A CAPITAL MARKET TEST OF REPRESENTATIVENESS

A Dissertation

by

MOHAMMAD URFAN SAFDAR

Submitted to the Office of Graduate Studies of
Texas A&M University
in partial fulfillment of the requirements for the degree of

DOCTOR OF PHILOSOPHY

May 2012

Major Subject: Accounting

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Approved by:

Chair of Committee,	Anwer Ahmed
Committee Members,	Senyo Tse
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ABSTRACT

A Capital Market Test of Representativeness. (May 2012)

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While some prior studies document that investors overreact to information in sales growth as consistent with representativeness bias, other studies find no evidence of investor overreaction to either sales or earnings growth. Other recent studies also show that sales growth does not predict stock returns after controlling for changes in outstanding shares and asset growth. I reexamine the role of representativeness by investigating whether the effects of this bias are confounded by the presence of another effect that has been extensively documented – investors' underreaction to fundamentals. Adjusting for investor under-reaction to fundamentals, I document strong evidence that investors overreact to sales growth as predicted under representativeness despite adding accruals, asset growth, and equity issuance as additional controls. In cross-sectional regressions of future stock returns on predictive variables that control for fundamentals, changes in equity shares, accruals, and lagged 36 month returns, I find that the coefficient on sales growth is highly significant over both the full sample period 1970-2009 (t-stat -3.12). Furthermore, asset growth, equity issuance, and accruals lose much of their significance in favor of sales growth. I also provide evidence that rejects a

theory based on fixation in favor of representativeness. These results document evidence of overreaction to past sales growth in firms where underreaction to fundamentals does not confound the overreaction due to representativeness bias.

DEDICATION

To my mother

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I would like to thank my committee chair, Dr. Ahmed, and my committee members, Dr. Tse, Dr. Wolfe, and Dr. Galpin, for their guidance and support throughout the course of this research.

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I. INTRODUCTION

Prior studies document mixed evidence on whether representativeness bias affects how investors process accounting information. While Lakonishok et al. (1994) document that investors overreact to information in sales growth as consistent with representativeness, Chan et al. (2004) find no evidence that investors overreact to either sales or earnings growth. Recent studies also show that sales growth does not predict stock returns after controlling for changes in outstanding shares and asset growth.[1] I reexamine the role of representativeness by investigating whether the effects of this bias are confounded by the presence of another effect that has been extensively documented in the accounting literature – investors' underreaction to fundamentals.[2] Controlling for investor under-reaction to fundamentals, I document strong evidence that investors overreact to sales growth as predicted under representativeness despite adding accruals, asset growth, and new shares as additional controls.

Understanding how investors process earnings and fundamental signals is important in both accounting and finance for readily evident reasons. For investors, it can help identify mispriced securities. For financial professionals, it can identify circumstances where security prices are biased relative to their fundamentals. This is especially relevant when market multiples are used to determine the values of public

This dissertation follows the style of Journal of Accounting and Economics.

[1]See Daniel and Titman (2006) for equity share issuance and Cooper et al. (2008) for asset growth.
[2]See Ou and Penman (1989), Lev and Thiagarajan (1992), Abarbanell Bushee (1997, 1998), and Piotroski (2000), for example.

offerings, acquisition targets, and private companies or prices are used to estimate the cost of capital since any bias in market prices will transmit to valuation estimates. Representativeness has been widely documented in psychology as an information processing error that has motivated studies of overreaction to financial signals in the stock market.[3] It can cause investors to update their beliefs about stock prices in an exaggerated fashion upon noticing attributes they generally associate with extraordinary valuations. For example, if investors observe good (*bad*) earnings signals, they may believe with too high a probability that a stock is a winner (*loser*) and overprice (*underprice*) the stock.

Overstating the probabilities of extreme valuations is known as making a 'base rate error.' Barberis et al. (1998) formalize this type of error into a theory where investors overreact to past trends in a firm's earnings performance. However, Chan et al. (2004) find that contrary to the Barberis et al. (1998) model's predictions, stocks do not become mispriced after long sequences of extreme earnings or sales growth. Chan et al. (2004) interpret this as evidence that investors' beliefs are not affected by representativeness while Daniel (2004) takes these results to mean that financial performance does not drive overreaction. However, the Chan et al. (2004) study does not consider whether the well documented underreaction to firm specific fundamentals such as operating margins and operating efficiency conceals the effects of overreaction to sales or earnings growth. The central thesis of this paper is that pricing errors due to

[3]See Kahneman and Tversky (1974) for a more details on representativeness and related evidence in psychology. See Debondt and Thaler (1985, 1987) and Lakonishok et al. (1994) for empirical studies of overreaction.

representativeness can be muted by the underreaction to fundamentals which diminishes the predictive power of sales growth and must be taken into account to identify investor overreaction.

The primary intuition underlying my empirical tests is that investors overreact to salient signals of financial performance such as sales or earnings growth that are widely followed as summary measures of growth by both analysts and other investors. They may however underreact to other fundamentals such as the rate of capital investment and operating efficiency where information about future growth may be more difficult to extract. Therefore, while investors overreact to good (*or bad*) financial performance signals, they may be underreacting to fundamentals that can be *either* good or bad. When the two types of signals agree, the net pricing error is muted rendering overreaction undetectable but when they diverge pricing errors are exacerbated and detectable. For example, a firm may experience great revenue growth but a decline in its operating margins may signal a weaker competitive position. Investors reacting to high revenue growth due to representativeness may overlook the latter and confer high valuations upon all such firms. The valuation error in firms with high revenue growth and strong margins will be significantly muted because the overreaction to high revenue growth is offset by the underreaction to strong margins. However, the overvaluation is exacerbated and likely to be detectable in firms with weak margins since underreaction to the latter causes further overvaluation; i.e., the errors reinforce each other. The net error can appear significantly smaller when averaged across all firms with high revenue growth. The interaction can be all the more severe since firms with extreme revenue are

also likely to exhibit other extreme fundamentals which when underweighted can have significant impact on the net pricing error.

Based on the argument above, it is theoretically possible for the pricing error due to representativeness (overreaction) to be muted by underreaction to fundamentals. Using this insight, I devise empirical tests that control for underreaction to fundamental signals to identify the likely patterns of mispricing due to representativeness. I measure direct earnings signals as the past three years' sales growth. To measure fundamentals, I construct a composite measure that forecasts future earnings using changes in firms' asset positions (inventories), investment activities (capital expenditures), and competitive strength (operating margins). I assign each firm a quintile ranking based on sales growth and an independent ranking based on fundamentals. The extreme quintiles are used to define the High/Low sales and Strong/Weak fundamentals portfolios. Pricing errors are measured using abnormal returns during the 12 months following portfolio formation using a four factor model based on Fama and French (1993) and Carhart (1997). Interaction portfolios are formed using firms that exhibit a particular sales growth and fundamentals based ranking; example Low/Strong, High/Weak etc.

I first document that future abnormal returns of firms within the High and Low sales growth portfolios depend upon their fundamentals. High/Strong firms earn insignificant abnormal returns of 0.04% (t-stat 0.30) while High/Weak firms earn significant abnormal returns of -0.44% per month (t-stat -3.91). When aggregated into a single portfolio of High sales growth firms, the portfolio exhibits an insignificant abnormal return of only -0.05% (t-stat -0.62). Within the Low sales growth portfolio,

the Low/Strong firms earn 0.38% (t-stat 2.05) while the Low/Weak firms earn only 0.08% per month (t-stat 0.54). When combined, the Low sales growth firms earn a combined average of 0.22% per month (t-stat 1.88). These figures suggest that underreaction to fundamentals can interact with overreaction to sales growth which weakens the power of sales growth to predict future returns in a sample unadjusted for underreaction to fundamentals, misleading the researcher into inferring an absence of behavioral errors caused by representativeness.

