent growth patterns and overprice consistent high growth firms and underprice consistent low growth firms ignoring the base rate or the relative frequencies of high growth and low growth firms in the population. Based on this argument, Chan et al. (2004) predict that firms with consistently extreme performance will experience greater return reversals than firms with extreme performance generated in an inconsistent manner.

Our extension of Chan et al. (2004) tests is based on the observation in Tversky and Kahneman (1974) that, in general, heuristics are quite useful but "sometimes they lead to severe and systematic errors" (p. 1124). In other words, use of heuristics in valuation could lead to correct pricing in some cases and mispricing in other cases. For example, a firm may report consistent high growth merely by chance and thus its high growth is unlikely to be sustainable. If investors erroneously extrapolate growth of such firms, these firms will be overpriced. On the other hand, other firms may report consistent high growth that is sustainable in the foreseeable future. If so, this group of firms would be correctly priced. Combining these two groups of firms likely reduces the power to detect mispricing induced by representativeness bias in tests performed by Chan et al. (2004).

To develop more powerful tests of representativeness, we separate firms that are likely to sustain past growth patterns and firms that are unlikely to sustain past growth patterns using a firm's fundamentals as an indicator of sustainable growth (Piotroski 2000, Piotroski and So 2012). We expect firms with consistent high past growth and weak fundamentals to be overpriced, and firms with consistent high past growth and strong fundamentals to be more or less correctly priced. Similarly, we expect firms with consistent low past growth and strong fundamentals to be underpriced and firms with consistent low past growth and weak fundamentals to be correctly priced. Put differently, we use fundamentals as an instrument to identify subsets of firms that are likely to be mispriced. This approach is similar to Piotroski and So (2012) who use fundamental strength to separate firms that are truly value firms from firms that appear to be value firms but are likely to perform poorly in the future.

To focus on identifying the effects of consistency in growth, we compare a portfolio of firms with consistent growth to a portfolio of firms with inconsistent growth that exhibit *similar* levels of growth and fundamental strength. Our main hypothesis can be stated as follows:

Hypothesis 1. *The returns of a portfolio of firms based on consistent sequences of sales growth reverse more strongly than the returns of a portfolio of firms with inconsistent sales growth when the pattern of sales growth is incongruent with the strength of the firms' underlying fundamentals.*

3. Research Design and Variable Measurement

3.1. Measurement of Sales Growth

To test our hypothesis, we need to identify performance signals that lead to investor overreaction. We note that the underlying behavioral theory in its current state does not tell us what essential growth characteristics may be used by investors to classify firms into various categories. This criticism applies to prior work, such as Chan et al. (2004) as well as to our study. We use sales growth to classify firms into different growth categories for the following reason. Standard approaches to valuation typically start with forecasting a full set of financial statements after a thorough analysis of the business. The first step in this exercise is to forecast sales growth (see, e.g., Penman 2007, Easton et al. 2013). More specifically, Penman (2007) notes that sales is the primary driver of forecasted future performance because "without customers, no value can be added in operations" (p. 549). Next, forecasted sales are multiplied by forecasted margins to generate forecasted expenses and forecasted asset turnover is applied to sales to yield forecasts of net operating assets. Thus, sales forecast is an essential basis of forecasted income statements and balance sheets.[6] Similarly, Easton et al. (2013) note that "The revenues (sales) forecast is, arguably, the most crucial and difficult estimate in the forecasting process ... because other income statement and balance sheet accounts derive from, among other factors, the revenues forecast" (p. 11-5). We measure long-term growth using annual sales data over a five-year horizon:

$$\Delta S_{5,t} = (Net\ Sales_t - Net\ Sales_{t-5})/Net\ Sales_{t-5}. \qquad (1)$$

3.2. Portfolio Formation Using Consistent Sequences of Sales Growth

Representativeness implies that investors overreact to firms with consistent patterns of good or bad performance. To test this prediction, we first classify firms into growth quintiles based on five-year SG each calendar year. We label quintiles five and one as High and Low SG firms, respectively. The remaining firms are classified as Moderate sales growth firms. Since our central hypothesis concerns effects of consistency in growth, this first sort establishes a control for the magnitude of sales growth.[7] Within the High and Low SG quintiles, we separate firms into three additional categories based on the degree to which the growth has been consistent. We classify High SG firms that outperform the sales growth of the median firm in the sample during *each* of the previous five years as Consistent-High SG firms. Similarly, we classify Low SG firms that underperform the sample median sales growth in *each* of the previous five years as Consistent-Low SG firms. This definition of consistency is equivalent to Chan et al. (2004).

We define two additional categories using the remaining High SG and Low SG firms, respectively. Our goal is to have a simple scheme for identifying inconsistent high and low growth firms while ensuring that there are enough firms to achieve diversified portfolios. To do so, we note that behavioral theories do not explain how many years in a row a firm exhibits extraordinary growth before becoming mispriced. However, the driver of mispricing is indicated to be repeated growth or decline. Based on this, we classify any High SG firm that fails to exhibit above-median growth in the most recent year as an Inconsistent-High SG firm. For example, if a High SG firm exhibited below-median growth in the portfolio formation year but above-median growth in earlier years, it is classified as an Inconsistent-High SG firm. All remaining firms are classified as Mid-Consistent-High SG; i.e., they are neither consistent nor inconsistent High SG firms. Inconsistent-Low SG and Mid-Consistent-Low SG firms are defined analogously.[8]

3.3. The Fundamentals Sort

Our final sort is based on fundamentals as measured by Piotroski's (2000) F-score. This score is based on a simple scheme where a score of 1 is added for each of nine financial statement signals whenever these signals indicate strong fundamentals and 0 otherwise. Following Piotroski (2000), each year we calculate the F-score for each firm for which data on all nine variables is available. The F-score ranges from a minimum of 0 to a maximum of 9 with lower scores indicating a firm with weaker financial fundamentals. Additional details including a description of the nine signals used to calculate this score are provided in the appendix. To identify firms mispriced because of representativeness, we sort firms in each of the sales growth and consistency-based categories defined earlier into two additional categories based on the F-score. Firms with F-scores of 0–4 are identified as Weak firms and firms with F-scores of 5–9 are categorized as Strong firms. We define our Consistent-Growth portfolio as taking a long position in a portfolio of Consistent-Low SG firms with Strong fundamentals and a short position in a portfolio of Consistent-High SG firms with Weak fundamentals:

$$\begin{aligned}&\textit{Consistent Growth Portfolio Return}\\&\quad = \textit{Consistent Low SG} \times \textit{Strong Portfolio Return}\\&\qquad - \textit{Consistent High SG} \times \textit{Weak Portfolio Return}.\end{aligned} \tag{2}$$

Similarly, we define an analogous Inconsistent-Growth portfolio as taking a long position in a portfolio of Inconsistent-Low SG firms with Strong fundamentals and a short position in a portfolio of Inconsistent-High SG firms with Weak fundamentals:

$$\begin{aligned}&\textit{Inonsistent Growth Portfolio Return}\\&\quad = \textit{Inconsistent Low SG} \times \textit{Strong Portfolio Return}\\&\qquad - \textit{Inconsistent High SG} \times \textit{Weak Portfolio Return}.\end{aligned} \tag{3}$$

Under representativeness, we expect that the Consistent-Growth portfolio to exhibit more positive abnormal returns than the Inconsistent-Growth portfolio. To test this prediction, we refer to the difference between these two portfolios as the Grand portfolio return for simplicity and define it as

$$\begin{aligned}&\textit{Grand Portfolio Return}\\&\quad = \textit{Consistent Growth Portfolio Return}\\&\qquad - \textit{Inconsistent Growth Portfolio Return}.\end{aligned} \tag{4}$$

Similar to Chan et al. (2004), this type of construction attempts to create a portfolio that is both growth neutral as well as (in our case) fundamentals neutral. In other words, returns of this portfolio should not be driven by differences in the magnitude of sales growth as in La Porta et al. (1997) or by differences in fundamentals as in Piotroski (2000). The reason is that both the Consistent- and Inconsistent-Growth portfolio firms are drawn from the same quintile of sales growth and possess similar fundamentals.

3.4. Portfolio Formation

We obtain financial statement data from the most recent fiscal year to assign firms to portfolios. Firms are assigned to portfolios beginning with the fourth month after fiscal year-end. Based on the portfolio assignments using firms' financial statement data, we calculate monthly portfolio returns. We describe calculation of abnormal returns in §4.

