The Role of Matching in Detecting Post-Earnings-Announcement Drift: An Intertemporal Analysis

Abstract

We show that temporal attenuation of post-earnings-announcement drift is much less pronounced when earnings news is measured using earnings components with greater matching (e.g., gross or operating profit). Notably, "well-matched" news measures continue to predict significant excess returns for firms with poorly matched bottom-line earnings whereas the excess return predictability of SUE (i.e., news in bottom-line earnings) has largely disappeared for these firms. Regression results show that well-matched news measures retain their autocorrelation structure over time and gain incremental power over SUE in predicting future profitability. Finally, transient institutional investors—who prior evidence suggests should be relatively sophisticated in their pricing of earnings news—do not appear to significantly exploit SUE signals on the basis of matching. Overall, our results suggest that markets are still relatively inefficient at pricing matching information in earnings news and that traditional news measures such as SUE are much less likely to detect this inefficiency in recent years.

1. Introduction

A long-standing literature in accounting examines an anomalously positive relation between earnings news and future stock returns, commonly known as post-earnings-announcement drift, or "PEAD" (Ball and Brown, 1968; Foster et al., 1984; Bernard and Thomas, 1989, 1990). However, recent years have witnessed a pronounced decline in PEAD (Johnson and Schwartz, 2001; Richardson et al., 2010; Chordia et al., 2014) coinciding with evidence of investor learning from research on stock return predictability (McLean and Pontiff, 2015; Milian, 2015) and diminishing transaction costs to exploit PEAD and other forms of mispricing (Chordia et al., 2014). Since a popular explanation of the drift suggests that predictable returns reflect earnings expectations that underweight the serial properties of earnings news (Bernard and Thomas, 1990; Ball and Bartov, 1996), PEAD attenuation appears to be consistent with an improved pricing of the implications of earnings news for future profitability.

In this paper, we take a closer look at this pricing process by examining investors' understanding of how fundamental accounting principles facilitate serial correlation in earnings and its components. Our investigation focuses on the matching principle, whereby income is determined based on a temporal "matching" of expenses to revenues in the period revenues are earned. A consideration of matching as it pertains to the pricing of earnings news is important for two reasons. First, matching has clear implications for the temporal properties of earnings. Dichev and Tang (2008) model poor matching as adding noise to the economic relation of advancing expenses to earn revenues, and they show empirically that poor matching increases volatility and decreases persistence in earnings, with the latter effect inducing negative autocorrelation in earnings changes.[1] Schutt (2012) finds that greater matching results in an accounting rate of return that more closely approximates a firm's internal rate of return (IRR). He further shows that better IRR approximations make earnings more informative to investors about the firm's underlying economic profitability. Thus, an efficient pricing of earnings news should reflect matching's role in facilitating the temporal properties of earnings.

Second, recent studies document a marked decline in matching over the past 40 years along with significant changes to earnings' temporal properties (Dichev and Tang, 2008; Donelson et al., 2011; Srivastava, 2014).[2] These changes pose challenges to interpretations of PEAD attenuation because some attenuation could arise mechanically as a result of declining serial correlation in earnings news. Recognizing the potential for mechanical attenuation is important for assessments of temporal gains in earnings news pricing efficiency, as a failure to control for evolving serial properties may lead to an overstatement of efficiency gains achieved over time.

However, a bigger and more immediate concern is that declining matching weakens the ability of traditional PEAD tests to detect inefficiencies in the pricing of earnings news. Evidence of a temporal decline in GAAP earnings informativeness (Collins, Maydew, and Weiss, 1997), along with a rise in the informativeness of "street" earnings that often exclude "mismatched" one-time items (Bradshaw and Sloan, 2002), suggests that declining matching renders bottom-line earnings increasingly inadequate for forecasting future profitability. Nevertheless, to the extent that "matched" earnings components have retained their forecasting abilities over time, reformulations of the

[1] Cao and Narayanamoorthy (2012) show that these annual properties translate to the quarterly setting and that quarterly earnings persistence is positively related with autocorrelation in quarterly earnings news.

[2] By "decline in matching," we mean the empirical decline in the proportion of earnings in which matching is the guiding recognition principle. Different explanations for this decline are discussed in Section 2.

traditional PEAD research design that focus on these components can provide suitable tests for earnings news pricing efficiency even in the presence of declining matching.

We begin our analysis by first examining how matching facilitates the earnings forecasting exercise. To this end, we track the evolution of serial correlation patterns for two classes of earnings news measures for the same firm: (a) "bottom-line" measures such as SUE (standardized unexpected earnings)[3] and (b) "well-matched" measures that we argue are less susceptible to temporal declines in matching, such as gross or operating profit.[4] According to the "degrees of matching success" outlined in Dichev and Tang (2008) gross profit and operating profit, relative to net income, should contain a greater composition of expenses guided by "direct matching" (e.g., cost of goods sold) and a lower composition of expenses that are recognized "as incurred" without regard for matching (e.g., goodwill impairment). Donelson et al. (2011) and Dichev (2013) show that "as incurred" expenses drive much of the documented changes to the properties of earnings, which suggests that gross profit and operating profit should exhibit relatively stable properties over time. Furthermore, Novy-Marx (2013) and Ball et al. (2015) find that gross profit and operating profit outperform net income as proxies for expected profitability in the context of dividend discount valuation models, which suggests that our well-matched measures should be informative about future profitability. Considering these factors, we expect our well-matched measures to exhibit (a) less deterioration in their serial correlation structure over time and (b) an increasing incremental ability to forecast future earnings news relative to SUE.

[3] Following prior PEAD literature, we exclude extraordinary items from "bottom-line" earnings.

[4] Throughout this paper, gross profit is defined as net sales minus cost of goods sold, and operating profit is defined as gross profit minus selling, general and administrative expense. See the Appendix for variable definitions.

Our empirical tests confirm these expectations. Over a sample period spanning 1979-2012, operating profit news (hereafter MSUE for "modified" or better "matched" SUE) sustains its ability to forecast future operating profit news in both univariate and multivariate regressions. The multivariate coefficient on MSUE increases from 0.56 in the pre-1990 period to 0.62 in the post-2000 period (about an 11% increase). Furthermore, MSUE gains incremental power over SUE in predicting future SUE. MSUE's coefficient increases from 0.19 pre-1990 to 0.23 post-2000 (about a 20% increase), whereas SUE's coefficient decreases from 0.42 to 0.33 (about a 20% decrease).

We also examine serial correlation patterns in samples of firms that we suspect have relatively poor matching in bottom-line earnings (e.g., firms with special items, losses, fourth quarter reporting, and extreme SUE realizations without corresponding extreme MSUE realizations). MSUE's incremental abilities are even stronger in these samples, which suggests that the benefits of extracting matching information from earnings increases when matching disparities between our news measures are greater.

We next examine the extent to which the pricing of earnings news has evolved in capturing matching's implications for future profitability. Since there is an overlap between SUE and MSUE, we expect the excess return predictability of both SUE and MSUE to attenuate over time as trading costs diminish and as information about the temporal properties of earnings becomes richer and more accessible to investors. However, if investors do not fully appreciate the role of matching in facilitating the serial properties of earnings, then we expect MSUE to continue to predict significant excess returns with magnitudes that increasingly outweigh those of SUE's excess returns.