In cross sectional regressions that control for other predictive variables including asset growth (Cooper et al., 2008), accruals (Sloan, 1996), lagged stock returns (Debondt and Thaler, 1985) and changes in outstanding shares (Daniel and Titman, 2006), sales growth is insignificant in predicting returns over all sample periods (t-stat of -0.84 for 1971-2009). To examine whether adjusting for the interactions documented above reveals the power of sales growth to predict returns vis-à-vis these control variables, I remove firms from the sample where underreaction to fundamentals offsets the overreaction to sales growth (e.g., high sales growth but strong fundamentals). In cross-sectional regressions of future stock returns on predictive variables that control for fundamentals, changes in equity shares, accruals, and lagged 36 month returns using this restricted sample, I find that the coefficient on sales growth is highly significant over the sample period 1971-2009 (t-stat -3.12). Furthermore, asset growth, change in shares, and accruals lose much of their significance in the restricted sample. These results document evidence of overreaction to past sales growth in firms where underreaction to fundamentals does not confound the overreaction due to representativeness bias. Similar

results do not obtain when past earnings growth is used to predict future returns which suggests that investors treat sales as an important signal representing a firm's potential growth. I also provide evidence that rejects a theory based on fixation rather than representativeness.

I also examine the effects of time series variation in investors' bias. Cooper et al. (2004) show that underreaction captured by stock price momentum varies strongly with past market trends, suggesting that periods of optimism and pessimism impact investor behavior. Therefore, I test hypotheses that state that during upward (*downward*) market trends, investors are more prone to overpricing (*underpricing*) stocks due to a greater tendency to declare winners (*losers*) prematurely (i.e., make extreme base rate errors) in a manner consistent with representativeness. The mispricing effects discussed earlier become significantly larger when tests are conditioned upon the overall market trend measured as the past three-year return of the overall market. Firms in the High-Sales/Weak-Fundamentals group experience significant negative abnormal returns of -0.79% per month following periods of positive market trends and firms in the Low-Sales/Strong-Fundamentals group experience significant positive abnormal returns of 1.44% per month following periods of negative market trends. These results suggest that the investors' error in undervaluing (*overvaluing*) firms with low (*high*) earnings signals due to representativeness is more severe during up (*down*) markets. These results survive additional tests based on liquidity risk and changes in volatility.

The primary contribution of this paper is that it documents evidence of representativeness in stock prices by jointly modeling earnings and fundamental signals,

which is in contrast to earlier work by Barberis et al. (1998) and Chan et al. (2004). The paper models these two signals to highlight circumstances under which investors' overreaction due to base rate errors interacts with their underreaction to fundamentals, leading to pricing errors that seem muted and can suggest an absence of cognitive errors. When the two effects are modeled jointly, significant evidence of pricing errors is revealed. In the remainder of the paper, section II discusses how this paper fits into various strands of related literature. Section III provides details of the analytical framework and hypothesis development. Section IV discusses the research design and methods followed by a discussion of the major results in this paper in section V. Section VI concludes.

II. RELATED LITERATURE

This study draws upon research from three specific areas: behavioral asset pricing, fundamental analysis, and return predictability. Notable behavioral theories such as Barberis et al. (1998) and Daniel et al. (1998) were developed to explain accumulating evidence on momentum and reversal in stock returns following Debondt and Thaler (1985, 1987) and Jegadeesh and Titman (1993). Whereas the Barberis et al. (1998) theory allows public information such as earnings to drive mispricing, the Daniel et al. (1998) model relies on private signals to generate similar effects. Since concise but excellent reviews of this literature can now be found in several prior papers,[4] the discussion here focuses upon studies involving representativeness specifically.

Since Barberis et al. (1998), representativeness has found its way into formal asset pricing theory a handful of times. Brav and Heaton (2002) provide a model to illustrate the similarity of stock price behavior under representativeness and estimation risk theory though their model considers only a single asset. Rabin (2002) uses representativeness to illustrate what Kahenman and Tversky (1974) refer to as *the law of small numbers*. In his model, people expect properties of the population to be reflected even in small samples, ignoring the law of large numbers. The resulting bias leads to under-reaction rather than reversals and is similar to the conservatism effect modeled by Barberis et al. (1998) to explain momentum. My study is primarily concerned with over-reaction due to representativeness so it does not test for momentum effects nor is it

[4] See Chan et al. (2004) and Daniel (2004), for example.

a test of the Barberis et al. (1998) model. Whereas Barberis et al. (1998) rely on patterns in earnings alone to model representativeness, my study relies on an alternative framework where investors' overreaction to earnings signals interacts with concurrent underreaction to other information to generate stock return patterns.

Empirical evidence on the role of representativeness in shaping actual stock prices is scarce. Chan et al. (2004) provide the first set of comprehensive empirical tests of representativeness based on Barberis et al. (1998) using long term trends and sequences of sales and earnings growth. They define trend by the magnitude of change in financial performance over a five-year period and identify a sequence of financial performance by the number of years over the five years during which the financial performance is above or below that of the median firm. In this manner, they identify firms that have consistently good or bad performance over the long run. Since they are unable to find cross sectional predictability in subsequent stock returns, they interpret this as evidence against representativeness. Since the Chan et al. (2004) results do not support the Barberis et al. (1998) model of representativeness, my paper proposes a new set of empirical tests.

Fundamental analysis plays an important role in this study. Research on fundamental analysis in accounting has generally focused on identifying variables that can forecast future earnings and stock returns. Ou and Penman (1989) construct a measure of fundamentals based on financial statement variables identified to be statistically relevant for forecasting future performance. My measure of fundamentals is similar though I use a much smaller set of variables based on Lev and Thiagarajan

(1993) and Abarbanell and Bushee (1997, 1998) that forecast future earnings. Although the ability of these variables to forecast future returns has been documented, researchers have only recently begun to develop explanations for the return predictability.[5] This paper provides evidence for the theory that representativeness causes investors to overlook these fundamentals by overweighting earnings signals.

The role of earnings signals in predicting return reversals has been extensively studied in prior papers. Lakonishok et al. (1994) show that sales growth is negatively related to future returns though they do not control for other variables that predict returns such as size and book-to-market. Their results are in direct conflict with Chan et al. (2004) who find no relationship between either long term sales or earnings growth and future returns at any horizon. More recently, Daniel and Titman (2006) show that five year sales per share growth is strongly negatively to future returns though they contend that the reversals are primarily due to intangible information and not tangible information. Furthermore, given that they use sales per share growth to forecast returns, they find that the forecasting power of sales growth is absorbed by a share issuance variable. Their argument confuses causes and effects since equity issuance does not cause mispricing. Rather, it potentially reflects managerial response to stock mispricing that can exist for multiple reasons. It is not surprising therefore that the forecasting power of *sales per share* is absorbed by such a variable. I examine both tangible information as well as intangible information and find that tangible information related to sales growth exhibits substantial forecasting power, contrary to their results.

[5] See Richardson et al. (2010) for recent advances in the empirical and theoretical aspects of fundamental analysis.

III. ANALYSIS AND HYPOTHESIS DEVELOPMENT

III.1 Cross Sectional Analysis

To develop testable hypotheses, the following framework is cast. Firms transition through regimes of growth, stability, and decline over time and fall into three basic types at any given time - winners, normal, or losers (i.e., experiencing a *high-growth* phase, a *stable growth* phase, or a *decline* phase). Investors determine the value of each firm by updating the posterior probability that a firm is a given type upon observing performance signals such as sales or earnings growth as well as other fundamentals. If investors update beliefs rationally, pricing errors are random and cannot be predicted using either earnings or fundamental signals. Under representativeness, investors commit base rate errors (i.e., overestimate the frequencies of winners and losers in the population) upon observing extreme earnings signals but underreact to other fundamentals. As a consequence, when investors overstate the frequency of winners (*losers*), they tend to overvalue (*undervalue*) firms but when they overlook other positive (*negative*) information, they tend to undervalue (*overvalue*) the firm. The undervalued firms experience positive abnormal returns in the future while the overvalued firms experience negative abnormal returns as prices are corrected. When the two effects coincide within the same firm, the overall pricing error is diminished and the market appears efficient if financial performance and fundamentals agree but exacerbated otherwise; the pricing error due to overreaction is more detectable in the latter case.