4. Results and Discussion

4.1. Sample and Descriptive Statistics

In this section, we begin by discussing descriptive statistics for our portfolios. Our sample spans all firms with data available on sales growth and financial variables needed to construct Piotroski's F-score over the period 1968–2012 with 1973 as the first portfolio formation year. This yields an average of 2,959 firms per year over our sample period to form portfolios. Panel A of Table 1 provides descriptive statistics on sales growth, F-scores, book to market, and market capitalization for Consistent- and Inconsistent-High and Low SG groups, respectively (before incorporating fundamentals). These statistics help in assessing whether there are significant differences in these variables across our Consistent and Inconsistent portfolios. Among Low SG firms, the median past five-year sales growth is similar in Consistent and Inconsistent growth firms at −24%. However, Consistent-High SG firms exhibit greater median sales growth than Inconsistent-High SG firms; 366% versus 286%.

Each calendar year, we assign firms into book-to-market (b/m) deciles using the fiscal year-end ratios. An examination of mean b/m deciles indicates that the firms in our Low and High SG groups are not extreme firms on average. The Consistent-High SG firms have a mean b/m decile of 4.0, whereas Consistent-Low SG firms have a mean b/m decile of 7.1. However, there is variation in book-to-market ratios across consistent and Inconsistent-Growth firms within both the High as well as Low SG groups. A similar degree of variation in firm size can also be seen based on mean market capitalization deciles. A degree of variation in fundamentals based on mean F-scores is also visible in panel A.

The variation in sales growth, size, book to market, and fundamentals observed in panel A raises the concern that sorting firms on consistency in growth captures variation in these characteristics. Because each of these characteristics is a previously known predictor of stock returns, we need to carefully control for these characteristics in our tests to ensure that our results capture the effect of consistency in growth. Therefore, our primary empirical test in Table 2 controls for these effects by calculating abnormal returns by subtracting returns of matching firms based on similar book-to-market ratios, size, and fundamentals. We discuss assignment of matching firms in the next section. We do not rely on matching firms using sales growth because of the small pool of Inconsistent-Growth firms available as matching candidates in each quintile, making the procedure unreliable.

Panel B of Table 1 affirms the results of earlier studies that future stock returns are related to past sales growth and fundamentals (Lakonishok et al. 1994, Piotroski 2000). Using five-year sales growth, firms in the Low SG portfolio outperform firms in the High SG portfolio by 0.38% per month on average with a t-statistic of 3.43. Firms in the Strong fundamentals category beat firms in the Weak fundamentals category by an average of 0.24% per month with a t-statistic of 2.52.

Table 1. Summary Statistics

Panel A: Descriptive statistics for portfolios based on consistency in sales growth

	Median five-year sales growth (%)	Average F-score	Mean book-to-market decile	Mean book-to-market B/M ratio	Mean market cap decile	Median market capitalization ($ million) ($)	Average no. of firms per year
High Growth (sales growth Q5)							
Consistent-High Growth	366	5.4	4.0	0.51	7.2	170.3	208
Mid-Consistent High	297	5.2	4.6	0.62	5.9	61.1	235
Inconsistent High	286	4.5	5.5	0.91	5.7	45.8	160
All High Growth	310	5.0	4.7	0.66	6.3	82.8	603
Low Growth (sales growth Q5)							
Consistent-Low Growth	−24.3	5.2	7.1	1.29	4.9	44.6	184
Mid-Consistent Low	−24.3	4.6	6.8	1.23	4.3	22.0	262
Inconsistent Low	−23.9	5.7	6.0	0.97	4.4	44.6	120
All Low Growth	−23.7	5.0	5.7	1.19	4.6	26.6	567
All firms	58.7	5.3	4.8	0.91	6.0	72.6	2,959
$N = 477$ months							

Panel B: Mean monthly returns of portfolios based on five-year sales growth and F-score

	Sales growth		Fundamentals	
	High (Q5)	Low (Q1)	Strong (F-score ≥ 5)	Weak (F-score < 5)
Mean return (%)	1.21	1.59	1.47	1.23
Time-series t-statistic	3.73	5.33	5.84	3.99
	Low – High		Strong – Weak	
Mean return (%)	0.38		0.24	
Time-series t-statistic	3.43		2.52	
$N = 477$ months				

Notes. Summary statistics are presented for the sample of firms in this paper, which constitutes all firms in the Center for Research in Security Prices (CRSP)/Compustat intersection that have fiscal year-ends 1973–2012. The firms have data available to calculate sales growth over the preceding five years, the book-to-market ratio, and the F-score, a measure of fundamentals described in Appendix I. Sales growth is measured as $(Sales_t/Sales_{t-5} - 1)$. Panel A reports statistics for firms identified based on consistency in sales growth. For each of the preceding five years, the sales growth of the median firm is identified as the benchmark using all firms available during the year. Among High SG firms (Q5), firms that exceed the benchmark firm's sales growth during each of the preceding five years are labeled as Consistent-High SG firms. All Q5 firms that underperform the benchmark in the most recent year are labeled as Inconsistent-High SG firms. The remaining firms are labeled Mid-Consistent-High SG firms. Consistent, Mid-Consistent, and Inconsistent-Low SG (Q1) firms are identified in analogous manner. The book-to-market ratio is calculated as book value of common equity divided by the market value of stock computed by multiplying common shares outstanding by the fiscal year-end stock price. The capitalization decile assignments are provided by CRSP. The book-to-market decile is identified by classifying all available firms into deciles each year. The table reports the time-series mean/median of cross-sectional means and medians. Panel B shows time-series mean of monthly returns of portfolios formed separately on the basis of overall five-year sales growth and the F-score. Firms are allocated to sales growth portfolios based on their most recent sales quintiles with a minimum three-month delay after fiscal year-end. Firms remain in a portfolio for a maximum of 12 months. Equally weighted returns to portfolios of Low (Q1) and High (Q5) SG portfolios are computed each month. Independently, firms are classified into two portfolios based on each firm's F-score at fiscal year-end. Firms with F-scores less than 5 are labeled Weak, whereas firms with F-scores greater than 4 are labeled Strong. Firms enter portfolios with a delay of three months after fiscal year-end and remain for a maximum of 12 months. Equally weighted return for each portfolio is computed. The time-series mean return and associated t-statistic for each portfolio are reported.

4.2. Evidence on Returns of Portfolios Based on Consistent Growth and Fundamentals

Table 2 provides evidence from our primary test of representativeness bias. We are interested in testing whether abnormal stock returns of our Consistent-Growth portfolio differ from those of the Inconsistent-Growth portfolio (after fundamentals are incorporated). To ensure that our tests are not influenced by differences in book to market, size, or fundamentals induced because of separating firms by consistency of growth, we adjust the return of each firm in our sample by subtracting the return of a *matching* firm whose fiscal year ends in the same calendar year as that of our sample firm; we refer to our portfolio firms as the *matched* firms.

To assign the matching firm, we first identify all firms that are in the same Center for Research in Security Prices (CRSP)-assigned size decile and are in the same fundamentals-based category as the matched firm. From this group, we choose the matching firm

Table 2. Returns to Portfolios Based on Consistency in Sales Growth After Incorporating Fundamentals

Panel A: Matching firm statistics

Sales growth category	Fundamentals category	Mean book-to-market ratio	Mean book-to-market ratio (matching firms)	Diff	Mean F-score	Mean F-score (matching firms)	Diff	Median market cap ($)	Median market cap (matching firms) ($)	Diff
Consistent-Low SG	Strong	0.99	0.98	0.01 (3.31)	6.51	6.24	0.27 (3.08)	37.8	32.7	\$5.1 (1.29)
Inconsistent-Low SG	Strong	1.26	1.23	0.02 (3.00)	6.28	6.28	0.00 (−0.02)	64.8	61.2	\$3.6 (0.74)
Inconsistent-High SG	Weak	0.88	0.84	0.04 (2.94)	3.08	3.32	−0.24 (−4.28)	39.3	52.7	−\$13.4 (−4.16)
Consistent-High SG	Weak	0.53	0.53	0.00 (−0.71)	3.46	3.37	0.09 (3.63)	145.3	140.0	\$5.4 (0.53)