When we construct hedge portfolios that take long (short) positions in the highest (lowest) decile of each of our news measures, we find that MSUE portfolios increasingly outperform SUE portfolios over time. For example, in the post-2000 period, MSUE's size-adjusted three-month hedge return is 3.29% (t-stat = 4.41), as compared to SUE's hedge return of 2.06% (t-stat = 2.54). Differences in portfolio returns are even more striking in our poorly matched earnings subsamples, where MSUE portfolios continue to predict significant excess returns while the return predictability of SUE portfolios dissipates and largely disappears in the post-2000 period. These results suggest that the excess return predictability of earnings news largely derives from news in "well-matched" components and that the excess return predictability of "well-matched" news remains significant even when the degree of matching in bottom-line earnings is poor.

To further solidify the notion that stock prices impound information provided by matching with a delay, we conduct two additional tests to corroborate our main results. First, we explore whether transient institutional investors use matching to extract stronger SUE signals on which to trade. We extend the main regression in Ke and Ramalingegowda (2006) by interacting SUE with indicators for well-matched earnings news, which should have stronger implications for predicting future earnings news and thus should induce more trading in well-matched stocks. While we see some support for the use of matching early in our sample period, results from the 1990s and later—when the benefits of identifying matching information are higher—do not support the significant use of matching by transient investors to extract stronger SUE signals.

Second, we perform hedge portfolio tests using *levels* of earnings and operating profit (rather than changes). Balakrishnan et al. (2010), Novy-Marx (2013) and Ball et al.

(2015) document long-term return predictability using levels specifications of the news measures we examine in our paper. Since matching disparities between our news measures should be reflected in their corresponding levels specifications, we expect to observe less attenuation in excess returns for the levels specifications of our well-matched measures. A levels analysis therefore provides a natural out-of-sample test of whether matching information underlies disparities in excess return predictability among our accounting variables. We find that hedge returns for bottom-line earnings levels declined about 50% in the post-2000 period relative to the pre-1990 period, while the hedge return gap for operating profit increased fourfold over the same period.

We run a battery of additional tests to confirm the robustness of our results. Fama-MacBeth regressions show that the return predictability of MSUE is consistently and increasingly incremental to that of SUE after we control for risk characteristics that are known to predict returns. We also show that our main hedge portfolio results are not explained by ex ante earnings volatility (Cao and Narayanamoorthy, 2012) or revenue news (Jegadeesh and Livnat, 2006). Lastly, our hedge portfolio results continue to hold under alternative MSUE definitions, news scalars, sub-period partitions and hedge portfolio holding window specifications.

Overall, our results suggest that news in "well-matched" earnings components continues to predict significant excess returns several months after earnings news is released. Thus, even as markets have evolved over time to more efficiently incorporate serial properties of earnings news into stock prices (Johnson and Schwartz, 2001; Richardson et al., 2010; Chordia et al., 2014), such gains do not appear to reflect a richer appreciation of matching's role in facilitating these properties.

Our study contributes to the literature in several ways. First, it contributes to the PEAD literature by identifying a potential source of time series variation in stock price drift that has strong implications for interpretations of PEAD attenuation. In particular, we find that the excess return predictability of earnings news stems largely from news in "well-matched" earnings components and that such predictability is surprisingly persistent over time, even in recent years. A key implication of this finding is that PEAD research designs that use bottom-line news measures such as SUE have less power to detect pricing inefficiencies as matching in bottom-line earnings declines. Consequently, studies that quantify PEAD attenuation using SUE-based research designs are more likely to provide "upper bound" estimates of efficiency gains achieved in the pricing of earnings news (e.g., Hung et al. 2014, Chordia et al. 2014, Richardson et al. 2010).[5]

Second, our study responds to a concern expressed in Richardson et al. (2010) about "how knowledge of the accounting system itself is not fully exploited (by researchers) to link accounting information to stock prices and returns" (p. 444). We exploit a fundamental and widely known accounting principal—matching—and show that it provides significant information about future profitability that is not fully impounded into stock prices by investors in a timely manner. By contrast, prior studies in the fundamental analysis literature tend to offer anecdotal or ad hoc explanations for the return predictability of their accounting variables (e.g., Ou and Penman, 1989; Lev and Thiagarajan, 1993; Abarbanell and Bushee, 1997; Piotroski, 2000).

Lastly, our study makes a case for the continued relevance of matching for forecasting future profitability. While evolving earnings properties threaten the

[5] We do not attempt to formally quantify matching's effect on PEAD attenuation in relation to other documented drivers. We leave a comparative analysis of the various drivers of PEAD attenuation identified in the literature for future research.

informativeness of bottom-line earnings (Collins, Maydew and Weiss, 1997; Givoly and Hayn, 2000; Dichev and Tang, 2008), we show that news measures that are less susceptible to declining matching exhibit robust serial correlation over time and have gained incremental power in predicting earnings news even when matching in current earnings is poor. These features likely underlie the recent rise in interest in gross and operating profit among investment professionals,[6] so it is instructional to highlight the role of evolving earnings characteristics in dictating the course of current practice.

The remainder of the paper is organized as follows. Section 2 reviews prior literature on PEAD and matching and presents our hypotheses. Section 3 describes our data. Section 4 outlines our tests and presents our results. Section 5 discusses and assesses alternative interpretations of our results. Section 6 offers concluding remarks.

2. Prior Literature and Hypothesis Development

2.1 Post-Earnings-Announcement Drift and Its Attenuation

Accounting researchers have long examined stock price drift in the direction of past earnings news (Ball and Brown, 1968; Foster et al., 1984; Bernard and Thomas, 1989, 1990). So pervasive is evidence of post-earnings-announcement drift (PEAD) that even staunch supporters of market efficiency concede that its place as an empirical regularity is "above suspicion" (Fama, 1998). Bernard and Thomas (1990) propose that PEAD reflects naïve earnings expectations that assume quarterly earnings news follows a seasonal random walk. Since successive realizations of earnings news are typically

[6] Providing anecdotal support for this claim, Brian Nowack, an analyst at Nomura Equity Research who upgraded his stock recommendation for Amazon from "neutral" to "buy" following Amazon's Q1 2012 earnings announcement, remarked that he was "beginning to see clouds part in the (Amazon) investment case as we believe we and the Street are under-appreciating the growing and expansive drivers within (Amazon's) gross margin" (Ray, 2012).

positively correlated, the authors argue that excess returns can be predicted based on the sign and magnitude of quarterly earnings news. While variants of this theory have been advanced over the years, the basic idea that PEAD captures an under-reaction to the implications of current earnings news for future earnings news has been widely adopted in the literature (Ball and Bartov, 1996; Fama, 1998; Soffer and Lys, 1999; DellaVigna and Pollet, 2009; Hirshleifer et al., 2009).

More recent evidence, however, suggests that PEAD has substantially declined over time. For example, Chordia et al. (2014) document a 55% decline in the characteristic premium for SUE in their post-2000 sample relative to their pre-2000 sample. The authors link PEAD attenuation to increases in liquidity and decreases in transaction costs that previously inhibited an arbitrageur's ability to exploit mispricing.[7] Johnson and Schwartz (2001), Richardson et al. (2010) and Milian (2015) suggest that PEAD attenuation reflects investor learning about temporal patterns in earnings news, consistent with more general evidence of investors learning from academic research on stock return predictors (McLean and Pontiff, 2015).[8] Hung et al. (2014) find that IFRS adoption, by enhancing reporting quality, significantly contributes to PEAD attenuation internationally. Collectively, these studies suggest that the pricing of earnings news has experienced significant efficiency gains over time as market participants learn about and have greater opportunities to profit from the temporal properties of earnings.