Sloan (1996) documents that investors overlook the degree to which accruals (defined as the non-cash component of earnings) constitute reported earnings relative to cash flows. He proposes that investors' tend to fixate on earnings, a type of behavioral error that leads to overpricing (*underpricing*) of firms with high (*low*) accruals. To distinguish representativeness from fixation, specify the firm's rationally determined stock price as the expected value of the true but unknown price *S* of the firm given all available information (Shiller, 1981). A rational investor who uses all information correctly sets the market price *P* as $\mathcal{E}(S|Y, X)$ where *Y* is a direct earnings signal such as sales growth and *X* is another fundamental signal. An irrational investor who fixates on *Y* and overlooks *X* sets the market price as an expectation using the earnings signal only: $P^* = \mathcal{E}(S|Y)$. The pricing error of the irrational investor under fixation is defined as:

$$e^* = P^* - P = E(S|Y) - E(S|Y,X) \qquad (1)$$

Using iterated expectations, the expected value of the irrational pricing error conditional on the earnings signal *Y* is:

$$E(e^*|Y) = E[E(P|Y)|Y - E(P|Y,X)|Y] = E(P|Y) - E(P|Y) = 0 \qquad (2)$$

This result shows that mispricing due to fixation cannot be predicted using the earnings signal *Y*. The intuition is that the mispricing error occurs due to an incorrect reaction to *X*, not *Y*. Therefore, overpricing (*underpricing*) occurs due to ignoring *X* when *X* represents bad (*good*) news that is ignored due to fixation. In contrast, equation (A) does not describe the investors' error under representativeness; i.e., $\mathcal{E}(e^*|Y)$ is not equal to zero. The intuition is that upon seeing an extreme positive (*negative*) earnings signal *Y*, the investor behaves as if this signal is *representative* of the entire information set and in

effect assumes a preponderance of good (*bad*) news, resulting in overpricing (*underpricing*). Therefore, under representativeness mispricing is driven by the earnings signal *Y* and is predictable using *Y* even after controlling for X.

Based on the analysis above, we can empirically distinguish representativeness from fixation by regressing future returns on both the earnings signal *Y* and the fundamental *X*. Under fixation, we expect the coefficient on *Y* to be zero especially after controlling for *X*. Under representativeness, the coefficient is expected to be negative. With this analysis in hand, we can state the first null hypothesis:

Hypothesis One: *Earnings signals do not predict future stock returns. I.e., the coefficient in a regression of future returns on past earnings signals is zero.*

Hypothesis one states that overreaction to earnings signals is not detectable without controlling for underreaction to fundamentals. A failure to reject hypothesis one indicates that either representativeness does not affect stock prices or overreaction due to this bias is confounded by underreaction to fundamentals. Hypothesis two makes the latter possibility explicit.

Hypothesis Two: *Controlling for underreaction to fundamentals, there is a negative relationship between earnings signals and future stock returns. I.e., the coefficient in a regression of future returns on past earnings signals is negative in firms where underreaction to fundamentals does not confound overreaction to earnings signals.*

A rejection of hypothesis two serves as evidence against representativeness bias.

III.2 Time Series Analysis

Formally, representativeness as described by Kahneman and Tversky (1974) is an error in updating the probability that an event is of a particular type given a stimulus.[6] For example, a good earnings stimulus may cause irrational investors to infer *too high* a probability that a firm is a winner rather than a loser despite that good earnings may not always indicate winners. This error is a result of neglecting base rates - i.e., overstating the probability of finding winners or losers in the population. Although macroeconomic conditions are usually not modeled in behavioral finance theories, it is useful to examine whether the overall market trend influences the investors' tendency to make systematic base rate errors. Specifically, the question I address next is whether investors tend to overstate the probability of finding winners (*losers*) in the population when the overall stock market is doing well (*poorly*), leading to stock mispricing.

To simplify, let us assume that firms are of three types as before: winners, normal, and losers. Define π_ω, π_η, and π_ι as the actual distribution of winner, normal, and loser firms in the population. Let π_ω^*, π_η^*, and π_ι^* be the investor's subjective distribution of winner, normal, and loser firms which differs from the actual distribution due to representativeness as follows: when the investor overstates the frequency of winners (*losers*), then $\pi_\omega^* > \pi_\omega$ ($\pi_l^* > \pi_l$). To measure market trends, I define three types of periods based on the return performance of the overall market: an Up-Mkt period during which the market return has been unusually high, a Down-Mkt period during

[6] Kahneman and Tversky (1974) suggest that the primary way that representativeness can manifest itself is through insensitivity to prior probability of outcomes.

which the market return has been unusually low, and a Normal-Mkt otherwise. The goal of the following analysis is to identify how the investor's subjective distribution differs from the actual distribution of firms during Up-Mkt and Down-Mkt periods and to make predictions about subsequent stock returns.

To benchmark the investor's error during Up-Mkt and Down-Mkt periods, I assume that investors overstate the frequencies of both winners and losers during a normal market, (i.e., $\pi_\omega^* > \pi_\omega$ and $\pi_\iota^* > \pi_\iota$) due to representativeness as illustrated in figure one. I assume under the null hypothesis that the investor's subjective distribution remains fixed but the actual frequency of winners (*losers*) increases during an Up-Mkt (*Down-Mkt*) period and decreases during a Down-Mkt (*Up-Mkt*) period. Under the alternative hypothesis, I assume that the actual distribution remains fixed but the investor overstates the frequency of winners (*losers*) more severely during an Up-Mkt (*Down-Mkt*) period. The important intuition underlying the resulting stock return predictions is that whenever π_ω^* and π_ω (π_l^* *and* π_l) are closer as under the null hypothesis, overpricing (*underpricing*) diminishes and whenever π_ω^* and π_ω (π_l^* *and* π_l) are farther apart as under the alternative hypothesis, overpricing (*underpricing*) is exacerbated. This is because a greater tendency to erroneously declare winners (*losers*) leads to greater overpricing (*underpricing*).

The analysis above provides the following insight: if market trends reflect base rate errors, then <u>under the null</u> (*under the alternative*) the overpricing is greatest during Down-Mkt (*Up-Mkt*) periods because that is when π_ω^* and π_ω diverge the most. Similarly, <u>under the null</u> (*under the alternative*) the underpricing is greatest during Up-

Mkt (*Down-Mkt*) periods because that is when π_t^* *and* π_t diverge the most. Based on the cross sectional results, overpricing (*underpricing*) if present is more likely to be found in firms that exhibit High (*Low*) earnings growth, Weak (*Strong*) fundamentals, or both. Conditional on market trend, I predict that under the null, the greatest overpricing occurs in firms with High earnings growth, Weak fundamentals, or both during Down-Mkt periods and under the alternative, during Up-Mkt periods; such firms produce negative abnormal returns subsequently. Similarly, I predict that under the null, the greatest underpricing occurs in firms with Low earnings or sales growth, Strong fundamentals, or both during Up-Mkt periods and under the alternative, during Down-Mkt periods; such firms produce positive abnormal returns subsequently.

Hypotheses 3-5 formally state the testable predictions. In hypothesis three, I test for additional mispricing information contained in the market trend variable. The hypothesis states that the difference in abnormal returns is largest between the most underpriced and the most overpriced stocks. Under the null (*alternative*), this is the difference between the abnormal returns of the Low-Earnings stocks during the Up-Mkt (*Down-Mkt*) period and the High-Earnings stocks during the Down-Mkt (*Up-Mkt*) period. To assess whether conditioning on the past market trend provides additional information, I subtract from this difference the average abnormal return of a long Low-Earnings and short High-Earnings portfolio.

Hypothesis Three Null: *The investor's subjective distribution of firms* $\{\pi_\omega^*, \pi_\eta^*, \text{ and } \pi_\iota^*\}$ *remains fixed but the actual distribution of firms* $\{\pi_\omega, \pi_\eta, \text{ and } \pi_\iota\}$ *varies as follows: in an Up-Mkt period,* $\pi_{\omega,\text{Up-Mkt}} > \pi_{\omega,\text{Normal-Mkt}}$ *and in a Down-Mkt period,* $\pi_{\iota,\text{Down-Mkt}} > \pi_{\iota,\text{Normal-}}$

$_{Mkt}$. *Under these conditions, future abnormal returns conditional on earnings growth and past market trends exhibit the following pattern:*

$$[R_{Low\ Earnings/Down\text{-}Mkt} - R_{High\ Earnings/Up\text{-}Mkt}] - [R_{Low\ Earnings} - R_{High\ Earnings}] < 0$$

Hypothesis Three Alternative: *The actual distribution of firms{π_ω, π_η, and π_ι} remains fixed but the investor's subjective distribution of firms {π_ω^*, π_η^*, and π_ι^*} varies as follows: in an Up-Mkt period, $\pi_{\omega\ ,Up\text{-}Mkt}^* > \pi_{\omega\ ,Normal\text{-}Mkt}^*$ and in a Down-Mkt period, $\pi_{\iota\ ,Down\text{-}Mkt}^* > \pi_{\iota\ ,Normal\text{-}Mkt}^*$. Under these conditions, future abnormal returns conditional on earning growth and past market trends exhibit the following pattern:*

$$[R_{Low\ Earnings/Down\text{-}Mkt} - R_{High\ Earnings/Up\text{-}Mkt}] - [R_{Low\ Earnings} - R_{High\ Earnings}] > 0$$

Hypothesis four states that under the null (*alternative*), the difference is greatest between the abnormal returns of the Strong-Fundamentals stocks during the Up-Mkt (*Down-Mkt*) period and the Weak-Fundamentals stocks during the Down-Mkt (*Up-Mkt*) period. To assess whether conditioning on the past market trend provides additional information, I subtract from this difference the average abnormal return of a long Strong-Fundamentals and short Weak- Fundamentals based portfolio.