Panel B: Returns to portfolios based on consistency in sales growth and fundamentals

			Column					
			(1)	(2)	(3)	(4)	(5)	(6)
			Raw (unadjusted) returns		Matched-firm adjusted		Market and momentum controls added	
Row	Portfolios	Consistency/Fundamentals	VW	EW	VW	EW	VW	EW
(1)	Consistent-Growth	Low/Strong – High/Weak (%)	0.58	0.80	0.35	0.31	0.51	0.43
		Std. deviation[a] (%)	5.71	4.29	8.30	5.11	0.33	0.20
			(2.02)	(4.14)	(1.05)	(1.58)	(1.54)	(2.15)
(2)	Inconsistent-Growth	Low/Strong – High/Weak (%)	−0.06	−0.01	−0.43	−0.55	−0.37	−0.49
		Std. deviation[a] (%)	4.27	2.78	5.58	3.90	0.34	0.22
			(−0.22)	(−0.04)	(−1.29)	(−2.47)	(−1.11)	(−2.20)
(3)	Grand portfolio	Row (1) – Row (2) (%)	0.64	0.81	0.78	0.86	0.88	0.92
		Std. deviation[a] (%)	6.29	4.22	7.30	4.35	0.45	0.29
			(1.99)	(3.50)	(1.77)	(3.01)	(1.96)	(3.15)
		N (months)	477	477	477	477	477	477

Notes. The table reports monthly raw and abnormal returns and t-statistics (shown in parentheses) for the Consistent- and Inconsistent-Growth portfolios after incorporating financial fundamentals. The overall sample and variable measurement is described in Table 1. Each firm is assigned a matching firm based on book-to-market ratio, size, and fundamentals. The matching firm is chosen as the firm with the closest book-to-market ratio (based on minimum absolute difference) within the same CRSP-assigned size decile and F-score-based category. Firms in the same sales growth consistency category are excluded from being matching firms. Panel A reports descriptive characteristics of the sample and matching firms. Panel B reports returns to various portfolios formed based on consistency in sales growth and fundamentals. Firms are first sorted into quintiles based on their five-year sales growth. Next, Consistent- and Inconsistent-Growth firms are identified as described in Table 1. Finally, to incorporate fundamentals, Consistent-Low SG firms with Strong fundamentals (F-score > 4) are used to form a Consistent-Low SG portfolio and Inconsistent-Low SG firms with Strong fundamentals are used to form an Inconsistent-Low SG portfolio. Similarly, Consistent-High SG firms with Weak fundamentals (F-score < 5) are used to form a Consistent-High SG portfolio and Inconsistent-High SG firms with Weak fundamentals are used to form an Inconsistent-High SG portfolio. The table reports the following portfolios' returns after incorporating fundamentals:

Row (1): difference in mean returns of Consistent-Low SG/Strong and Consistent-High SG/Weak firms.

Row (2): difference in mean returns of Inconsistent-Low SG/Strong and Inconsistent-High SG/Weak firms.

Row (3): difference in mean returns of Consistent-Growth and Inconsistent-Growth firms (i.e., row (1) – row (2)), labeled the Grand portfolio return. Standard deviations of monthly portfolios returns are reported for portfolios in rows (1)–(3).

Columns (1) and (2) report mean value-weighted and equally weighted portfolio returns without subtracting matching firm returns. Columns (3) and (4) report mean returns after adjusting the monthly return of each firm by subtracting the return of a matched firm. For value-weighted returns, the matching firm is assigned the same weight as the weight of the matched firm. In columns (5) and (6), market and momentum based controls are added in the following regression to estimate abnormal returns:

$$R_{p,t} = \alpha + b_1 Mktrf_t + b_2 UMD_t + u_t,$$

where $R_{p,t}$ is the monthly portfolio return after adjusting for the matched firm returns as described above, $Mktrf_t$ is the monthly stock market return minus the risk free rate, and UMD_t is the monthly return to a momentum-based portfolio.

[a]Standard error of regression intercept in columns (5) and (6).

based on minimum absolute difference in book-to-market ratio compared to our portfolio firm. For example, a sample firm with a capitalization decile of five and in the Strong fundamentals category (F-score > 4) is matched to all available firms in capitalization decile five with Strong fundamentals. From this group, the matching firm is chosen as the firm with the minimum absolute difference in book-to-market ratio relative to the matched firm. To ensure that we do not subtract away the effects of consistency, we do not use firms with the same sales growth consistency as that of the matched firm as matching firms.

Panel A of Table 2 compares the characteristics of the matched firms and matching firms to gauge the success of our matching procedure. We report the time-series mean (or median) of each portfolio characteristic. Overall, our matching procedure is quite successful in controlling for book-to-market ratios, size, and fundamentals. In the Consistent-Low SG-Strong firms, the mean difference between matched and matching firms in book-to-market ratios is only 0.01, whereas in Consistent-High SG-Weak firms, both the matched and matching firms have a similar mean book-to-market ratio of 0.53. The mean F-score differs by only 0.27 in the Consistent-Low SG-Strong firms and by 0.09 in Consistent-High SG-Weak firms. Similarly, the median market capitalization of matched firms and matching firms differs by only $5 million in both the Consistent-Low SG-Strong firms as well as in Consistent-High SG-Weak firms. Similar observations can be made regarding Inconsistent-Growth portfolios. These results give us confidence that the matching procedure is successful in controlling for differences in book-to-market ratios, size, and fundamentals across Consistent- and Inconsistent-Growth portfolios.

Panel B of Table 2 presents our primary evidence on abnormal returns related to consistency in growth. As described in §3, our tests examine Low SG firms with strong fundamentals and High SG firms with weak fundamentals.

We obtain a number of insights from the results in panel B of Table 2. We begin with a discussion of raw monthly returns reported in columns (1) and (2) without additional controls. In row (1), results for the equally weighted Consistent-Growth portfolio show that Consistent-Low SG firms with strong fundamentals outperform Consistent-High SG firms with weak fundamentals by 0.80% per month (t-statistic 4.14), whereas there is no evidence of mispricing of Inconsistent-Growth portfolio firms in row (2); the mean monthly return of the Inconsistent-Growth portfolio is an insignificant −0.01% per month. Our equally weighted Grand portfolio return, which reflects the difference between rows (1) and (2), shows that the Consistent-Growth portfolio outperforms the Inconsistent-Growth portfolio by 0.81% per month (t-statistic 3.50). It is worth noting that consistency in sales growth is a much stronger predictor of stock returns than simple sales growth; by comparison, the return to the Low minus High sales growth portfolio in panel B of Table 1 is only 0.38% per month. We draw similar inferences from rows (1)–(3) of column (1) using the value-weighted raw returns. The value-weighted Consistent-Growth portfolio outperforms the value-weighted Inconsistent-Growth portfolio by 0.64% per month (t-statistic 1.99).

The results in columns (1) and (2) are based on raw returns without adjustments using matching firms. To account for potential differences in book-to-market ratios, size, and fundamentals caused by variation in consistency of growth, in columns (3) and (4) we report mean returns after subtracting the return of a firm matched on book-to-market ratio, size, and fundamentals. To ensure comparability, we value weight the matching firm using the same weight as the matched portfolio firm; i.e., the value weight is based on the market value of the matched firm. In columns (5) and (6), we add the market premium and the return to a momentum-based portfolio as additional controls. The mean abnormal return is estimated as the intercept in the following regression:

$$R_{p,t} = \alpha + b_1 Mktrf_t + b_2 UMD_t + u_t, \qquad (5)$$

where $R_{p,t}$ is the monthly portfolio return after adjusting for the matched firm returns as described above, $Mktrf_t$ is the monthly stock market return minus the risk free rate, and UMD_t is the monthly return to a momentum-based portfolio. We obtain the time series of market and momentum factor returns from Ken French's data library.[9]

For brevity, we primarily discuss the results in columns (5) and (6) because they include controls for market risk and momentum and provide inferences similar to columns (3) and (4). From equally weighted portfolio returns in column (6), the inferences are very similar to those provided by raw (unadjusted) portfolio returns in column (2). Despite the addition of these controls, there remains significant evidence that consistency in sales growth plays a role in determining future stock returns. In row (1), the mean monthly return of firms in the Consistent-Growth portfolio is 0.43% (t-statistic 2.15) and the Grand portfolio return in row (3) is 0.92% (t-statistic 3.15). In column (5), a similar inference can be made based on the value-weighted Grand portfolio return of 0.88% (t-statistic 1.96), indicating that the Consistent-Growth portfolio outperforms the Inconsistent-Growth portfolio. The results support the hypothesis that investors' valuations are influenced by consistency in sales growth because of representativeness bias.[10]