While PEAD attenuation evidence is consistent with an underlying investor learning effect, not much is known about the nature of investor learning as it pertains to

[7] Mendenhall (2004) and Ke and Ramalingegowda (2006) find that PEAD is not significantly exploited when arbitrage risks and transaction costs are sufficiently high.
[8] Richardson et al. (2010) suggest that PEAD attenuation may be consistent with adaptive market efficiency (e.g., Grossman and Stiglitz, 1980; Lo, 2004) whereby "capital market participants learn about the relevance of information for security prices, and prices adjust accordingly" (p. 442).

PEAD. For example, if investors learn about PEAD through academic research that documents autocorrelation patterns in seasonally differenced earnings (e.g., Bernard and Thomas, 1990), it is unclear whether investors simply use autocorrelation patterns in earnings changes to forecast future earnings or if they seek out the underlying drivers of these patterns to enhance the quality of their forecasts. The former learning activity is satisfactory from an efficiency perspective as long as autocorrelation data are representative of future data. However, to the extent that temporal patterns evolve over time, a deeper understanding of what causes predictable changes in earnings may be necessary for an efficient pricing of earnings news.

2.2 Matching in Earnings

The matching principle—which calls for expenses to be recognized concurrent with their associated revenues in the determination of net income—has long guided accounting practice and the formation of formal accounting standards across the globe.[9] Since many economic transactions occur in periods divorced from their related cash flows, matching enhances the ability of earnings to communicate how operations contributed to earned capital in a given period. To the extent that outsiders base contracting and capital allocation decisions on information conveyed by earnings, matching should enhance the efficiency of decision making among outsiders by providing a more transparent measure of the underlying economic profitability of a firm.

Academic research sheds light on the channels through which matching enhances the usefulness of earnings. Schutt (2012) finds that greater matching in earnings makes accounting rates of return closer approximations of a firm's internal rate of return.

[9] Early accounting texts and academic research that discuss matching include Paton and Littleton (1940), Blocker (1949), and Jarrett (1970).

Consequently, earnings become more informative to investors about the firm's underlying economic profitability. Dichev and Tang (2008) model mismatching in earnings as a form of noise in the economic relation of advancing expenses to earn revenues. Using analytical and archival methods, they show that mismatching increases volatility and decreases persistence in annual earnings, with the latter effect inducing negative autocorrelation in earnings changes. Cao and Narayanamoorthy (2012) show that these annual properties hold in the quarterly setting and that quarterly earnings persistence is positively related with positive autocorrelation in quarterly earnings news. This latter finding is particularly relevant for pricing earnings news as it suggests that matching strengthens the autocorrelation structure of quarterly earnings news, thereby enhancing the predictability of next quarter's earnings.

Nevertheless, as with PEAD, matching in earnings has been on the decline in recent years. Consistent with their analytical model, Dichev and Tang (2008), using a sample of the 1,000 largest U.S. firms, document a 15% drop in the contemporaneous correlation between revenues and expenses, a doubling in earnings volatility, and a roughly 30% decline in earnings persistence over a 40-year period. While this evidence coincides with evolving U.S. accounting standards that increasingly shy away from matching considerations, researchers have linked declining matching to multiple causal sources. Donelson et al. (2011) find that an increased incidence of large special items driven by real economic events (rather than evolving standards per se) is largely responsible for declining matching.[10] Srivastava (2014) argues that evidence of evolving

[10] Dichev (2013) finds that large special items reported in economic downturns significantly contribute to increasing GAAP earnings volatility, but such volatility is considerably dampened when earnings are measured following National Income and Product Accounts (NIPA) standards used by the U.S. Bureau of Economic Analysis (BEA).

earnings properties predominately reflects a changing composition of firms over time. He shows that newer firms exhibit greater intangible intensity, creating earnings streams characterized by greater mismatching, higher volatility and lower relevance. Regardless of the source, evidence suggests that declining matching has had profound effects on the temporal properties of earnings, calling into question earnings' continuing role as a gauge of a firm's underlying economic profitability (Dichev and Tang, 2008).

2.3 The Role of Matching in Detecting PEAD

Given the documented effects of declining matching on earnings properties, we argue that gauging investors' understanding of matching and its implications for future profitability is increasingly important for assessments of earnings news pricing efficiency. Prior research suggests that declining matching is likely to diminish autocorrelation in earnings news, complicating an investor's ability to forecast future earnings based on temporal patterns in bottom-line earnings alone. Therefore, to the extent that matching continues to guide the recognition of economically significant components of earnings, an efficient pricing of earnings news will increasingly depend on knowledge of how matching facilitates predictable earnings time series patterns.

A central feature of our analysis is that we exploit *within-firm* variation in matching over time by analyzing two types of earning news measures with varying susceptibility to the temporal decline in matching. The first type is a "bottom-line" measure of news using earnings before extraordinary items. Studies of declining matching in earnings typically focus on bottom-line earnings (Dichev and Tang, 2008; Donelson et al., 2011; Srivastava, 2014), so we expect bottom-line earnings news measures to be highly susceptible to declining matching. By contrast, the second type consists of "well-matched" measures of news using gross profit or operating profit, both of which we argue should be less susceptible to declining matching relative to bottom-line earnings.

There are two reasons we expect our well-matched measures to be less susceptible to declining matching. First, both gross and operating profit should have a greater composition of expenses that are "directly matched" to their related revenues in the period in which revenues are recognized (e.g., cost of goods sold, sales commissions).[11] Second, both measures should have a lower composition of expenses that are recognized "as incurred," meaning that recognition of the expense is not contingent on a temporal matching with its associated revenues. Much of the evolution in earnings' temporal properties has been attributed to the proliferation of large income-decreasing special items that are predominately recognized "as incurred" on the income statement (Donelson et al., 2011; Dichev, 2013). These items (e.g., goodwill impairments, restructuring charges) are not considered recurring components of income and so are conventionally excluded from gross profit and operating profit.[12]

Equipped with two types of quarterly news measures, we form our first set of hypotheses around predicted differences in their serial correlation characteristics. Following Dichev and Tang (2008) and Cao and Narayanamoorthy (2012), we expect to observe less decay in the first-order autocorrelation of well-matched news measures

[11] Dichev and Tang (2008) discuss three degrees of matching success: "direct matching" for costs that are directly and specifically matched to associated revenue (e.g., cost of goods sold), "indirect matching" for costs that are matched indirectly by allocating them to periods (e.g., depreciation, taxes), and "no matching" or "expense as incurred" for costs where matching considerations are entirely absent (e.g., most R&D and advertising).

[12] While Compustat attempts to isolate many of these "as incurred" expenses in the variable *Special Items*, we note that GAAP does not specifically define special items, and their classification in Compustat is somewhat arbitrary (Burgstahler, Shevlin and Jiambalvo, 2002). While this implies that operating profit may contain some of these items, this should bias against finding matching disparities between our measures.

relative to bottom-line measures if declining matching deteriorates the persistence of bottom-line measures at a faster rate than the persistence of well-matched measures.

> ***H1: The first-order autocorrelation of well-matched quarterly earnings news measures will exhibit less decay over time relative to first-order autocorrelation in bottom-line quarterly earnings news measures.***

In addition, we expect well-matched measures to gain incremental power over bottom-line measures in predicting future bottom-line earning news as matching declines over time. While we expect part of this gain to reflect stronger persistence in well-matched earnings components, news in well-matched measures may also provide a more reliable signal of innovations in the firm's underlying economic profitability. Novy-Marx (2013) and Ball et al. (2015) show that gross profit and operating profit outperform bottom-line earnings as proxies for expected profitability in the context of dividend discount models of equity valuation. Therefore, even as bottom-line earnings becomes increasingly mismatched, news in well-matched measures likely contains information about underlying profitability that will persist in future earnings streams.