Hypothesis Four Null: *The investor's subjective distribution of firms {π_ω^*, π_η^*, and π_ι^*} remains fixed but the actual distribution of firms{π_ω, π_η, and π_ι} varies as follows: in an Up-Mkt period, $\pi_{\omega,Up\text{-}Mkt} > \pi_{\omega,Normal\text{-}Mkt}$ and in a Down-Mkt period, $\pi_{\iota,Down\text{-}Mkt} > \pi_{\iota,Normal\text{-}Mkt}$. Under these conditions, future abnormal returns conditional on fundamental strength and past market trends exhibit the following pattern:*

$$[R_{Strong\ Fund.\ /Down\text{-}Mkt} - R_{Weak\ Fund.\ /Up\text{-}Mkt}] - [R_{Strong\ Fund.} - R_{Weak\ Fund.}] < 0$$

Hypothesis Four Alternative: *The actual distribution of firms{π_ω, π_η, and π_ι} remains fixed but the investor's subjective distribution of firms {π_ω^*, π_η^*, and π_ι^*} varies as follows: in an Up-Mkt period, $\pi_{\omega,Up\text{-}Mkt}^* > \pi_{\omega,Normal\text{-}Mkt}^*$ and in a Down-Mkt period, $\pi_{\iota,Down\text{-}Mkt}^* > \pi_{\iota,Normal\text{-}Mkt}^*$. Under these conditions, future abnormal returns conditional on fundamental strength and past market trends exhibit the following pattern:*

$$[R_{Strong\ Fund./Down\text{-}Mkt} - R_{Weak\ Fund./Up\text{-}Mkt}] - [R_{Strong\ Fund.} - R_{Weak\ Fund.}] > 0$$

Hypothesis five states that under the null (*alternative*), the difference is greatest between the abnormal returns of the Low-Earnings/Strong-fundamentals stocks during the Up-Mkt (*Down-Mkt*) period and the High-Earnings/Weak fundamentals stocks during the Down-Mkt (*Up-Mkt*) period. To assess whether conditioning on the past market trend provides additional information, I subtract from this difference the average abnormal return of a long Low-Earnings/Strong-Fundamentals and short High-Earnings/Weak-Fundamentals based portfolio.

Hypothesis Five Null: *The investor's subjective distribution of firms {π_ω^*, π_η^*, and π_ι^*} remains fixed but the actual distribution of firms{π_ω, π_η, and π_ι} varies as follows: in an Up-Mkt period, $\pi_{\omega,Up\text{-}Mkt} > \pi_{\omega,Normal\text{-}Mkt}$ and in a Down-Mkt period, $\pi_{\iota,Down\text{-}Mkt} > \pi_{\iota,Normal\text{-}Mkt}$. Under these conditions, abnormal returns conditional on earnings signals, fundamental strength and past market trends exhibit the following pattern:*

$$[R_{Low\ Earnings/Strong\ Fund./Down\text{-}Mkt} - R_{High\ Earnings/Weak\ Fund./Up\text{-}Mkt}] - [R_{Low\ Earnings/Strong\ Fund.} - R_{High\ Earnings/Weak\ Fund.}] < 0$$

Hypothesis Five Alternative: *The actual distribution of firms{π_ω, π_η, and π_ι} remains fixed but the investor's subjective distribution of firms {π_ω^*, π_η^*, and π_ι^*} varies as*

follows: in an Up-Mkt period, $\pi_{\omega}^{*}{}_{,Up\text{-}Mkt} > \pi_{\omega}^{*}{}_{,Normal\text{-}Mkt}$ *and in a Down-Mkt period,* $\pi_{\iota}^{*}{}_{,Down\text{-}Mkt} > \pi_{\iota}^{*}{}_{,Normal\text{-}Mkt}$. *Under these conditions, abnormal returns conditional on earnings signals, fundamental strength and past market trends exhibit the following pattern:*

$$[R_{Low\ Earnings/Strong\ Fund./Down\text{-}Mkt} - R_{High\ Earnings/Weak\ Fund./Up\text{-}Mkt}] \; - \; [R_{Low\ Earnings/Strong\ Fund.} - R_{High\ Earnings/Weak\ Fund.}] > 0$$

IV. RESEARCH DESIGN AND METHODS

IV.1 A Composite Fundamental Strength Proxy

The empirical tests examine whether abnormal stock returns follow the patterns described in hypotheses 1-7. To obtain variation across both the observed earnings performance as well as fundamental strength, I create 5x5 (25 total) portfolios of firms based on independent sorts using sales growth and a measure for the strength of a firm's business fundamentals. Throughout this paper, earnings growth and sales growth for each firm are calculated every year over the previous three-year period using the following formulas:

$$\Delta E_{i,t,t-3} = (E_{i,t} - E_{i,t-3})/A_{i,t-3} \quad (3)$$

$$\Delta S_{i,t,t-3} = (S_{i,t} - S_{i,t-3})/A_{i,t-3} \quad (4)$$

where $E_{i,t}$ and $S_{i,t}$ are firm *i's* reported net income without adjustments and net sales in year *t* and $A_{i,t-3}$ are total assets reported in year *t-3*.

I use several financial statement variables that have the potential to inform investors about the strength of a firm's investment opportunities and profitability. Prior research has found that these variables are associated with future earnings growth beyond information that is contained in current earnings growth (see Lev and Thiagarajan,1992). The variables used in this study include changes in inventory (INV), accounts receivable (AR), capital expenditures (CAPX), gross margin (GM), selling and

administrative expenses (SGA), effective tax rate and (ETR). I refer the reader to Abarbanell and Bushee (1997) for further exposition.[7]

To develop a composite measure of fundamental strength, at December end of each year I obtain the variables described above for each firm in the cross section from Compustat files and perform the following cross sectional regression:[8]

$$\Delta E_{i,t} = \theta_0 + \sum_{j=1}^{n} \theta_{j,t-1} f_{i,j,t-1} + \nu_{i,t} \quad (5)$$

where $\Delta E_{i,t}$ is firm i's one year earnings growth and $f_{i,j,t-1}$ are the financial statement data described above for firm *i* available at the end of year *t-1*. Given the estimates $\hat{\theta}_j$ and the values of fundamentals $f_{i,j,t}$ for firm *i* at the end of year *t*, I estimate the composite measure of fundamental strength $\hat{X}_{i,t}$ as:

$$\hat{X}_{i,t} = \hat{\theta}_0 + \sum_{j=1}^{n} \hat{\theta}_{j,t-1} f_{i,j,t} \quad (6)$$

The proxy above provides an estimate of next year's earnings growth predicted by the most recently available information about the variables described above. The estimated coefficients $\hat{\theta}_j$ from equation (5) are averaged over the past four years before being used in equation (6).

IV.2 Portfolio Formation

The earnings signals in this paper are measured as either three-year earnings growth or sales growth. To create the portfolios, at each December year-end *t* I rank all available firms in the cross section into five categories based on the magnitude of their total earnings growth or sales growth. The extreme and normal earnings growth

[7] I drop variables used in Abarbanell and Bushee (1997) that lead to substantial reductions in the data.
[8] For firms that have a non-December fiscal year-end, I use quarterly statements to obtain financial statement data for the trailing 12-month period ending closest to end of December.

categories are defined as: Rank 5 (HIGH, highest earnings or sales growth), Rank 3 (MEDIUM, normal growth), and Rank 1 (LOW, greatest decline). I limit the measurement interval for available information to three years because as the measurement interval becomes longer, the mispricing effects diminish since earnings and fundamentals signals are unlikely to diverge over long periods.