We note that in Table 2 column (5), the value-weighted Consistent-Growth portfolio generates 0.51%

per month but appears insignificant because of a t-statistic of 1.54. However, the 0.51% per month is economically significant and greater than the equally weighted portfolio return of 0.43% (t-statistic 2.15) in column (6), yet it appears statistically insignificant. The reason for this is that the value-weighted tests are less powerful because value-weighting distributes most of the weight to very large firms in each portfolio. Given our triple sort on growth, consistency, and fundamentals, there are often fewer than 100 firms per portfolio. In smaller portfolios, the value-weighted portfolios appear to be less diversified than the equally weighted portfolios, reducing power despite economic significance. The evidence for this is seen in the standard error estimates for abnormal returns that accompany rows (1)–(3). For example, in column (5), row (1), the value-weighted Consistent-Growth portfolio abnormal return estimate has a standard error of 0.33%, whereas the equally weighted portfolio has a standard error of 0.22%, the former being about 50% greater. Therefore, the value-weighted Consistent-Growth portfolio return seems insignificant despite that it is greater than that of the equally weighted portfolio (0.51% versus 0.43%, respectively). Similar observations can be made from columns (1) and (2) where the standard deviation of value-weighted portfolio returns is higher in column (1) compared to column (2), diminishing statistical power. Despite the reduced power however, the mean value-weighted return to our Grand portfolio in row (3) is statistically significant.

4.3. Fama–MacBeth Regressions with Controls for Size, Book to Market, and Momentum

In this section, we perform Fama–MacBeth type regressions to examine whether the variation in stock returns related to consistency in sales growth observed in Table 2 can be explained by controlling for firm-level characteristics; i.e., the logarithms of market value, book to market, and momentum in cross-sectional regressions. Each month, we use the most recent financial statement data (with a minimum three-month delay from fiscal year-end) to run the following cross-sectional regression that captures the returns to our consistency and fundamentals-based firms using dummy variables while adding controls:

$$\begin{aligned} r_{i,t+1} = {} & \mathit{Intercept} + c_1 \mathit{Low\ SG}_{i,t} + c_2 \mathit{High\ SG}_{i,t} \\ & + c_3 \mathit{Consistent\ Low\ SG} \times \mathit{Strong}_{i,t} \\ & + c_4 \mathit{Consistent\ High\ SG} \times \mathit{Weak}_{i,t} \\ & + c_5 \mathit{Inconsistent\ Low\ SG} \times \mathit{Strong}_{i,t} \\ & + c_6 \mathit{Inconsistent\ High\ SG} \times \mathit{Weak}_{i,t} \\ & + c_7 \mathit{Consistent\ Low\ SG} \times \mathit{Weak}_{i,t} \\ & + c_8 \mathit{Consistent\ High\ SG} \times \mathit{Strong}_{i,t} \\ & + c_9 \mathit{Inconsistent\ Low\ SG} \times \mathit{Weak}_{i,t} \\ & + c_{10} \mathit{Inconsistent\ High\ SG} \times \mathit{Strong}_{i,t} \\ & + b_1 \mathrm{Ln}(\mathit{MktVal})_{i,t} + b_2 \ln(B/M)_{i,t} \\ & + b_3 \mathrm{Ln}(1 + R_{mom})_{i,t} + e_{i,t+1}, \end{aligned} \tag{6}$$

where

$r_{i,t+1}$ = firm i's raw stock return in month $t+1$;

$\mathit{Low\ SG}_{i,t}$ = dummy variable equal to 1 if the firm falls in quintile one based on its most recent five-year sales growth and 0 otherwise;

$\mathit{High\ SG}_{i,t}$ = dummy variable equal to 1 if the firm falls in quintile five based on its most recent five-year sales growth and 0 otherwise;

$\mathrm{Ln}(\mathit{MktVal})_{i,t}$ = natural logarithm of the firm's most recent fiscal year-end market capitalization;

$\mathrm{Ln}(B/M)_{i,t}$ = natural logarithm of the firm's fiscal year-end book-to-market ratio;

$\mathrm{Ln}(1+R_{mom})_{i,t}$ = natural logarithm of one plus the firm's past six-month buy-and-hold stock return calculated as of three months after fiscal year-end;

$\mathit{Consistent\ Low\ SG} \times \mathit{Strong}_{i,t}$ = dummy variable equal to 1 if the firm exhibits Consistent-Low SG based on its most recent five-year sales growth *and* exhibits Strong fundamentals (has an F-score > 4), and equal to 0 otherwise;

$\mathit{Inconsistent\ Low\ SG} \times \mathit{Strong}_{i,t}$ = dummy variable equal to 1 if the firm exhibits Inconsistent-Low SG based on its most recent five-year sales growth *and* exhibits Strong fundamentals (has an F-score > 4), and equal to 0 otherwise;

$\mathit{Consistent\ Low\ SG} \times \mathit{Weak}_{i,t}$ = dummy variable equal to 1 if the firm exhibits Consistent-Low SG based on its most recent five-year sales growth *and* exhibits Weak fundamentals (has an F-score < 5), and equal to 0 otherwise;

$\mathit{Inconsistent\ Low\ SG} \times \mathit{Weak}_{i,t}$ = dummy variable equal to 1 if the firm exhibits Inconsistent-Low SG based on its most recent five-year sales growth *and* exhibits Weak fundamentals (has an F-score < 5), and equal to 0 otherwise;

$\mathit{Consistent\ High\ SG} \times \mathit{Weak}_{i,t}$ = dummy variable equal to 1 if the firm exhibits Consistent-High SG based on its most recent five-year sales growth *and* exhibits Weak fundamentals (has an F-score < 5), and equal to 0 otherwise;

$\mathit{Inconsistent\ High\ SG} \times \mathit{Weak}_{i,t}$ = dummy variable equal to 1 if the firm exhibits Inconsistent-High SG based on its most recent five-year sales growth *and* exhibits Weak fundamentals (has an F-score < 5), and equal to 0 otherwise;

$\mathit{Consistent\ High\ SG} \times \mathit{Strong}_{i,t}$ = dummy variable equal to 1 if the firm exhibits Consistent-High SG based on its most recent five-year sales growth *and* exhibits Strong fundamentals (has an F-score > 4), and equal to 0 otherwise;

Inconsistent High SG × *Strong*$_{i,t}$ = dummy variable equal to 1 if the firm exhibits Inconsistent-High SG based on its most recent five-year sales growth and exhibits Strong fundamentals (has an *F*-score > 4), and equal to 0 otherwise.

We report the time-series means and *t*-statistics of the coefficients from Equation (6) in Table 3. The interpretation of the coefficients (leaving aside control variables) in Equation (6) is as follows. The intercept represents the average return of firms that have mod-

Table 3. Fama–MacBeth Regressions with Size, Book-to-Market, and Momentum Controls