> ***H2: Well-matched quarterly earnings news measures, relative to bottom-line news measures, will gain incremental power over time in predicting one-quarter-ahead bottom-line earnings news.***

Our last hypothesis concerns the evolution of investors' use of matching in the pricing of earnings news. Supporting the case for efficiency gains in the pricing of matching is evidence that investors have learned over time about the forecast relevance of relatively nuanced accounting variables such as accruals (Richardson et al., 2010; Green et al., 2011). Furthermore, with diminishing limits to arbitrage over time, sophisticated users of financial information (e.g., sell-side analysts, institutional investors) should be increasingly capable of capitalizing on any lingering excess return predictability.[13]

Supporting the case for prevailing inefficiencies in the pricing of matching is evidence in Prakash and Sinha (2013) that investors and analysts do not fully understand the implications of changes in deferred revenue liabilities for future profit margins. Changes in deferred revenue liabilities tend to be negatively associated with current profit margins because of mismatching in earnings (e.g., recognizing expenses associated with "unearned" cash receipts). In turn, statement users fail to anticipate future reversals in profit margins when mismatching gets corrected over time. Penman and Zhang (2002) document a similar phenomenon for investments (e.g., R&D, advertising) that are conservatively expensed in periods preceding recognition of their associated revenues.

While we do not have strong priors on the evolution of the pricing of matching information in earnings news, we find that the body of evidence on PEAD attenuation weakens support for the view that matching information in earnings news is significantly mispriced in today's market. Even as there are indications that learning about PEAD can lead to overreaction to the implications of earnings news (Milian, 2015), diminishing transaction costs over time suggest that sophisticated users should be in an increasingly good position to quickly abate temporary inefficiencies in the pricing of earnings news.

> ***H3: Investor learning about PEAD encompasses an improved understanding of matching and its implications for future profitability.***

3. Sample Data and Descriptive Statistics

[13] Cross-sectional evidence of a negative association between financial statement user sophistication and PEAD include Bartov et al. (2000), Mikhail et al. (2003), and Ke and Ramalingegowda (2006).

We draw our sample from the CRSP monthly returns database and the Compustat quarterly database for fiscal years spanning 1979 through 2012. We require firms to have stock prices exceeding $1 per share. Following Ball et al. (2015), we require each firm-quarter to have non-missing Compustat data necessary to compute both well-matched and bottom-line earnings news measures to ensure a consistent sample across our two classes of news measures (both are defined below and in the Appendix).

Table 1 provides data on sample size by year. Our total sample size from 1979-2012 is 388,249 firm-quarters. We see a steady rise in observations from 5,396 firm-quarters (1.39% of the sample) in 1979 to a peak of 15,869 firm-quarters (4.09%) in 1999, followed by a slight leveling off to 13,091 firm-quarters (3.37%) in 2012.

Our measure of "bottom-line" earnings news is *SUE* (i.e., standardized unexpected earnings) defined as quarterly earnings per share minus expected earnings per share scaled by the standard deviation of quarterly earnings growth over the previous eight quarters, as in Jegadeesh and Livnat (2006).[14] Expected earnings are assumed to follow a seasonal random walk with drift. The drift term is measured as the average of quarterly earnings growth over the previous eight quarters. Our primary measure of "well-matched" earnings news, *MSUE*, is analogous to *SUE* except that *MSUE*'s news variable is operating profit, which we define as sales minus cost of goods sold and sales, general and administrative expense, following Ball et al. (2015).[15]

As in Thomas and Zhang (2011), our return window is the three-month period beginning in the first month of the calendar quarter that is at least three months

[14] News measure results are insensitive to the choice of the earnings expectation model employed.
[15] Results are qualitatively unaffected when we replace operating profit with gross profit. Firms have considerable discretion over whether to include certain items in "cost of goods sold" or "sales, general and administrative expense" (Weil, Schipper, and Francis, 2014). Therefore, it is largely an empirical question whether gross profit or operating profit is "better matched" in practice.

subsequent to fiscal quarter-end to ensure that earnings information is released to the market before the holding period begins.[16] Throughout the paper, we use *ADJ_RET*, which is the size-adjusted buy-and-hold three-month stock return calculated as described in Barber et al. (1999) to demonstrate our results. In multiple regression tests, we also employ a set of known risk characteristics: *SIZE* is measured as the natural log of the market capitalization at the end of the most recent fiscal quarter for which data are available; *BM* is the book-to-market ratio, calculated as the book value of equity divided by the market value of equity at the end of the most recent fiscal quarter for which data are available; *MOM* is the buy-and-hold six month raw stock return leading up to the month prior to the return holding window.

Table 2 provides descriptive statistics for our primary variables of interest. All variables except *ADJ_RET* are winsorized quarterly at the 1st and 99th percentiles. Panel A provides summary statistics for variables used in our regressions. *SUE* has a mean (median) of -0.440 (-0.046) and a standard deviation of 5.118. By comparison, *MSUE* has a mean (median) of -0.117 (0.037) and a standard deviation of 4.095. *MSUE*'s lower volatility is consistent with theoretical implications in Dichev and Tang (2008) that link better matching in earnings to lower earnings volatility. Distribution statistics for *ADJ_RET*, *SIZE*, *BM* and *MOM* are in line with values tabulated in prior literature.

Table 2, Panel B documents the degree of overlap between the *SUE* and *MSUE* decile portfolios (formed quarterly), reported by sub-period. The purpose of this panel is to highlight the differential composition of firm-quarters within each decile portfolio and to check for trends in the degree of overlap. As expected, the degree of overlap is highest

[16] With regard to our portfolio tests, we implement the model with the most flexible design rather than the model with the maximum return. Results are qualitatively unchanged under various holding windows and portfolio formation dates. Section 4.5 further discusses portfolio test considerations.

for the extreme decile portfolios in all three sub-periods (1979-1989, 1990-1999, 2000-2012).[17] However, there is a decreasing trend in the degree of overlap in the extreme decile portfolios. For example, the highest (lowest) decile portfolios report a 52.96% (57.95%) overlap from 1979-1989, a 50.69% (55.22%) overlap from 1990-1999, and a 47.58% (51.66%) overlap from 2000-2012. These trends suggest that extreme *SUE* values are increasingly driven by larger non-operating earnings components over time.

Table 2, Panel C presents the correlations of our news measures (*SUE* and *MSUE*) with future size-adjusted returns (*ADJ_RET*) by sub-period. We observe attenuation in return predictability for both *SUE* and *MSUE*, though the attenuation for *MSUE* (correlation coefficient declining from 0.060 to 0.031) is much milder than the attenuation for *SUE* (correlation coefficient declining from 0.056 to 0.009). These trends provide a preliminary indication that earnings news driven by news in "well-matched" components continues to predict economically significant excess returns.