Since the intent is to use fundamental information that is incremental to the information already available in contemporaneous earnings signals, I estimate an annual cross sectional least squares regression using information available at December end of year *t*:

$$\hat{X}_{i,t} = \alpha_t + \beta_{1t}\Delta E_{i,t,t-3} + \beta_{2t}\Delta S_{i,t,t-3} + \hat{x}_{i,t} \quad (7)$$

where $\hat{X}_{i,t}$ represents the composite fundamental strength proxy estimated in equation (3), $\Delta E_{i,t,t-3}$ and $\Delta S_{i,t,t-3}$ represent the past three year earnings growth and sales growth, and $\hat{x}_{i,t}$ represents the information in $\hat{X}_{i,T}$ that is orthogonal to the contemporaneous earnings signals. To form portfolios based on $\hat{x}_{i,t}$ I independently rank all firms at time *t* into quintiles based on $\hat{x}_{i,T}$ and specify rank 5 as STRONG (fundamentals) and Rank 1 as WEAK.

Having formed portfolios based on univariate sorts, I intersect each earnings (or sales growth) category with each fundamentals based category to form portfolios based on joint rankings. For example, firms that are in both the HIGH earnings growth category as well as in the independently sorted STRONG fundamentals category are organized into a {High/Strong} portfolio, and so forth.

IV.3 Estimating Abnormal Returns

To track the abnormal return performance of each portfolio, I use monthly stock returns from CRSP files to compute equally weighted returns to each $\{\Delta E_{i,t}\ or\ \Delta S_{i,t}\ , \hat{x}_{i,t}\}$ based portfolio formed at December end of year *t*. I add delisting returns where available as the last available monthly return for each stock. The portfolio returns are computed for each of the next 12 months starting in April of year *t+1*. The procedure is repeated each year and the annual sequences of monthly portfolio returns is linked together from one year to the next to create a time series of portfolio returns for each portfolio. For portfolio based tests, I perform 4-factor excess return regressions for each portfolio of firms to estimate abnormal returns as regression alphas. Factor returns and risk free returns are obtained from WRDS files:

$$R_{pt} - r_f = \alpha_p + \beta_{mkt}(R_{mkt}-r_f) + \beta_{SMB}(R_{SMB}) + \beta_{HML}(R_{HML}) + \beta_{UMD}(R_{UMD}) + e_{pt} \quad (8)$$

where R_{pt} is the monthly portfolio return, r_f is the one month risk free return, R_{mkt} is the market return, R_{SMB} is the return on a size-based factor portfolio, R_{HML} is the return on a value-based factor portfolio, and R_{UMD} is the return on a momentum-based factor portfolio. The estimated alpha (α_p) reflects the average monthly return that is unexplained by exposures to these factors.

V. EMPIRICAL RESULTS AND DISCUSSION

V.1 Descriptive Statistics

The overall sample of firms is constructed using the intersection of Compustat and CRSP databases over the time period 1962-2009. An average of 1,658 firms are available per year that meet all the financial statement and stock return data requirements. All financial statement based variables are Winsorized at the 1% and 99% levels. For stock return based analysis, returns are Winsorized at the 0.5% and 99.5% level to diminish the influence of extreme returns from some microcap stocks. Results are also duplicated without Winsorizing the stock returns. Table 1 reports pooled sample means for the {High/Strong}, {High/Weak}, {Medium/Strong}, {Medium/Weak}, {Low/Strong}, and {Low/Weak} portfolios formed based on annual, 5x5 sorts using the past three-year sales growth (scaled by lagged total assets) and the fundamental strength measure $\hat{x}_{i,t}$ estimated using equation (6). The latter measures the predicted income growth for year *t+1* given information about fundamentals at the end of year *t*. The descriptive statistics reveal that the firms in the reported categories exhibit extreme characteristics on the intended dimensions – i.e., growth and fundamentals. Firms in the highest sales growth categories are younger with a mean age around 10 years while firms in the low sales growth categories are comparatively older with a mean age around 16 years. An examination of the past asset growth and sales growth illustrates that firms with strong fundamentals grow more efficiently since they achieve similar or higher sales growth with a lower level of investment compared to firms with

Table 1
Summary Statistics (Sample: 1962-2009)

Sales Growth	Fundamentals Strength	Age (Years)	$\hat{x}_{i,t}$	Mkt Val Decile	Asset Growth	Income Growth	Sales Growth	Mkt/Book	Average Firms
High	**Strong**	9.9	2.5%	4.8	323%	-9.4%	347%	2.95	89
High	**Weak**	9.5	-3.6%	4.7	326%	-5.8%	273%	3.34	83
Medium	**Strong**	15.7	2.2%	4.8	33.3%	-5.4%	31.6%	1.97	42
Medium	**Weak**	15.9	-2.6%	5.0	44.3%	0.7%	31.8%	2.37	54
Low	**Strong**	15.7	2.5%	3.4	-10.3%	-8.5%	-35.0%	1.83	62
Low	**Weak**	15.9	-2.8%	3.6	4.4%	-3.3%	-35.3%	2.17	54
Full Sample		13.1	-0.3%	5.1	151%	-5.8%	134%	2.54	1,658

weak fundamentals. Firms in the high sales categories are of average size with a mean market value decile of 4.75 while firms in the low sales categories are smaller with a mean market value decile of 3.5. The market value deciles are measured at the end of the year and are updated annually for these calculations. Firms in the strong fundamentals categories exhibit positive expected income growth while firms in the weak categories exhibit negative expected income growth. To examine the ability of $\hat{x}_{i,t}$ to predict future earnings growth, I estimate the following panel regression :

$$\Delta E_{i,t+1,t} = Intercept + \beta_1 \hat{x}_{i,t} + \beta_2 \Delta E_{i,t,t-3} + \beta_3 \Delta S_{i,t,t-3} + e_{i,t} \quad (9)$$

where $\Delta E_{i,t,t-3}$ and $\Delta S_{i,t,t-3}$ are three year net income and sales growth in year t for firm i, scaled by lagged assets. The regression finds a strong positive relation between $\hat{x}_{i,t}$ and one year ahead earnings growth $\Delta E_{i,t+1,t}$ with a t-stat of 12.93.

V.2 Interaction Between Pricing Errors

I first document evidence of interaction between underreaction to fundamentals and overreaction to sales growth. Table 2 reports the average monthly abnormal returns of portfolios constructed based on either past 3-year sales growth or fundamentals as well as based on both characteristics. The abnormal returns are measured using regression intercepts (alpha, henceforth) from the 4-factor excess return regression model in equation (5). Results for sales based portfolios show a notable asymmetry: the low sales growth firms generate a positive alpha of 0.22% per month (t-stat: 1.88) whereas the high sales growth firms experience no predictable price reversals (alpha: -0.05%, t-stat: -0.62). A similar asymmetry is observable in the fundamentals based portfolios: firms with strong fundamentals show a monthly alpha of 0.27% (t-stat: 3.76)

Table 2

Mean Abnormal Returns to Portfolios Based on Quintiles of Past 3-Year Sales Growth and Fundamental Strength $\hat{x}_{i,t}$ (Sample: 1962-2009)

			3 Year Sales Growth		
			Low	High	Low-High
			0.22%	-0.05%	0.27%
			(1.88)	(-0.62)	(2.86)
$\hat{x}$	Strong	0.27%	0.38%	0.04%	0.34%
		(3.76)	(2.05)	(0.30)	(2.03)
	Normal	0.25%	0.20%	0.08%	0.12%
		(4.08)	(1.63)	(0.74)	(0.85)
	Weak	-0.15%	0.08%	-0.44%	0.53%
		(-1.74)	(0.54)	(-3.91)	(3.92)
	Strong-Weak	0.42%	0.30%	0.48%	
		(5.69)	(1.97)	(4.17)	

but firms with weak fundamentals exhibit somewhat insignificant abnormal returns (alpha: -0.15%, t-stat: -1.74).