	Model			
Independent variable	(1)	(2)	(3)	(4)
Intercept (%)	1.43 (5.74)	2.19 (6.04)	2.19 (6.04)	2.16 (6.20)
Low SG (%)	0.15 (1.58)	−0.01 (−0.08)	−0.01 (−0.08)	0.01 (0.08)
High SG (%)	−0.22 (−2.06)	−0.33 (−3.36)	−0.33 (−3.36)	−0.33 (−3.50)
Consistent Low SG × *Strong* (%)		2.23 (6.11)	2.23 (6.11)	2.19 6.23
Consistent High SG × *Weak* (%)		1.71 (3.80)	1.71 (3.80)	1.69 (4.01)
Inconsistent Low SG × *Strong* (%)		2.05 (5.42)	2.05 (5.42)	2.02 (5.54)
Inconsistent High SG × *Weak* (%)		2.06 (4.20)	2.06 (4.20)	2.07 (4.41)
Consistent Low SG × *Weak* (%)		−0.45 (−3.04)	−0.45 (−3.04)	−0.45 (−3.09)
Consistent High SG × *Strong* (%)		0.34 (3.68)	0.34 (3.68)	0.35 (3.88)
Inconsistent Low SG × *Weak* (%)		−0.37 −1.422	−0.37 −1.42	−0.34 −1.33
Inconsistent High SG × *Strong* (%)		0.62 (5.02)	0.62 (5.02)	0.63 (5.18)
Ln(*MktVal*) (×100)			−0.133 (−3.14)	−0.138 (−3.37)
Ln(*B/M*)			0.311 (4.53)	0.294 (4.69)
Ln$(1+R_{mom})$				0.207 (1.34)
Adjusted R^2 (%)	0.50	0.85	2.19	2.60
Months	477	477	477	477
	Model			
Coefficient tests	(1)	(2)	(3)	(4)
Low SG − *High SG* (%)	0.37 (3.38)	0.70 (4.78)	0.32 (2.68)	0.34 (2.83)
Consistent Low SG × *Strong* − *Consistent High SG* × *Weak* (%)		0.96 (5.09)	0.52 (3.01)	0.50 (3.11)
Inconsistent Low SG × *Strong* − *Inconsistent High SG* × *Weak* (%)		0.13 (0.59)	−0.01 (−0.07)	−0.05 (−0.25)
Grand portfolio (*Consistent SG* − *Inconsistent SG*) (%)		0.83 (3.58)	0.54 (2.49)	0.55 (2.57)

Notes. The table reports estimates of mean returns and tests of differences in mean returns for Equation (6) using a Fama–MacBeth regression framework. The sample, identification of consistency in growth, and fundamentals are as described in Table 2. Using lagged data on these variables, we run the following monthly cross-sectional regression:

$$\begin{aligned} r_{i,t+1} = {} & Intercept + c_1 Low\ SG_{i,t} + c_2 High\ SG_{i,t} + c_3 Consistent\ Low\ SG \times Strong_{i,t} + c_4 Consistent\ High\ SG \times Weak_{i,t} \\ & + c_5 Inconsistent\ Low\ SG \times Strong_{i,t} + c_6 Inconsistent\ High\ SG \times Weak_{i,t} + c_7 Consistent\ Low\ SG \times Weak_{i,t} \\ & + c_8 Consistent\ High\ SG \times Strong_{i,t} + c_9 Inconsistent\ Low\ SG \times Weak_{i,t} + c_{10} Inconsistent\ High\ SG \times Strong_{i,t} \\ & + b_1 \mathrm{Ln}(MktVal)_{i,t} + b_2 \mathrm{Ln}(B/M)_{i,t} + b_3 \mathrm{Ln}(1+R_{mom})_{i,t} + e_{i,t+1}. \end{aligned}$$

See §4.3 for description of regression variables. See Table 1 for definitions of sales growth consistency, book-to-market ratio, and market capitalization. The table reports the time-series means of regression coefficients and associated *t*-statistics (shown in parentheses) estimated from the cross-sectional regressions. Tests for differences in coefficients are reported with associated *t*-statistics.

erate sales growth (i.e., when the High SG and Low SG dummy variables are zero). The coefficients on the Low SG and the High SG variables reflect the incremental mean returns to firms with Mid-Consistent-Low and High SG, respectively. The coefficients on the remaining dummy variables capture incremental mean returns to portfolios formed on consistency of sales growth and strength of fundamentals.[11] As an example, the mean returns to the portfolio with Consistent-Low SG, and Strong fundamentals is captured by (Intercept + c_1 + c_3). The variables Ln(B/M), Ln($MktVal$), and Ln($1+R_{mom}$) control for the predictive relation between future stock returns and these characteristics.

In Table 3, model (1) captures the returns to simple sales growth-based portfolios as in Lakonishok et al. (1994). The coefficient test indicates that the mean difference in the Low and High sales growth quintiles is 0.37% per month (t-statistic 3.38), confirming the sales growth effect. In model (2), we add variables based on Equation (6) to capture the full set of interactions between sales growth consistency and fundamentals. We use the estimates for the dummy variables that capture interactions between consistency and fundamentals to construct coefficient tests reported in Table 3. More specifically, to examine the difference in returns of firms with Consistent-Growth and Inconsistent-Growth (or the Grand portfolio return), we define the test as follows:

$$\begin{aligned}&\text{Grand Portfolio Return}\\&=[(\text{Intercept}+c_1+c_3)-(\text{Intercept}+c_2+c_4)]\\&\quad-[(\text{Intercept}+c_1+c_5)-(\text{Intercept}+c_2+c_6)]. \qquad (6a)\end{aligned}$$

The terms in the first square bracket represent the returns to the Consistent-Growth portfolio, and the second square bracket represents the returns to the Inconsistent-Growth portfolio. In model (2) without additional controls, the coefficients test reveals that the Consistent-Growth portfolio outperforms the Inconsistent-Growth portfolio by 0.83% (t-statistic 3.58).

Controlling for market value and book to market in model (3), this difference drops to 0.54% per month but remains significant (t-statistic 2.49). Adding the momentum control in model (4) in Table 3 leaves this difference essentially unchanged; 0.55% per month (t-statistic 2.57). Notably, we find that the Inconsistent-Growth portfolio does not exhibit evidence of mispricing in any of the models, affirming the results of panel B, Table 2.

4.4. Controls for the Value-Glamour Effects in Piotroski and So (2012)

Piotroski and So (2012) show that only high book-to-market stocks with strong fundamentals and low book-to-market stocks with weak fundamentals experience future return reversals. Another possible criticism of our results in Tables 2 and 3 is that our results are simply picking up the effects previously documented by Piotroski and So (2012) with sales growth substituting for the book-to-market ratio. We note that in Table 2, we calculated abnormal returns by subtracting the return of a matching firm based on both book to market as well as fundamentals. Nevertheless, it is possible that our research design did not fully control for the Piotroski and So effect. To rule out this potential alternative explanation for our results, we first replicate Table 3 of Piotroski and So (2012), which documents abnormal returns to value and glamour stocks after incorporating fundamentals. Then, we augment their regression with additional dummy variables that capture the interaction between consistency in sales growth and fundamentals as described in Equation (6) as follows:

$$\begin{aligned}r_{i,t+1} = {}& b_1 Glamour_{i,t} + b_2 Glamour_{i,t} \times LowScore_{i,t}\\&+ b_3 Glamour_{i,t} \times MidScore_{i,t} + b_4 Value_{i,t}\\&+ b_5 Value_{i,t} \times HighScore_{i,t}\\&+ b_6 Value_{i,t} \times MidScore_{i,t} + b_7 Middle_{i,t}\\&+ b_8 Middle_{i,t} \times LowScore_{i,t}\\&+ b_9 Middle_{i,t} \times HighScore_{i,t}\\&+ c_1 Low\ SG_{i,t} + c_2 High\ SG_{i,t}\\&+ c_3 Consistent\ Low\ SG \times Strong_{i,t}\\&+ c_4 Consistent\ High\ SG \times Weak_{i,t}\\&+ c_5 Inconsistent\ Low\ SG \times Strong_{i,t}\\&+ c_6 Inconsistent\ High\ SG \times Weak_{i,t}\\&+ c_7 Consistent\ Low\ SG \times Weak_{i,t}\\&+ c_8 Consistent\ High\ SG \times Strong_{i,t}\\&+ c_9 Inconsistent\ Low\ SG\\&\times Weak_{i,t} c_{10} Inconsistent\ High\ SG\\&\times Strong_{i,t} + c_{11} SizeDecile_{i,t}\\&+ c_{12} MomentumDecile_{i,t} + e_{i,t+1}, \qquad (7)\end{aligned}$$

where $r_{i,t+1}$ represents the stock return of firm i in month $t+1$. Similar to Piotroski and So (2012), *Glamour*, *Middle*, and *Value* are dummy variables that represent stocks with the lowest 30%, middle 40%, and highest 30% of book-to-market ratios, respectively. Also as in their paper, *LowScore*, *Mid*, and *HighScore* represent stocks with F-scores of 0–3, 4–6, and 7–9, respectively. Similar to Piotroski and So (2012), we also add the size and momentum deciles of a stock as additional controls and exclude the intercept. The interpretation of the coefficients on the Consistent and Inconsistent portfolio interactions is similar to that in Equation (6) except that these variables now capture any effects incremental to the effects in Piotroski and So (2012).