4. Empirical Results

4.1 Serial Correlation in SUE and MSUE

Before we examine the evolution of the pricing of matching information in earnings news, we first examine temporal properties of our bottom-line news measure (*SUE*) and our well-matched news measure (*MSUE*). Recall that we expect *MSUE* to experience less decay in its first-order autocorrelation structure relative to *SUE* (H1) and an increasing incremental ability to forecast one-quarter-ahead *SUE* (H2), consistent with the idea that well-matched quarterly news measures are less susceptible to temporal

[17] Higher overlap in the extreme deciles is expected because as news in operating profit becomes more extreme (good or bad), it is more likely to comprise a larger portion of "overall" earnings news and thus less likely to be diluted by opposite-sign news in non-operating profit.

declines in matching relative to bottom-line news measures. Evidence supporting H1 and H2 would provide stronger motivation for assessing whether investors price earnings news using information provided by matching.

To test H1 and H2, we estimate the following two regression models for the full sample and by sub-period using the Fama-MacBeth approach (1973):

$$MSUE_{i,t+1} = \alpha_0 + \alpha_1 R\_MSUE_{i,t} + \alpha_2 R\_SUE_{i,t} + \varepsilon_{i,t+1} \qquad (1)$$

$$SUE_{i,t+1} = \beta_0 + \beta_1 R\_MSUE_{i,t} + \beta_2 R\_SUE_{i,t} + \varepsilon_{i,t+1} \qquad (2)$$

To facilitate comparison between coefficients, we rank-transform our news variables in ascending order from 0 to 9 each calendar quarter. Hence, *R_MSUE* (*R_SUE*) is the rank-transformed version of *MSUE* (*SUE*). Our test for H1 is to compare the trend in α_1 over our three sub-periods to the trend in β_2, and we expect the rate of decline in α_1 to be smaller than the rate of decline in β_2. Our test for H2 is to examine the trend in β_1 over our three sub-periods, and we expect β_1 to increase over time.

Table 3 provides Fama-MacBeth regression results for our estimations of equations 1 and 2. Panel A presents the results for equation 1, which regresses one-quarter-ahead *MSUE* on *R_MSUE* and *R_SUE*, for the full sample ("Overall" column) and for each sub-period of our analysis ("1979-1989," "1990-1999," "2000-2012"). Looking at the Overall column, we see that the coefficient on *R_MSUE* is 0.587 and highly significant, while the coefficient on *R_SUE* is much lower at 0.025. These results support the idea that there is strong serial correlation in *MSUE* and that *SUE* does not add significant value to predicting *MSUE* beyond what is already provided by current *MSUE*. Looking at the sub-period columns, the coefficient on *R_MSUE* exhibits an increasing trend, starting with a value of 0.559 from 1979-1989 and increasing to a value of 0.616 from 2000-2012, amounting to an 11% increase over time.

Table 3, Panel B presents the results for equation 2, which regresses one-quarter-ahead *SUE* on *R_MSUE* and *R_SUE* for the full sample and for each sub-period of our analysis. Looking first at the coefficient on *R_SUE*, we see a decreasing trend over the 3 sub-periods, starting with a value of 0.423 in the pre-1990 period and decreasing to a value of 0.336 in the post-2000 period, amounting to a roughly 20% decrease. Considered in combination with the increasing coefficient trend for *R_MSUE* in Panel A, the evidence in Table 3 supports H1 in that bottom-line earnings news loses more serial predictive power over time than well-matched earnings news.[18] Turning to the trend in the *R_MSUE* coefficient in Panel B, we see an overall increase from 0.191 in the pre-1990 period to 0.231 in the post-2000 period, which amounts to a roughly 20% increase over time. This trend, along with the decreasing trend for the coefficient on *R_SUE*, supports H2, suggesting that well-matched earnings news has gained incremental ability to forecast future bottom-line earnings news beyond what can be forecast from current bottom-line earnings news. Looking at the Overall column, we note that while the coefficient on *R_SUE* is 0.389, the corresponding coefficient on *R_MSUE* is only 48% smaller at 0.202 (both coefficients are highly significant). This suggests that well-matched earnings news contributes significant incremental information to predicting bottom-line earnings news throughout our sample period, highlighting the added benefit that well-matched earnings components provide to the earnings forecasting exercise.[19]

[18] Univariate versions of equations 1 and 2 (untabulated) provide similar evidence consistent with H1.

[19] We also adapt the regression in Dichev and Tang (2008) Table 3 to the quarterly setting (untabulated) and find that the key temporal patterns from that table (i.e., a decreasing contemporaneous revenue-expense relation and an increasing relation between revenues and past and future expenses) continue to hold.

4.2 Return Predictability of SUE and MSUE

Table 4 reports the time-series means of future size-adjusted stock returns (*ADJ_RET*) for decile portfolios formed on *MSUE* (Panel A) and *SUE* (Panel B). At the end of each calendar quarter, firms are sorted into ten portfolios based on the value of the sorting variable (e.g., in Panel A, firms with the lowest *MSUE* values belong to decile 1, while firms with the highest *MSUE* values belong to decile 10). Size-adjusted buy-and-hold returns for each stock are calculated over the three months subsequent to the portfolio formation date, and an equal-weighted mean return is computed for each portfolio. We then form a zero-investment hedge portfolio for each variable by going long (short) in the highest (lowest) decile portfolio, and we compute Fama-MacBeth t-statistics based on the time-series distribution of the mean hedge portfolio returns.

Panel A of Table 4 reports *MSUE* decile portfolio returns for the full sample (i.e., in the "Overall" column) and by sub-period. In the Overall column, there is a smooth monotonic increase in returns, ranging from a -1.55% return for decile 1 to a 2.17% return for decile 10. The *MSUE* hedge portfolio return for the full sample is 3.72%, which is highly significant (t-stat = 9.90). Panel B of Table 4 reports the corresponding *SUE* results. In the Overall column, we see a similarly smooth monotonic increase in returns, with a hedge portfolio return of 3.05% that is highly significant (t-stat = 7.69). Thus, over the full sample, *MSUE* generates superior hedge returns to *SUE*.

In the sub-period columns for *MSUE* (Panel A) and *SUE* (Panel B), there is an overall temporal decline in portfolio returns, consistent with findings in the PEAD attenuation literature. However, temporal attenuation in returns is much lower for *MSUE* portfolios than for *SUE* portfolios. For example, the hedge return for *SUE* (Panel B) decreases from 3.64% in the 1979-1989 sub-period to 2.06% in the 2000-2012 sub-period, a 43% decline, while the hedge return for *MSUE* (Panel A) decreases from 3.77% in the 1979-1989 sub-period to 3.29% in the 2000-2012 sub-period, a 13% decline.[20] Furthermore, the *MSUE* hedge return strictly dominates the *SUE* hedge return in every sub-period with a progressively increasing excess return gap ranging from a 0.13% gap in the 1979-1989 sub-period to a 1.23% gap in the 2000-2012 sub-period. Also note that in the 2000-2012 sub-period, the decile 1 return for *MSUE* is more negative than the corresponding return for *SUE* (-1.31% versus -0.64%), while the decile 10 return for *MSUE* is more positive than the corresponding *SUE* return (1.98% versus 1.42%), which suggests that the *MSUE* portfolio sort is superior in identifying winners and losers.

Figure 1 plots, for each hedge portfolio, the value of a dollar invested at the beginning of the period over various time intervals. The overall picture that emerges from the figure is that the *MSUE* hedge strategy, once virtually indistinguishable from the *SUE* strategy, gradually yields superior returns, especially from 2000 onward, with no indication of reversion in the immediate future. These results, along with the results in Table 4, do not provide strong support for H3, which predicted that investor learning about PEAD encompasses learning about matching's implications for future profitability.