Prima facie, these observations suggest that weak fundamentals are not ignored and no overreaction to high sales growth exists. However, table 2 also reveals evidence of substantial interaction between underreaction and overreaction. In firms with strong fundamentals, the high sales growth portfolio exhibits an insignificant alpha of 0.04% (t-stat 0.30) and in firms with weak fundamentals, the low sales growth portfolio exhibits an alpha of 0.08% per month (t-stat 0.54). These results are especially strong evidence of interaction between overreaction to sales growth and underreaction to fundamentals since neither the high sales firms nor the weak-fundamentals firms exhibit significant abnormal returns based on univariate sorts alone. Most notably however, the overreaction to low (*high*) sales growth is evident only in firms with strong (*weak*) fundamentals (alpha 0.38%, t-stat 2.05 for low/strong firms and alpha -0.44%, t-stat -3.91 for high/weak firms). Collectively, these results suggest that overreaction to sales growth if present is potentially masked by investors' underreaction to other fundamentals. However, they do not by themselves reject or support the presence of representativeness bias in the absence of control variables that may further diminish the forecasting power of sales growth.

V.3 Sales Growth and Other Variables

In this section, I test hypotheses one and two using cross sectional regressions to determine whether investors overreact to sales growth. Hypothesis one states that the coefficient in a regression of future returns on past sales growth is zero. Each month

beginning in April of year *t+1* to March of year *t+2*, I perform Fama-MacBeth[9] type cross-sectional regressions of monthly firm returns on the past 3-year sales growth $\Delta S_{i,t,t-3}$, earnings growth $\Delta E_{i,t,t-3}$, fundamentals measure $\hat{x}_{i,t}$ and several control variables including total accruals (Sloan, 1996), one year asset growth (Cooper et al., 2008), and change in shares outstanding (Daniel and Titman, 2006) observed at the end of year t. Each of these control variables have been shown to predict future stock returns. I also include logs of market value of equity (MV) and the book-to-market value of equity ratio (BM) as additional controls. To test hypothesis one, regressions are performed using the full sample.

Table 3 shows the time series mean of regression coefficients and test-statistics estimated using 465 cross sectional regressions for the full sample; i.e., without adjusting the sample for underreaction to fundamentals. In model 1 with only MV and BM used as controls, the coefficient on sales growth is significantly negative (t-stat -2.99) while the coefficient on fundamentals is significantly positive (t-stat 4.62). Based on the analysis in section III.1, under fixation we expect a positive coefficient on the fundamentals measure but zero on sales growth. The strongly significant negative coefficient on sales growth is evidence of overreaction to sales growth due to representativeness rather than fixation. In model 2, including total accruals as an additional control per Sloan (1996) diminishes the forecasting power of sales growth but the coefficient remains significantly negative (t-stat -2.35). The results of models 1 and 2 discount the possibility of a fixation based explanation for the forecasting power of

[9] See Fama and Macbeth (1973).

Table 3
Fama-Macbeth Regressions of Monthly Stock Returns on Predictive Variables (Sample: 1971-2009)

Model	Dependent Variable	$\Delta S_{i,t,t-3}$	$\Delta A_{i,t}$	$\Delta Shares_{i,t,t-3}$	$R_{i,t,t-3}$	$Acc_{i,t}$	BM_t	MV_t	$\hat{x}_{i,t}$	Avg. Firms	Months
1	**Ret**	**-0.08**					0.28	-0.03	9.10	1,748	465
T-stat	(1971-2009)	**(-2.99)**					(4.01)	(-0.72)	(4.62)		
2	**Ret**	**-0.06**				-1.01	0.33	-0.03	6.94	1,197	465
T-stat	(1971-2009)	**(-2.35)**				(-3.92)	(4.44)	(-0.68)	(3.26)		
3	**Ret**	**-0.03**	-0.36			-0.90	0.31	-0.03	4.31	1,196	465
T-stat	(1971-2009)	**(-1.14)**	(-2.84)			(-3.37)	(4.29)	(-0.59)	(1.97)		
4	**Ret**	**-0.02**	-0.34	-0.06		-0.92	0.30	-0.02	4.38	1,183	465
T-stat	(1971-2009)	**(-0.77)**	(-2.67)	(-2.77)		(-3.43)	(4.07)	(-0.50)	(1.99)		
5	**Ret**	**-0.03**	-0.41	-0.12	0.0001	-1.09	0.28	-0.03	3.67	1,047	465
T-stat	(1971-2009)	**(-0.84)**	(-3.22)	(-3.53)	(0.15)	(-3.91)	(3.84)	(-0.62)	(1.54)		
6	**Ret**	**-0.07**	-0.39	-0.16	0.002	-1.33	0.33	-0.01	3.52	950	237
T-stat	(1971-1990)	**(-1.60)**	(-1.87)	(-3.36)	(2.05)	(-3.40)	(3.75)	(-0.17)	(0.81)		
7	**Ret**	**0.02**	-0.42	-0.08	-0.002	-0.84	0.23	-0.05	3.83	1,148	228
T-stat	(1991-2009)	**(0.59)**	(-3.10)	(-1.62)	(-1.86)	(-2.11)	(1.95)	(-0.65)	(2.10)		
8	**Ret (Price > $5)**	**-0.01**	-0.36	-0.11	0.0004	-1.48	0.19	-0.03	6.56	843	465
T-stat	(1971-2009)	**(-0.43)**	(-2.61)	(-2.97)	(0.67)	(-4.57)	(2.37)	(-0.78)	(2.31)		

sales growth. However, Cooper et al. (2008) show that one year asset growth significantly reduces the forecasting power of sales growth. Furthermore, Daniel and Titman (2006) examine whether return reversals such as those documented in Debondt and Thaler (1985) can be explained by sales growth and find that equity issuance factors absorb the forecasting power of sales growth. In models 3-5, I include asset growth, the change in total shares outstanding over the past three years, and the lagged 36 month stock return as additional controls. Controlling for these variables makes the coefficient on sales growth in model 5 insignificant (t-stat -0.84) while asset growth, the change in shares, and accruals remain highly significant as in prior studies with t-stats of -3.22, -3.53, and -3.91, respectively. In the 1971-1990 and 1991-2009 subperiods (models 6 and 7), the coefficient on sales growth is statistically insignificant with t-stats of -1.60 and 0.59, respectively. In model 8, the sample is restricted to firms with share prices greater than $5 per share. Using the full set of control variables, the coefficient on sales growth remains insignificant (t-stat -0.43) while asset growth, change in shares outstanding and accruals remain highly significant. Based on these results, we are unable to reject the null that there is no overreaction to sales growth as stated in hypothesis one once we add other control variables.

To test whether controlling for the underreaction to fundamentals can reveal the presence of overreaction due to representativeness as stated in hypothesis 2, I restrict the sample to firms where underreaction to fundamentals is least likely to offset the overreaction. To accomplish this, I remove firms that are in sales growth quintiles 1 and 2 but fundamentals based quintiles 1-4. Similarly I remove firms with sales growth

Table 4

Regressions for Restricted Sample (Adjusted for Interaction Between Sales Growth and Fundamentals) (Sample: 1971-2009)

Model	Depend. Variable	$\Delta S_{i,t,t-3}$	$\Delta E_{i,t,t-3}$	$\Delta A_{i,t}$	$\Delta Shares_{i,t,t-}$	$R_{i,t,t-3}$	$Acc_{i,t}$	BM_t	MV_t	$\hat{x}_{i,t}$	Firms	Months
1	**Ret**	**-0.18**						0.28	-0.03	6.04	640	465
T-stat	(1971-2009)	**(-3.82)**						(3.32)	(-0.72)	(1.73)		
2	**Ret**	**-0.16**					-0.91	0.30	-0.03	4.99	448	465
T-stat	(1971-2009)	**(-3.22)**					(-2.35)	(3.24)	(-0.67)	(1.42)		
3	**Ret**	**-0.19**	0.75				-1.06	0.30	-0.04	5.27	447	465
T-stat	(1971-2009)	**(-3.65)**	(2.70)				(-2.78)	(3.29)	(-0.81)	(1.50)		
4	**Ret**	**-0.16**	0.80	-0.36			-0.95	0.28	-0.04	2.08	446	465
T-stat	(1971-2009)	**(-2.94)**	(2.87)	(-2.14)			(-2.31)	(3.18)	(-0.75)	(0.56)		
5	**Ret**	**-0.15**	0.85	-0.34	-0.08		-0.94	0.26	-0.03	2.39	441	465
T-stat	(1971-2009)	**(-2.83)**	(3.03)	(-1.99)	(-2.18)		(-2.27)	(2.91)	(-0.69)	(0.64)		
6	**Ret**	**-0.21**	1.00	-0.31	-0.10	-0.0003	-0.89	0.23	-0.04	1.62	389	465
T-stat	(1971-2009)	**(-3.12)**	(2.81)	(-1.75)	(-1.88)	(-0.40	(-2.06)	(2.37)	(-0.89)	(0.44)		
7	**Ret**	**-0.20**	1.63	-0.33	-0.17	0.002	-1.19	0.33	-0.02	-1.18	337	237
T-stat	(1971-1990)	**(-1.91)**	(2.48)	(-1.10)	(-2.38)	(1.48	(-1.97)	(2.85)	(-0.29)	(-0.18)		
8	**Ret**	**-0.22**	0.35	-0.29	-0.02	-0.002	-0.58	0.12	-0.07	4.53	443	228
T-stat	(1991-2009)	**(-2.61)**	(1.43)	(-1.60)	(-0.26)	(-2.31	(-0.93)	(0.78)	(-0.88)	(1.65)		
9	**Ret (Price > $5)**	**-0.21**	0.77	-0.17	-0.06	0.0003	-1.35	0.11	-0.08	8.69	308	465
T-stat	(1971-2009)	**(-2.61)**	(2.00)	(-0.88)	(-1.04)	(0.47	(-2.54)	(1.14)	(-1.71)	(1.96)		