Table 4. Effects of Consistency in Sales Growth upon Stock Returns After Controlling for Piotroski and So (2012) Effects

	Model				
Independent variable	(1)	(2)	(3)	(4)	(5)
Glamour (%)	0.95	1.28	1.70	1.32	1.74
	(3.14)	(4.59)	(4.75)	(5.03)	(4.84)
Glamour × *LowScore* (%)		−0.71	−0.27	−0.32	−0.27
		(−3.34)	(−3.69)	(−4.17)	(−3.72)
Glamour × *MidScore* (%)		−0.33	−0.73	−0.72	−0.74
		(−4.20)	(−4.21)	(−3.72)	(−4.42)
Middle (%)	1.37	1.29	1.72	1.30	1.73
	(5.22)	(5.10)	(5.09)	(5.42)	(5.13)
Middle × *LowScore* (%)		−0.20	−0.21	−0.18	−0.20
		(−1.24)	(−1.56)	(−1.26)	(−1.56)
Middle × *HighScore* (%)		0.27	0.21	0.28	0.22
		(4.64)	(3.75)	(4.83)	(4.01)
Value (%)	1.88	1.47	0.50	0.64	0.52
	(6.58)	(4.16)	(3.29)	(4.24)	(3.54)
Value × *MidScore* (%)		0.41	0.35	0.41	0.35
		(3.19)	(2.98)	(3.36)	(3.07)
Value × *HighScore* (%)		0.63	1.79	1.45	1.78
		(3.83)	(4.30)	(4.45)	(4.33)
Low SG (%)			0.00	0.25	0.15
			(−0.05)	(2.17)	(1.61)
High SG (%)			−0.10	−0.28	−0.32
			(−1.26)	(−2.56)	(−3.32)
Consistent Low SG × *Strong* (%)				0.09	0.01
				(1.01)	(0.10)
Consistent High SG × *Weak* (%)				−0.33	−0.30
				(−2.57)	(−2.41)
Inconsistent Low SG × *Strong* (%)				−0.10	−0.24
				(−0.88)	(−2.37)
Inconsistent High SG × *Weak* (%)				0.17	0.20
				(0.98)	(1.20)
Consistent Low SG × *Weak* (%)				−0.33	−0.32
				(−2.16)	(−2.12)
Consistent High SG × *Strong* (%)				0.19	0.26
				(2.00)	(2.86)
Inconsistent Low SG × *Weak* (%)				−0.28	−0.33
				(−1.08)	(−1.28)
Inconsistent High SG × *Strong* (%)				0.58	0.60
				(4.71)	(4.91)
Decile (*size*) (%)					−0.08
					(−3.05)
Decile (*momentum*) (%)					0.02
					(1.31)
Adjusted R^2 (%)	10.94	11.33	12.48	11.79	12.66
Months	477	477	477	477	477

Table 4. (Continued)

	Model				
Coefficient tests	(1)	(2)	(3)	(4)	(5)
Value − *Glamour* (%)	0.93	0.19	0.09	0.12	0.04
	(6.37)	(0.87)	(0.50)	(0.62)	(0.26)
Value × *HighScore* − *Glamour* × *LowScore* (%)		1.34	1.23	1.36	1.26
		(3.95)	(4.38)	(4.49)	(4.72)
Consistent Low SG Strong − *Consistent High SG Weak* (%)				0.42	0.31
				(2.69)	(2.05)
Inconsistent Low SG Strong − *Inconsistent High SG Weak* (%)				−0.27	−0.44
				(−1.44)	(−2.28)
Grand Portfolio (*Consistent SG* − *Inconsistent SG*) (%)				0.69	0.75
				(3.14)	(3.46)

Notes. The table reports estimates of regression coefficients from Equation (7), which controls for Piotroski and So (2012) effects. At each fiscal year-end, we identify the five-year sales growth, F-score, book-to-market ratio, and market capitalization of each firm in the sample as described in Table 1. For each firm, we also identify whether it is a Consistent or Inconsistent-High SG or Low SG firm as described in Table 1. We run the following cross-sectional regression using lagged data for the firms:

$$\begin{aligned} r_{i,t+1} = {} & b_1 Glamour_{i,t} + b_2 Glamour_{i,t} \times LowScore_{i,t} + b_3 Glamour_{i,t} \\ & \times MidScore_{i,t} + b_4 Value_{i,t} + b_5 Value_{i,t} \times HighScore_{i,t} \\ & + b_6 Value_{i,t} \times MidScore_{i,t} + b_7 Middle_{i,t} + b_8 Middle_{i,t} \\ & \times LowScore_{i,t} + b_9 Middle_{i,t} \times HighScore_{i,t} + c_1 Low\ SG_{i,t} \\ & + c_2 High\ SG_{i,t} + c_3 Consistent\ Low\ SG \times Strong_{i,t} \\ & + c_4 Consistent\ High\ SG \times Weak_{i,t} + c_5 Inconsistent\ Low\ SG \\ & \times Strong_{i,t} + c_6 Inconsistent\ High\ SG \times Weak_{i,t} \\ & + c_7 Consistent\ Low\ SG \times Weak_{i,t} + c_8 Consistent\ High\ SG \\ & \times Strong_{i,t} + c_9 Inconsistent\ Low\ SG \\ & \times Weak_{i,t} c_{10} Inconsistent\ High\ SG \times Strong_{i,t} \\ & + c_{11} SizeDecile_{i,t} + c_{12} MomentumDecile_{i,t} + e_{i,t+1}. \end{aligned}$$

See §4.4 for description of regression variables. See Table 1 for definitions of sales growth consistency, book-to-market ratio, and market capitalization. The table reports the time-series means of regression coefficients and associated t-statistics (shown in parentheses) estimated from the cross-sectional regressions. Tests for differences in coefficients are reported with associated t-statistics.

Table 4 shows results from replicating Table 3 of Piotroski and So (2012). We report the time-series means and t-statistics of the regression coefficients along with additional coefficient tests. In models (1) and (2), we first replicate the primary Piotroski and So (2012) result, who show that the book-to-market effect is primarily present in value firms with strong fundamentals and glamour firms with weak fundamentals. In model (2), the difference between the returns to the Glamour and Value portfolios is an insignificant 0.19% (t-statistic 0.87) after incorporating fundamentals. Similar to their paper, the book-to-market effect is captured by value firms with strong fundamentals and glamour firms with weak fundamentals. This portfolio earns 1.34% per month (t-statistic 3.95). This affirms replication of their research design and captures their primary result in Table 4.

Next, in model (3) we add variables based on high and low sales growth (unconditional). The Piotroski and So effect remains robust to including these variables. In model (4) we include interaction variables representing our consistent sales growth firms after incorporating fundamentals. Once again, our primary test of the Grand portfolio is as defined in Equation (6a). In model (4), this coefficient test indicates that the Consistent-Growth portfolio outperforms the Inconsistent-Growth portfolio by 0.69% (t-statistic 3.14) per month, a number that is both economically and statistically significant despite controlling for the Piotroski and So effect. In model (5), adding controls for size and momentum does not alter this conclusion where the difference is 0.75% (t-statistic 3.46) on average.

The empirical evidence in Table 4 demonstrates that consistency in sales growth has incremental explanatory power for stock returns after controlling for the effects documented in Piotroski and So (2012). Again, this evidence affirms the results that we document in Tables 2 and 3. To further delineate the incremental contribution of our study, it is also important to note that Piotroski and So (2012) do not test for a mechanism for stock mispricing, whereas we provide evidence on the effects of consistency in financial performance as captured by sales growth on investors' expectations. Based on this collective evidence, we are confident that our results are incremental to the Piotroski and So (2012) effects in establishing consistency in sales growth as an important predictor of stock returns.

4.5. Analysis of Subsequent Earnings Announcement Returns

A frequently used technique for testing whether the market is surprised by cash flow news from a group of firms is to examine daily returns around subsequent earnings announcements. Differences in daily returns are less susceptible to be driven by cross-sectional differences in risk. For example, La Porta et al. (1997) use earnings announcement returns to show that the future announcement period returns of firms with low past sales growth exceed those of high sales growth firms. We construct a similar test to examine whether a predictable difference in earnings announcement returns exists between our Consistent-Growth and Inconsistent-Growth firms. We obtain earnings announcement dates for our firms from quarterly data in Compustat and calculate buy and hold returns for windows ranging from three to seven days in length centered on the announcement day. If the announcement day falls on a market holiday, we treat the next trading day as the announcement day. For each firm, we obtain the announcement returns for each of four quarterly earnings announcements over the same year for which we previously calculated monthly returns. We report market-adjusted returns, calculated by subtracting the buy-and-hold value-weighted CRSP index returns over the same window as the earnings announcement returns. We also report matching-firm-adjusted returns, calculated by subtracting the buy and hold earnings announcement return of a matching firm chosen based on the book-to-market ratio, size decile, and fundamentals as described in Table 2. We calculate the matching firm's earnings announcement return for the same calendar quarter as for the matched firm.