Figure 2 plots the trend in *SUE* and *MSUE*'s trailing five-year Sharpe ratios over the course of our sample period. It shows that the trailing five-year Sharpe ratio for *MSUE* (the smooth line) largely dominates the corresponding ratios for *SUE* (the dotted line) starting from the mid-1990s. Also note that the *MSUE* ratios exhibit a much less

[20] There are a few reasons hedge returns for well-matched measures might decline over time: (a) chance, (b) inadequate controls for time varying risk in our tests and/or (c) efficiency gains from learning about PEAD and exploiting it.

precipitous decline than the *SUE* ratios during the crisis of 2008-2009. In untabulated results, the full sample Sharpe ratio for *SUE* is 0.56, while the corresponding ratio for *MSUE* is 0.74, or 30% higher than the *SUE* value. Moreover, the *MSUE* strategy also mitigates crash risk. For example, the worst three-month return for the *SUE* hedge portfolio is -25.6%, while the worst return for the *MSUE* hedge is only -10.2%, which is 2.5 times smaller than the *SUE* decline. Overall, these patterns speak to the relative stability of the *MSUE* hedge strategy over time.

4.3 Serial Correlation and Return Predictability in "Mismatched" Samples

Tables 5 and 6 repeat our serial correlation and return predictability analyses for subsets of firms where matching disparities between *MSUE* and *SUE* are suspected to be relatively large. We examine these subsets for two reasons. The first is to better highlight the distinct information conveyed by *MSUE* that continues to predict excess returns in today's market. The second is to show that much of *SUE*'s excess return predictability stems from information conveyed by *MSUE*, especially in recent years.

We begin by examining a "non-overlapping" subset of our firm-quarters. To form this subset, we drop firm-quarters with identical extreme decile ranks (i.e., ranks of 1 or 10) for *SUE* and *MSUE*. Thus, the *SUE* hedge portfolio is less likely to be driven by extreme news in *MSUE*, and vice versa. Table 5, Panel A shows that serial correlation properties of *MSUE* and *SUE* are largely unaffected by exclusion of extreme overlap firm-quarters, which simply reflects their relatively small representation in the sample (note that extreme overlap firm-quarters comprise only about 10% of the sample).

However, when we turn to Table 6, Panel A, which looks at excess returns to non-overlapping hedge portfolios formed on *MSUE* and *SUE*, we see that excess returns to the *MSUE* hedge strategy do not attenuate over time. In fact, hedge returns slightly increase from 2.72% (t-stat = 4.89) in the 1979-1989 sub-period to 2.88% (t-stat = 4.45) in the 2000-2012 sub-period. In stark contrast, *SUE* hedge returns sharply attenuate from 2.50% (t-stat = 4.04) in the 1979-1989 sub-period to 0.54% (t-stat = 0.73) in the 2000-2012 sub-period. These results suggest that *MSUE* conveys information distinct from that conveyed by *SUE* that is mispriced throughout our sample period. Meanwhile, *SUE*'s return predictability, after we purge information conveyed by *MSUE*, sharply dissipates over time and largely disappears after 2000. Since the non-overlapping *SUE* hedge portfolio likely contains poorer matching relative to the full sample *SUE* portfolio (since extreme *SUE* can be driven by extreme *MSUE* in the full sample), the sharp drop in hedge returns here suggests that *SUE*'s remaining return predictability in recent years likely stems from information conveyed by earnings components that are well-matched.[21]

Next, we consider income-decreasing special item firms and firms reporting losses. We suspect that special item firms have relatively poor matching in bottom-line earnings because special items are recognized "as incurred," and therefore are not explicitly matched to revenues. Loss firms are likely to report special items as well, but losses could also arise from investments that are expensed as incurred without a temporal matching to revenues (e.g., research and development expense, advertising expense).[22]

[21] Note that the decline in *SUE* returns for non-overlapping firms could be interpreted as investors learning about temporal implications of *mismatching*, which can be viewed as a form of learning about matching. However, our view is that using matching information efficiently implies having an understanding of the temporal implications of <u>both</u> matching and mismatching. See Section 5 for additional discussion.

[22] Our definition of *MSUE* (tabulated using operating profit) may include certain "as incurred" expenses such as R&D expense. We find that our *MSUE* results are insensitive to the exclusion of R&D, which we attribute largely to our use of quarterly data.

Table 5 presents serial correlation results for special item firms (Panel B) and loss firms (Panel C). In contrast to the full sample results, these results show that the coefficient on *MSUE* for both subsets dominates the coefficient on *SUE* when predicting future *SUE*, though the coefficient gap is decreasing somewhat over time. We also note that the coefficients on *MSUE* are much larger for these subsets than they are for the full sample. These differences are consistent with poor matching being intrinsic to the bottom-line earnings of special item and loss firms in all sub-periods. The decreasing coefficient gap may reflect a rise in the number of firms reporting "serial" special items and losses, as well as a rise in firms misclassifying routine operating expense items as special items or losses from discontinued operations (McVay, 2006; Fan et al., 2010).

Table 6, Panels B and C report the corresponding hedge portfolio results for special item firms and loss firms. In Panel B (special item firms), we observe some return attenuation for the *MSUE* portfolio, though excess returns remain significant in the post-2000 sub-period (return = 2.61%, t-stat = 2.86). By contrast, the returns to the *SUE* portfolio are at least 50% lower in all sub-periods and are no longer significant in the post-2000 sub-period (return = 0.76%, t-stat = 0.90). In Panel C (loss firms), we observe similar results, as the *MSUE* hedge return remains strong (return = 3.42% from 2000-2012, t-stat = 3.45), while the *SUE* hedge return is always much smaller and never significant (return = 1.18% from 2000-2012, t-stat = 1.00). Again, these results suggest that well-matched components of earnings news continue to predict excess returns, even when matching in bottom-line earnings is likely to be poor.

Lastly, we consider serial correlation and return predictability of *SUE* and *MSUE* for firms that are reporting results for their fourth fiscal quarter. In terms of intrinsic poor matching factors, the fourth quarter contains many year-end adjustments that "true up" revenue and expense items to their annual figures (e.g., adjustments to effective tax rate estimates that impact income tax expense). Since adjustments partially reflect corrections of estimation errors made during interim periods, they are less likely to arise based on matching considerations. In terms of susceptibility to declining matching factors, researchers have found that large special items—whose reporting frequency has increased over time (Donelson et al., 2011)—are disproportionately recognized in the fourth quarter (Kinney and Trezevant, 1997; Burgstahler et al., 2002).

Table 5, Panel D shows evidence of both intrinsic mismatching (likely due to year-end adjustments) and susceptibility to declining matching over time (likely due to increased special items). Consistent with intrinsic mismatching effects, the serial correlation of *SUE* and *MSUE* is noticeably lower in the fourth quarter than in the full sample (consistent with evidence in Sloan and Rangan, 1998). Nevertheless, unlike *SUE*, *MSUE* shows a temporal rise in its serial correlation, and it also gains incremental predictive power for *SUE*, consistent with bottom-line earnings' added susceptibility to declining matching in the fourth fiscal quarter.

Table 6, Panel D shows that the *MSUE* hedge returns for fourth quarter firms are consistently large and significant (the 2000-2012 return is 5.03%, t-stat = 2.11), while the corresponding *SUE* hedge returns have sharply dissipated over time and are no longer statistically significant (the 2000-2012 return is 1.73%, t-stat = 0.59).