quintiles 4 and 5 but fundamentals based quintiles of 2-5. The goal of this technique is to restrict the sample to firms where fundamentals are least likely to confound the pricing error due to overreaction. These filters reduce the sample size by about 65% to 399 firms on average. Table 4 shows time series means and t-stats from Fama-Macbeth type regressions using this restricted sample while controlling for fundamentals to ensure that the filters do not induce a spurious correlation between returns and sales growth via fundamentals. As in table 3, models 1 and 2 show significantly negative coefficients on sales growth (t-stats -3.82 and -3.22, respectively) despite including fundamentals and accruals as controls. In model 3, I include the past 3-year earnings growth as an additional variable to detect any overreaction to earningsgrowth. However, the coefficient on earnings growth is strongly positive with a t-stat of 2.70 while sales growth remains significantly negative with a t-stat of -3.65.

In models 4-6, I discover that in contrast to table 3, the coefficient on sales growth remains significantly negative despite the addition of asset growth, equity issuance, accruals, and the lagged 36-month stock return as controls. In model 6, the coefficient on sales growth is significantly negative with a t-stat of -3.12 while asset growth, change in shares, and accruals are considerably less significant with t-stats of -1.75, -1.88, and -2.06, respectively. The fundamentals measure exhibits an insignificant positive coefficient with a t-stat of 0.44 demonstrating that in this restricted sample, sales growth drives the mispricing rather than fundamentals. The coefficient on sales growth is highly significant during the 1991-2009 subperiod (model 8) with a t-stat of -2.61 while it is somewhat less significant for the 1971-1990 subperiod (model 7) with a t-stat

of -1.91. In model 9, I remove stocks with prices below $5 per share from the restricted sample since Fama and French (2008) note that many asset pricing anomalies can be located to microcap stocks which make up a minor fraction of the total market. The coefficient on sales growth remains significantly negative with a t-stat of -2.61 in this sample as well. These results strongly suggest that long term revenue growth is a powerful predictor of future stock returns due to overreaction to sales growth in firms where underreaction to fundamentals does not mute the overreaction.

V.4 Tests of Hypotheses 3-5

Hypothesis three predicts a role for time series variation in representativeness, i.e. the severity of base rate errors made by investors (i.e., overestimating the frequency of winners vs. overestimating the frequency of losers in the population) under different market conditions. If representativeness varies over time, it is reasonable to expect that investors are more prone to overestimate the frequency of winners (*losers*) when the overall market trend is positive (*negative*). To test hypothesis three, I compute the market return for the past 36 months for each year in the full sample (1962-2009). Each 36-month period is then ranked into quintiles based on the magnitude of the return. Quintile 5 - the highest returns - represent a positive market trend while quintile 1 - the lowest returns - represent a negative market trend with the remaining periods identified as a 'normal' market.

To perform tests of hypothesis three, I create dummy variables Up-mkt and Down-mkt that take on the value of 1 *during* the 12 months (April of year *t+1* to March of year *t+2*) *following* periods ranked in quintiles 5 and 1 of market returns, respectively,

and 0 otherwise. To estimate abnormal returns, equation (8) is modified to include these dummy variables:

$$R_{pt} - r_f = \alpha_{p,Normal} + \beta_{Up\text{-}mkt}\, Up\text{-}mkt + \beta_{Down\text{-}mkt}\, Down\text{-}mkt + \beta_{mkt}(R_{mkt}-r_f) + [\beta_{SMB}(R_{SMB}) + \beta_{HML}(R_{HML}) + \beta_{UMD}(R_{UMD})] + e_{pt} \quad (10)$$

The alphas conditional on the recent market trend are estimated as:

Post-Normal Market alpha $\alpha_{Normal} = \alpha_{p,Normal}$ (11)

Post-Up-mkt alpha $\alpha_{Up\text{-}mkt} = \alpha_{p,Normal} + \beta_{Up\text{-}mkt}$ (12)

Post-Down-mkt alpha $\alpha_{Down\text{-}mkt} = \alpha_{p} + \beta_{Down\text{-}mkt}$ (13)

Table 5 reports estimates of abnormal returns from the multifactor model using equations (11)-(13) based on sales growth and fundamental strength individually under different market trends.[10] As predicted by hypothesis three (alternative), the difference in the abnormal returns of firms with low sales growth following a Down-Mkt period and firms with high sales growth following an Up-Mkt period exceeds the difference in average abnormal returns of firms with low vs. high sales growth by 0.5% per month (F-test p-value of 5.65% using a 4-factor model to estimate abnormal returns). This result provides some support to the alternative in hypothesis three that the overall market trend has significant explanatory power in identifying investors' base rate errors. The results suggest that investors are more prone to overestimating the frequency of losers (*winners*) when the overall market trend has been negative (*positive*). The evidence is weaker when I use earnings growth as the earnings performance signal instead of sales growth (F-test p-value of 13.12%, not shown).

[10] Results using CAPM regressions are stronger and more significant in nearly every case.

Table 5

Mean Abnormal Returns to Portfolios Based on Quintiles of Past 3-Year Sales Growth and Fundamental Strength $\hat{x}_{i,t}$ Conditional on Market Trends (Sample: 1962-2009)

Portfolio	Months	$\alpha_{\text{Up-mkt}}$	$\alpha_{\text{Down-mkt}}$	
		Sales Growth		**Tests of Hypothesis 3**
R_{Low}	525	0.36%	0.76%	$[R_{\text{Low Earnings,DOWNMKT}} - R_{\text{High Earnings,UPMKT}}] - [R_{\text{Low Earnings}} - R_{\text{High Earnings}}] = 0.50\%$
T-stat		1.34	2.52	
R_{High}	525	-0.17%	0.47%	**F-Test P-Value = 5.65%**
T-stat		-0.92	2.49	
		Fundamental Strength		**Test of Hypothesis 4**
R_{Strong}	525	0.47%	0.94%	$[R_{\text{Strong Fund.,DOWNMKT}} - R_{\text{Weak Fund.,UPMKT}}] - [R_{\text{Strong Fund.}} - R_{\text{Weak Fund.}}] = 0.67\%$
T-stat		1.90	3.74	
R_{Weak}	525	-0.23%	0.18%	**F-Test P-Value = 2.32%**
T-stat		-1.18	0.92	
		Sales Growth/Fundamental Strength		**Test of Hypothesis 5**
$R_{Low/Strong}$	525	0.83%	1.44%	$[R_{\text{Low Sales/Strong Fund./Down-mkt}} - R_{\text{High Sales/Weak Fund./Up-Mkt}}] - [R_{\text{Low Sales/Strong Fund.}} - R_{\text{High Sales/Weak Fund.}}] = 1.11\%$
T-stat		1.89	3.21	
$R_{High/Weak}$	525	-0.79%	0.05%	**F-Test P-Value = 4.92%**
T-stat		-3.08	0.19	

As predicted under the alternative in hypothesis four, the difference in the abnormal returns of firms with strong fundamentals following a Down-Mkt period and firms with weak fundamentals following an Up-Mkt period exceeds the difference in average abnormal returns of firms with strong vs. weak fundamentals (F-test p-value of 2.32% using the 4-factor model). Again, this result suggests that the overall market trend plays a role in determining the impact of ignoring fundamentals on stock prices. For example, investors are more likely to ignore strong (*weak*) fundamentals when the overall market trend has been negative (*positive*).