For each year in the sample, we first calculate the average quarterly announcement return (or the market or matching-firm adjusted return) across all firm quarters in the portfolio over the following year. Then we calculate a time-series mean announcement return over all years in the sample. Table 5 reports the average quarterly buy-and-hold earnings announcement returns calculated over a five-day (+/−2 days around the announcement) window for firms in the Consistent-Growth, Inconsistent-Growth, and Grand portfolios after incorporating fundamentals.

We find that the Consistent-Growth portfolio firms exhibit raw, market-adjusted, and matching-firm-adjusted five-day returns of 0.64% (t-statistic 5.32), 0.61% (t-statistic 5.29), and 0.36% (t-statistic 2.33) per announcement period on average, respectively. In contrast, the Inconsistent-Growth portfolio firms exhibit insignificant earnings announcement returns. The difference in five-day announcement returns is reflected in the announcement returns of the Grand portfolio, which are 0.47% (t-statistic 2.26) using the matching-firm adjustment; results are similar using raw returns and market-adjusted returns. This suggests that the market is surprised by the net positive cash flow news of the Consistent-Growth firms but no surprise is evident for the Inconsistent-Growth firms. Note that the Grand portfolio is neutral on both the sales growth as well as the fundamentals dimensions. Therefore, the results are incremental to previously document results regarding earnings announcement effects of sales growth and fundamentals-based portfolios. The results are consistent with the hypothesis that investors are influenced by consistency in sales growth and affirm the evidence in our primary tests presented in Table 2.

4.6. Analysis of Analyst Growth Forecasts and Recommendations

Our central hypothesis examines the potential effect of representativeness on investor interpretation of past growth. An interesting related question is whether analyst forecasts exhibit similar patterns. Therefore, we also examine whether the potential effect of the bias extends to analysts. For each of our portfolio firms described in Table 3, we collect three types of consensus analyst forecasts from Thomson Reuters' Institutional Brokers' Estimate System (IBES) database to perform our tests: one-year sales growth, long-term growth in earnings per share (EPS), and analyst recommendations. Long-term revenue growth forecasts are sparse in IBES but one-year revenue forecasts are populated for a sufficient number of firms for us to conduct our test during the period 1996–2012. We obtain the first consensus one-year revenue forecast during the year after portfolio formation for each firm and use the previous actual reported sales to compute the

Table 5. Quarterly Earnings Announcement Returns for Consistent- and Inconsistent-Growth Portfolios

				Matching firm earnings
		Raw return	Market adjusted	Annual return adjusted
Portfolios		+/−2 days	+/−2 days	+/−2 days
Consistent-Growth	Low − High	0.64% (5.32)	0.61% (5.29)	0.36% (2.33)
Inconsistent-Growth	Low − High	0.19% (1.45)	0.16% (1.25)	−0.11% (−0.62)
Grand portfolio [Consistent − Inconsistent]	Time-series mean	0.45% (2.76)	0.45% (2.91)	0.47% (2.26)
Annual periods		40	40	40

Notes. The table reports mean quarterly earnings announcement returns for Consistent- and Inconsistent-Growth firms along with associated t-statistics (shown in parentheses) after incorporating fundamentals. Portfolio identification is described in Table 2. For each firm, the five-day buy-and-hold earnings announcement raw return is collected centered on each earnings announcement day for four quarterly announcements beginning three months following fiscal year-end. Next, the mean five-day earnings announcement return across all firms in a reported portfolio is calculated. The table reports the time-series mean of these earnings announcement returns for Consistent- and Inconsistent-Growth portfolios as described in Table 2. The market adjusted return is calculated by subtracting the buy-and-hold five-day value-weighted CRSP index return for the earnings announcement period. The matching-firm adjusted return is calculated by subtracting the buy-and-hold five-day earnings announcement return of a book-to-market ratio matched firm with similar financial fundamentals as described in Table 2. The Grand portfolio represents the difference in mean earnings announcement returns of the Consistent- and Inconsistent-Growth portfolios. See §4.5 for additional details.

consensus one-year revenue growth. We calculate the portfolio-level mean sales growth forecast and report the time-series mean for each portfolio in Table 6. Per our earlier hypothesis, we expect that the revenue growth forecasts for the Consistent-Growth portfolio is lower than that of the Inconsistent-Growth portfolio despite the fact that both portfolios are based on similar prior sales growth. We find that the Grand portfolio mean sales growth forecast is −9.49% (t-statistic −2.88) on average as expected under the representativeness hypothesis. Adjusting for the sales growth of matching firms as in Table 2 does not change this effect as shown in column (3) of Table 6.

We apply the procedure above to long-term growth in EPS and find similar results. In column (2) of Table 6, the long-term EPS growth forecast of the Grand portfolio is −7.61% (t-statistic −12.8), again consistent with our expectation under representativeness. Adjusting for matching firms shown in column (4) of Table 6 yields a similar result.

We also examine analyst buy/sell recommendations available from Thomson Reuters over the period 1992–2012 for our sample firms. Thomson Reuters assigns a numerical value of 1 to a Buy recommendation and 5 to a Sell recommendation. Under representativeness, we expect the mean recommendation of the Consistent-Growth portfolio to be numerically higher (i.e., more sells) than that of the Inconsistent-Growth portfolio. Column (6) of Table 6 reports that the mean recommendation of the Grand portfolio, which reflects this difference is 0.36 (t-statistic 5.46), as expected under representativeness.

4.7. Controls for Alternative Asset Pricing Risk Factors

We also examine evidence on whether the returns related to consistency in sales growth can be explained by business cycle risk factors. Asset pricing theory generally states that assets with positive exposure to the business cycle are riskier and therefore are expected to generate higher returns on average (Chen et al. 1986, Fama 1990, Petkova 2006). A risk-based explanation predicts that the exposure of the Consistent-Growth portfolio to innovations in business cycle variables is greater than that of the Inconsistent-Growth portfolio. We test this prediction using proxies for business cycle risk factors. These include the *Term* spread (the difference in the yields of 10-year treasury notes and short-term T-bills), *Def* (the difference in the yields of Aaa and Baa rated bonds), the risk free rate *TB-Yield* (the one-month T-Bill Yield), and *DivYield* (the dividend yield of the value-weighted CRSP index).[12]

We regress the Grand portfolio return on contemporaneous and lagged innovations in these business cycle variables (measured using AR(1) models). In nontabulated results, we find that the regression coefficients (also known as factor betas) for the Grand portfolio are generally insignificant. These results do not support a risk-based explanation. Furthermore, the economic and statistical significance of the estimates of abnormal returns captured by the regression intercepts for either the value-weighted or the equally weighted Grand portfolio remain unaffected compared to estimates observed in Table 2. In short, we do not find evidence in support of a risk-based explanation for the abnormal returns to the Grand portfolio.