Overall, the results in Tables 5 and 6 strongly suggest that excess return predictability in earnings news largely emanates from news in well-matched earnings components. Furthermore, differences between *MSUE* and *SUE* hedge returns appear to be more pronounced in recent years (i.e., 2000-2012), which is inconsistent with the conjecture that efficiency gains from investor learning about PEAD capture an improved understanding of the implications of matching for future profitability (H3). Figure 3 plots the widening hedge return differential among mismatched subsample firms since 2000.

4.4 The Use of Matching by Transient Institutional Investors

We next examine whether the trading behavior of transient institutional investors is sensitive to matching information embedded in earnings news. Ke and Ramalingegowda (2006) find that transient institutional investors—who hold highly diversified portfolios and actively trade stocks for short-term gain—exploit SUE signals and significantly mitigate PEAD as a result. This evidence suggests that transient investors are relatively sophisticated users of financial information, so if investor learning about PEAD encompasses learning about the temporal implications of matching, transient institutions should be among the learned.

To test whether transient institutions use matching to extract stronger SUE signals, we estimate the following model adapted from Ke and Ramalingegowda (2006):

$$\begin{aligned}\Delta Transient_{i,t} = {} & \beta_0 + \beta_1 R\_SUE_{i,t} + \beta_2 D_{i,t} + \beta_3 D * R\_SUE_{i,t} + \beta_4 R\_Size_{i,t} \\ & + \beta_5 R\_BM_{i,t} + \beta_6 R\_MOM_{i,t} + \varepsilon_{i,t+1}\end{aligned} \tag{3}$$

Δ*Transient* is the change in the percentage of shares owned by transient institutions over the calendar quarter in which earnings are announced. *D* is an indicator variable for firm-quarters where we suspect *SUE* is driven by well-matched earnings components. We estimate (3) using two different indicator variables. In our first specification, *D* = 1 when *SUE* and *MSUE* fall in the same top or bottom decile, otherwise D = 0. In our second specification, D = 1 when *SUE* is in the top or bottom decile and no special items are reported, otherwise D = 0. All other variables are rank-transformations of variables that we defined earlier. Therefore, if transient institutions exploit matching information when trading on earnings news, then we expect $\beta_3 > 0$.[23]

Table 7 presents the results of our estimations of equation (3). Panel A shows the results when D indicates overlapping extreme *SUE* and *MSUE* firm-quarters. Consistent with Ke and Ramalingegowda (2006), we find that the coefficient on *R_SUE* is positive and significant for the full sample and in each sub-period, which suggests that transient institutions trade more heavily on extreme earnings news as indicated by *SUE*. For our test variable, *D*R_SUE*, we find some support for transient institutions exploiting matching information over the full sample (coefficient = 0.0122, t-stat = 2.40). However, when we look at the sub-period results, *D*R_SUE* is not significant in the latter two sub-periods, i.e., when extracting matching information from earnings news matters most. Furthermore, the coefficient on *D*R_SUE* in Panel B, where D indicates extreme*SUE* firm-quarters without special items, is not significant in the full sample or in any of the three sub-periods. Overall, the results in Table 7 do not offer strong evidence that transient institutions significantly exploit matching information when trading.

4.5 Time-Series Return Predictability in Earnings Levels

Next, we repeat our hedge portfolio analysis from Section 4.2 using quarterly *levels* of "bottom-line" earnings (i.e., earnings before extraordinary items) and "well-

[23] We do not consider loss or fourth quarter firms in this test for the following reasons. First, removing loss firms will likely result in a disproportionate removal of bottom decile firms, making *D*R_SUE* difficult to interpret. Second, use of an interim quarter dummy makes a specious assumption that trading behavior in interim quarters is not different from behavior in the fourth quarter (absent matching considerations).

matched" earnings (i.e., operating profit). Balakrishnan et al. (2010), Novy-Marx (2013) and Ball et al. (2015) show that levels of both bottom-line and well-matched earnings predict significant returns over long horizons. Since matching information in our news variables derives from matching information present in their levels components, a levels design provides a natural out-of-sample test of investor efficiency with respect to matching information in earnings. Table 8 presents the excess hedge returns for levels of operating profit (*OP*) and earnings (*IB*). The operating profit hedge yields returns ranging from 5.45% in the pre-1990 sub-period to 4.39% in the post-2000 sub-period (all highly significant), while the corresponding returns to the earnings hedge range from 5.00% to 2.79% (the latter return is only weakly significant). These results further support the idea that the excess return predictability of earnings news stems from matching information.

4.6 Additional Tests and Robustness Checks

We wrap up our analysis with a series of robustness tests. In this subsection, we test alternative explanations of our main findings and perform sensitivity checks for our main hedge portfolio results. In Section 5, we discuss the virtues of our matching framework, and we further contrast our results with related results in prior literature.

First, an alternative explanation of our main hedge portfolio results is that firms selected into our *MSUE* portfolios tend to exhibit less earnings volatility over time than *SUE* portfolio firms. Therefore, the widening excess return gap that we document merely reflects lower ex ante earning volatility for *MSUE* portfolio firms (Cao and Narayanamoorthy, 2012). To rule out this explanation, we partition our sample into three volatility groups (low, medium, and high) based on the variance of each firm's bottom-line earnings (scaled by average assets) over the previous eight quarters. Table 9 presents the returns to *MSUE* and *SUE* hedge portfolios formed within each ex ante earnings volatility group. We find that *SUE* hedge returns generally diminish as ex ante earning volatility increases, consistent with the findings of Cao and Narayanamoorthy (2012). By contrast, the *MSUE* hedge returns generally increase with increasing ex ante earnings volatility with significant returns in each tercile in each sub-period. Therefore, it is unlikely that ex ante earnings volatility differences between portfolios explain our results.

Second, we run Fama-MacBeth regressions to test whether our main findings are robust to controls for known risk characteristics. Table 10 presents the results of this analysis. Our dependent variable is three-month buy-and-hold raw returns, and our independent variables are rank-transformations of *MSUE*, *SUE*, *Size*, *BM*, and *MOM*. Note that the rank-transformations restrict our independent variables to vary from 0 to 1, so we can interpret coefficients as three-month buy-and-hold hedge returns on the high-low portfolio for each variable. In the Overall column, we see that the coefficients on *R_MSUE* and *R_SUE* are both positive and highly significant, suggesting that each variable predicts incremental excess returns over the other. Turning to the sub-period results, we see that the coefficient on *R_MSUE* during the post-2000 period is 0.021, which implies a roughly 8.4% excess return on an annualized basis, while the coefficient on *R_SUE* is 0.008, which translates to a roughly 3.2% annualized excess return. Therefore, *MSUE*'s widening dominance over *SUE* in recent years remains robust to the inclusion of known risk characteristic controls.

We also run Fama-MacBeth regressions to test whether our results are subsumed by controls for quarterly revenue news. Jegadeesh and Livnat (2006) show that quarterly revenue news predicts excess returns incremental to returns predicted by quarterly earnings news. Since revenue news excludes poorly matched earnings components, we want to be sure that our results aren't simply a manifestation of the return predictability of revenue news. In untabulated analysis, we find that the excess return predictability of revenue news is subsumed by our well-matched news measures.