Hypothesis five makes predictions about stock return performance conditional on earnings performance, fundamental strength, and past market trends. Table 5 provides estimated abnormal returns from equations (12a)-(12c) for portfolios formed jointly on past three year sales growth and fundamental strength.[11] The results provide substantial support for the alternative in hypothesis five. The High/Weak and Low/Strong portfolios experience average abnormal returns of -0.79% per month (4-factor alpha, p-value < 1%) and 1.44% per month (p-value < 1%) following Up-Mkt and Down-Mkt periods, respectively. The difference in these returns exceeds the abnormal returns of a portfolio long in the Low/Strong and short in High/Weak stocks by 1.11% per month (4-factor p-value < 5%). Collectively, these results in table 5 lend strong support to the hypothesis that time series variation in how investors ignore base rates are important in locating evidence of mispricing due to representativeness. The results suggest that during positive market trends, investors overestimate the frequency of winners and

[11] Results using CAPM regressions are stronger and more significant in nearly every case.

underweight weak fundamentals and during negative market trends, they overestimate the frequency of losers while underweighting strong fundamentals. Overall, the evidence supports the influence of representativeness on the time series of stock returns.

Although the market factor in equation (10) should account for any market related reversals in returns, I nevertheless examine average market returns following Up-Mkt and Down-Mkt periods to see if returns reverse for the broader market portfolio. There is no evidence that such reversals exist. Table 6 shows that the average market return following Up-Mkt periods is 0.86% per month compared to 0.96% per month following Down-Mkt periods. An F-test for the difference in these average returns has a p-value of 87.5%, indicating that market returns are substantially similar following both periods.

Table 6
Average Monthly Returns to Market, SMB, HML, and UMD portfolios Conditional on Market Trends (Sample: 1962-2009)

	Post-Upmkt Avg. Ret	F-Stat P-Value	Post-Downmkt Avg. Ret	F-Stat P-Value	DOWNMKT-UPMKT F-Stat P-Value
Mkt Return	0.86%	3.9%	0.96%	3.9%	**87.50%**
SMB	-0.14%	63.2%	0.82%	2.5%	**4.65%**
HML	0.76%	0.4%	0.91%	0.2%	**71.15%**
UMD	0.65%	10.0%	-0.23%	62.1%	**14.29%**

VI. CONCLUSIONS

The primary contribution of this paper is that it identifies the importance of modeling investors' joint error of ignoring base rates by focusing on representative signals while overlooking other useful information. Prior tests have been unable to detect evidence of mispricing of stock due to representativeness. In this paper, I highlight the importance of empirical tests that condition upon both the information about fundamentals that is ignored by investors as well as the influence of overall market trends on investor sentiment. The evidence indicates that representativeness-induced bias in stock returns is not only detectable but significantly supported by the existence of predictable stock return reversals in various sales growth based portfolios. I find that when firms are cross-sectionally disaggregated within extreme performance categories based on the fundamental strength, return reversals are detected for both High and Low sales growth firms. The results indicate that substantial interaction exists between pricing errors related to sales growth and fundamentals.

Furthermore, I find that when variation in investors' bias due to base rate errors is conditioned upon positive and negative market trends, the reversal effects become more pronounced. Following positive market trends, reversals become more pronounced for firms in High earnings category firms and following negative market trends, reversals become more pronounced in Low earnings category firms. This evidence points to shifting estimations on the part of investors regarding the frequency of winners and losers when overall trends vary in the market. Overall, the results of this study support

the existence of representativeness in stock returns though I find that at least some of the implied mispricing for the Low earnings and Weak fundamental strength categories of firms may reflect a premium due to exposure to transitory liquidity factors such as price impact. I also provide evidence that rejects a theory based on fixation rather than representativeness.

The results of this paper also motivate further study of representativeness, a frequently studied heuristic in cognitive psychology, by finding evidence consistent with its effect in stock returns in the time series of stock returns. Given the results discovered in this paper, I believe that investigation of representativeness merits deeper exploration before it is consigned as descriptively invalid as in Chan et al. (2004) when identifying credible explanations for anomalous stock returns.

REFERENCES

Abarbanell, J., Bushee, B., 1997. Fundamental analysis, future earnings, and stock prices. Journal of Accounting Research 35, 1-24.

Abarbanell, J., Bushee, B., 1998. Abnormal returns to a fundamental analysis strategy. The Accounting Review 73, 19-45.

Baker, M., Wurgler, J., 2006. Investor sentiment and the cross section of stock returns. Journal of Finance 61, 1645-1680.

Barberis, N., Shleifer, A., Vishny, R., 1998. A model of investor sentiment. Journal of Financial Economics 49, 307–343.

Brav, A., Heaton, J., 2002. Competing theories of financial anomalies. Review of Financial Studies 15, 575-606.

Carhart, M., 1997. On the persistence of mutual funds. Journal of Finance 52, 57-82.

Chan, W., Frankel, R., Kothari, S., 2004. Testing behavioral finance theories using trends and consistency in financial performance. Journal of Accounting and Economics 38, 3-50.

Cooper, M., Gulen, H., Schill, M., 2008. Asset growth and the cross section of stock returns. Journal of Finance 63, 1609-1651.

Cooper, M., Gutierrez, R., Hameed, A., 2004. Market States and Momentum. Journal of Finance 59, 1345-1365.

Daniel, K., 2004. Discussion of: "Testing behavioral finance theories using trends and consistency in financial performance." Journal of Accounting and Economics 38, 51-64.

Daniel, K., Hirshleifer, D., Subrahmanyam, A., 1998. Investor psychology and security market under- and overreactions. Journal of Finance 53, 1839–1885.

Daniel, K., Titman, S., 2006. Market reactions to tangible and intangible information. Journal of Finance 61, 1605-1643.

DeBondt, W., Thaler, R., 1985. Does the stock market overreact? Journal of Finance 40, 793–805.

DeBondt, W., Thaler, R., 1987. Further evidence of investor overreaction and stock market seasonality. Journal of Finance 42, 557–581.

Fama, E., French, K., 2008. Dissecting anomalies. Journal of Finance 63, 1653-1678.

Fama, E., MacBeth, J., 1973. Risk, return, and equilibrium: empirical tests. Journal of Political Economy 81, 607-636.

Hong, H., Stein, J., 1999. A unified theory of underrreaction, momentum trading, and overreaction in asset markets. Journal of Finance 54, 2143–2184.

Jegadeesh, N., Titman, S., 1993. Returns to buying winners and selling losers: implications for stock market efficiency. Journal of Finance 48, 65–91.

Kahneman, D., Tversky, A., 1974. Judgement under uncertainty: heuristics and biases. Science 185, 1124–1131.

La Porta, R., Lakonishok, J., Shleifer, A., Vishny, R., 1997. Good news for value stocks: further evidence on market efficiency. Journal of Finance, 859-874.

Lakonishok, J., Shleifer, A., Vishny, R., 1994. Contrarian investment, extrapolation, and risk. Journal of Finance 49, 1541–1578.

Lev, B., Thiagarajan, S., 1993. Fundamental information analysis. Journal of Accounting Research 31, 190-215.

Ou, A. J., Penman, S., 1989. Financial statement analysis and the prediction of stock returns. Journal of Accounting and Economics 11, 295-330.

Piotroski, J. D., 2000. Value investing: the use of historical financial statement information to separate winners from losers. Journal of Accounting Research 38, 1-41.

Rabin, M., 2002. Inference by believers in the law of small numbers. Quarterly Journal of Economics 117:3, 775-816.

Richardson, S., Tuna, I., and Wysocki, P., 2010. Accounting anomalies and fundamental analysis: a review of recent research advances. Journal of Accounting and Economics 50, 410-454.

Shiller, R., 1981. Do stock prices move too much to be justified by subsequent changes in dividends? The American Economic Review 71, 421-436.

Sloan, R., 1996. Do stock prices fully reflect information in accruals and cash flows

about future earnings? The Accounting Review 71, 289-315.

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