Table 6. Analysts' Growth Forecasts and Recommendation

			Column					
			(1)	(2)	(3)	(4)	(5)	(6)
			Analyst growth forecasts		Matched-firm adjusted growth forecasts		Mean analyst recommendation	Match adjusted analyst recommendation
Row	Portfolios	Consistency/Fundamentals	Sales	EPS	Sales	EPS		
(1)	Consistent-Growth	Low/Strong – High/Weak	−19.4%	−10.1%	−11.12%	−8.45%	0.19	0.25
			(−10.28)	(−18.88)	(−5.30)	(−12.06)	(4.86)	(5.79)
(2)	Inconsistent-Growth	Low/Strong – High/Weak	−9.95%	−2.46%	−0.20%	−0.76%	−0.16	−0.13
			(−2.80)	(−3.60)	(−0.06)	(−7.29)	(−3.92)	(−2.57)
(3)	Grand portfolio	Rows (1)–(2)	−9.49%	−7.61%	−10.92%	−7.70%	0.35	0.38
			(−2.88)	(−12.80)	(−2.46)	(−7.29)	(5.87)	(5.46)
		Annual periods	17	33	17	33	21	21

Notes. This table shows analyst forecasts and recommendations for firms classified as Consistent- or Inconsistent-Growth based on five-year sales growth. See Tables 1 and 2 for definitions of consistency. The analyst data are collected as the first available consensus forecast during the period April to December of each year following firm classification. Only one observation per firm per year is used. Columns (1) and (3): One-year sales growth calculated by taking the consensus revenue forecast for each firm for the next year, dividing by the actual sales from the latest income statement, and subtracting one. In column (3), the forecast sales growth of a matching firm is subtracted and the mean is calculated across all available firms. See Table 2 for a description of the matching procedure. The reported figures are time-series means. Sales growth forecasts are available beginning in 1996 and ending in 2012. Columns (2) and (4): Long-term growth in earnings per share (EPS) is obtained as the consensus long-term growth forecast for EPS each year. In column (4), the long-term growth forecast of a matching firm is subtracted. See Table 2 for a description of the matching procedure. The reported figures are time-series means. EPS growth forecasts are collected beginning in 1979 and ending in 2012. Columns (5) and (6): Consensus analyst recommendations are obtained for firms in the sample each year from 1991 to 2012. The recommendations are assigned a numerical value by Thomson Reuters where 1 is a strong buy and 5 is a strong sell. Column (6) subtracts the consensus recommendation of a matching firm. See Table 2 for a description of the matching procedure. The reported figures are time-series means, with t-statistics shown in parentheses.

5. Conclusions

We document evidence supporting the presence of representativeness bias in investor processing of consistent patterns of sales growth. In contrast with earlier studies, we identify firms that are likely to be mispriced by incorporating fundamentals to discriminate between firms where past patterns of consistent growth are likely to continue from firms where past patterns of consistent growth are unlikely to continue. More specifically, we find that firms with consistently high or low long-term sales growth that is incongruent with contemporaneous fundamental strength exhibit mispricing consistent with the presence of representativeness bias. We also examine the pattern of subsequent earnings announcement returns and find evidence that corroborates our main findings. Our results are robust to a broad range of controls including business cycle risk exposures as well as the value-glamour effects documented in Piotroski and So (2012).

Our results are noteworthy because a critical assumption in behavioral finance theories is that investors exhibit information processing biases and Chan et al. (2004) do not find any evidence consistent with the presence of representativeness bias. We show that by incorporating information about underlying fundamentals, there is evidence in support of representativeness bias affecting investor processing of past sales growth. Thus, our findings are of potential interest to researchers who attempt to understand the psychology of investor behavior as well as to investment professionals.

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Appendix. Measurement of Piotroski's (2000) F-Score

Piotroski's F-score is the sum of nine indicator variables that are defined using financial statement data. The variables are chosen based on traditional interest by valuation analysts in evaluating the strength of a firm's financial fundamentals. Several of the variables overlap with variables used by earlier studies of fundamental analysis (see, e.g., Abarbanell and Bushee 1997, 1998). Piotroski categorizes the nine signals into three categories: profitability, leverage and liquidity, and operating efficiency. Details regarding the logic underlying these variables can be found in Piotroski (2000). In the following subsections, we describe the measurement of the underlying variables used to calculate the F-score.

A.1. Variable Measurement for *F*-score Calculation

In the following descriptions, Compustat data names are provided in quotations within parentheses.

1. *ROA* is income before extraordinary items ("IB") divided by the beginning of the year total assets ("AT"). The indicator variable *I_ROA* equals 1 if $ROA > 0$ and 0 otherwise.

2. *CFO* is measured as the cash flow from operations ("CFO," measured as funds from operations when "CFO" not available) scaled by beginning of year total assets ("at"). The indicator variable *I_CFO* equals 1 if $CFO > 0$ and 0 otherwise.

3. *ACCRUAL* is the difference between income before extraordinary items ("IB") scaled by beginning of year total assets ("AT") and cash flow from operations as described above. The indicator variable *I_ACC* equals 1 if $ACCRUAL < 0$ and 0 otherwise.

4. *DROA* is measured as the difference between current year's ROA and the previous year's ROA. The indicator variable *I_DROA* equals 1 if $DROA > 0$ and 0 otherwise.

5. *DLEVER* is measured as the difference between the current year's debt-to-assets ratio and the previous year's debt-to-assets ratio. The debt-to-assets ratio is measured as long-term debt ("DLT") divided by total assets ("AT"). The indicator variable *I_DLEV* equals 1 if $DLEVER < 0$ and 0 otherwise.

6. *DLIQUID* is the difference between current year's current ratio and the previous year's ratio. The current ratio is measured as current assets ("ACT") divided by current liabilities ("CLT"). The indicator variable *I_DLIQ* equals 1 if $DLIQUID > 0$ and 0 otherwise.

7. *ISSUANCE* is measured as the amount of stock issued by a firm in a given year ("SSTK"). The indicator variable *I_SSTK* equals 1 if $SSTK = 0$ and 0 otherwise.

8. *DMARGIN* is measured as the difference between the current year's gross margin ratio and the previous year's ratio. The gross margin ratio is measured as one minus the ratio of cost of goods sold ("COGS") and net sales ("SALE"). The indicator variable *I_DM* equals 1 if $DMARGIN > 0$ and 0 otherwise.

9. *DTURN* is measured as the difference between the current year's asset turnover ratio and the previous year's turnover ratio. The asset turnover ratio is measured as net sales ("SALE") divided by total assets ("AT"). The indicator variable *I_DTURN* equals 1 if $DTURN > 0$ and 0 otherwise.

The aggregated *F*-score is calculated as

$$F\text{-score} = I\_ROA + I\_CFO + I\_ACC + I\_DROA + I\_DLEV + I\_LIQ + I\_SSTK + I\_DM + I\_DTURN.$$

Endnotes

[1] Kahneman and Tversky (1972) define representativeness as a way of assessing the subjective probability of an event or a sample by "the degree to which it is similar in essential characteristics to its parent population and reflects the salient features of the process by which it is generated" (p. 430). One manifestation of representativeness bias is that individuals ignore base rate frequencies in evaluating probabilities and Kahneman and Tversky (1973) document experimental evidence consistent with this effect.

[2] We focus on long-term SG because it is both a salient financial signal and a common starting point for forecasting future growth as input into valuation models (see, e.g., Penman 2007, Easton et al. 2013).

[3] This criticism applies to prior work including Chan et al. (2004) as well as to our study.

[4] See Gigerenzer and Gaissmaier (2011) for a recent review of the literature on heuristics.

[5] One of the earliest tests of the representativeness hypothesis in accounting is presented in Johnson (1983), who argues that given that judgment and choice behavior is sensitive to the formal structure and content of a task, it is not clear whether experimental evidence on representativeness in psychology can be generalized to other decision contexts such as those in accounting and finance.

[6] Sales growth has also been frequently used by researchers in prior studies as a summary growth measure (La Porta et al. 1997, Daniel and Titman 2006). Jegadeesh and Livnat (2006) show that revenue growth has significant incremental explanatory power for stock returns over earnings. They argue that revenues are simpler and more persistent than expenses that reflect a heterogeneous mixture of costs.

[7] In subsequent regression-based tests, we also control directly for the magnitude of sales growth.

[8] In our tests, the definition of inconsistent growth differs from Chan et al. (2004). The reason is that the Chan et al. (2004) approach frequently limits the number of firms in the Inconsistent Growth portfolios to fewer than 20 firms. This is because they classify firms with two or fewer years of above-median or below-median sales growth to be Inconsistent-Growth firms. There are very few such firms in quintiles one and five of sales growth. Since we plan to execute an additional sort based on fundamentals (described in §3.3), the Chan et al. (2004) definition of inconsistent growth sometimes leaves very few firms or *no* firms at all in the desired portfolios.

[9] http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

[10] In a robustness test, we examine whether our results are more pronounced among smaller firms where one would expect representativeness bias to have the greatest impact. Untabulated results confirm this expectation.

[11] We note that consistency of growth is defined only for firms with High or Low sales growth.

[12] Each of these variables is a potential proxy for macroeconomic risk that tracks expected stock returns (Fama 1990, Petkova 2006).

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