Lastly, we perform a series of sensitivity checks for our main hedge portfolio analysis and tabulate the results in Table 11. In Panel A, we form *MSUE* portfolios using gross profit and find that the same patterns observed in Table 4 continue to hold.[24] In Panel B, we rescale both *SUE* and *MSUE* by total assets and find that our results are largely unaffected. In Panel C, we re-partition our full sample into four equally spaced sub-periods and continue to see significant excess return predictability for *MSUE* across all sub-periods, whereas *SUE*'s return predictability is insignificant in the last sub-period (i.e., 2004-2012). In Panel D, we adjust the portfolio-holding period to the three days surrounding next quarter's earnings announcement and use cumulative market-adjusted returns over that window. The results show that returns generally decline over time; however, by the post-2000 period, *SUE*'s hedge return is insignificant whereas *MSUE*'s return remains highly significant. Finally, in untabulated analyses, we experiment with varying portfolio formation dates (e.g., one month after earnings announcement) and portfolio holding windows (e.g., 3 to 12 months). We find that the tenor of our results holds under various formation date and holding window specifications. Therefore, our

[24] We find similar results when we define *MSUE* as news in earnings before special items.

results cannot be fully explained by earlier dissemination of bottom-line earnings news over our sample period.[25]

5. Discussion

Throughout the paper, we have argued that an efficient pricing of earnings news should incorporate the implications of matching for future profitability. Ultimately, our analysis addresses a more fundamental question concerning the extent to which investors use information provided by accounting conventions to price earnings news. Our choice to address this question in the context of matching follows from theoretical and empirical considerations. On the theoretical front, matching has clear implications for earnings' serial properties. On the empirical front, evidence of a temporal decline in matching coincides with evidence of a temporal decline in PEAD, so a consideration of matching lends structure to assessments of the drivers of PEAD attenuation. Thus, we view matching as an important and useful framework for gauging the scope of investor learning activities as they pertain to the pricing of earnings news.

Other studies attribute evolving earnings properties to phenomena that are closely related to matching. Givoly and Hayn (2000) link evolving earnings, accruals and cash flow properties to an increase in financial reporting conservatism over time. Meanwhile, Bushman et al. (2014) document a temporal weakening in the negative contemporaneous correlation of accruals and cash flows, driven by temporal increases in economic shocks and non-timing-related accruals. Our view is that neither phenomenon—increasing conservatism or the weakening accrual/cash flow relation—can be cleanly isolated from

[25] We also find that our return patterns hold for (a) samples of the top 3,000 firms by market capitalization and (b) analyst-covered firms where earnings news is measured based on analyst earnings expectations.

matching considerations. In particular, increasing conditional conservatism requires timelier recognition of expenses (i.e., it creates "mismatching" in earnings), while a weakening accrual/cash flow relation suggests a weakening role of accruals as a "correction mechanism" for timing mismatches between related cash flow and earnings realizations. We therefore believe that return predictability attributable to either phenomenon supports the position that matching information relevant for predicting earnings is not efficiently priced at the time of earnings announcement.

Another related concept underlying evolving earnings properties is the more general notion of earnings quality (e.g., Dechow, Ge and Schrand, 2010; Dichev, Graham, Harvey and Rajgopal, 2013). An alternative framing of our return predictability results could be that investors underweight earnings quality (EQ) characteristics such as persistence when pricing earnings news (e.g., Jegadeesh and Livnat, 2006). Similarly, returns could reflect an overweighting of low persistence components such as special items (Burgstahler, Jiambalvo and Shevlin, 2002; Dechow and Ge, 2006). While our results may be viewed through a persistence lens, we believe the matching framework provides a more comprehensive perspective on the inefficiencies we document. For example, an efficient pricing of matching requires investors to recognize both (a) the higher persistence of "well-matched" earning components and (b) the lower persistence of "mismatched" earnings components. This joint condition allows investors to recognize EQ signals (e.g., they understand (a) or (b) individually) without being fully efficient with respect to quality information in earnings. Furthermore, our matching framework offers guidance on how to extract high quality information from overall "low quality" earnings, a feature that the EQ literature has not extensively examined to date.

Our selection of “well-matched” news measures evokes findings from the fundamental analysis literature (e.g., Lipe, 1986; Ou and Penman, 1989; Lev and Thiagarajan, 1993; Abarbanell and Bushee, 1997; Piotroski, 2000; Amir et al., 2010; Akbas et al., 2014). We emphasize that our choice of measures is guided by theory relating matching to the serial properties of earnings and that our primary interest is to assess the extent to which the pricing of earnings news impounds these theoretical links. By contrast, in the bulk of the fundamental analysis literature, researchers motivate their selection of accounting measures based on ad-hoc or anecdotal factors that typically lack theoretical grounding. In addition, our analysis is mainly intertemporal in nature as we tackle a research question with implications for interpretations of PEAD attenuation over time, whereas fundamental analysis is most typically deployed in cross-sectional settings.

Finally, Doyle, Lundholm and Soliman (2006) and Livnat and Mendenhall (2006) use research designs that compare drift arising from time-series-based earnings news measures (e.g., SUE) to drift arising from IBES-based news measures. Both papers (DLS and LM) find that the magnitude of drift is larger for IBES-based measures. We note a few key distinctions between the DLS and LM analyses and our own. First, DLS and LM compare their news measures using cross-sectional analysis, whereas we employ both cross-sectional and time-series analysis. Second, in untabulated analysis, we find that IBES-based measures do not predict significant excess returns in the last sub-period of our sample (2000-2012), whereas our “well-matched” measures continue to predict significant excess returns (for firms with or without analyst following). Third, DLS and LM necessarily use samples of firms with analyst following, so it is not clear whether their sources of differential drift would generalize to the full Compustat population.

6. Conclusion

In this paper, we find that “well-matched” measures of earnings news continue to predict significant excess returns even as “bottom-line” news measures lose return predictability over time. Widening excess return disparities between well-matched and bottom-line earnings news coincide with increasing incremental abilities of well-matched measures to predict future news in bottom-line earnings. Excess return disparities are greater when bottom-line earnings exhibit poorer matching andbottom-line news for poorly matched firms does not predict significant excess returns after 2000. Matching information in earnings news does not appear to be significantly exploited by transient institutional investors in recent years, and our return predictability patterns show up in levels specifications of our earnings measures. Our results are insensitive to scalar, sub-period, and holding window choices; alternative measures of “well-matched” news; and controls for risk, revenue news, and ex ante earnings volatility.

Collectively, our results suggest that investors remain relatively inefficient at pricing earnings news driven by well-matched earnings components. This inefficiency is much less apparent when we focus on bottom-line earnings news in recent years, likely because bottom-line news is increasingly driven by mismatched earnings components that tend to have limited implications for future profitability. Therefore, recent findings of significant PEAD attenuation do not appear to reflect efficiency gains from investors learning about matching. Nevertheless, our results suggest that matching information in earnings continues to contribute significantly to predicting future profitability, even as the degree of matching in bottom-line earnings erodes over time.

Appendix
Variable Definitions

Variable Name		Definition
MSUE	=	Standardized unexpected operating profit, calculated as quarterly operating profit per share minus expected operating profit, scaled by the standard deviation of quarterly operating profit growth over the previous eight quarters. Operating profit is defined as revenue minus cost of goods sold and selling, general and administrative expense, as in Ball et al. (2015). Expected operating profit follows a seasonal random walk with drift. The drift term is the average of quarterly operating profit growth over the previous eight quarters.
SUE	=	Standardized unexpected earnings, calculated as quarterly earnings per share minus expected earnings per share scaled by the standard deviation of quarterly earnings growth over the previous eight quarters, as in Jegadeesh and Livnat (2006). Expected earnings are assumed to follow a seasonal random walk with drift. The drift term is the average of quarterly earnings growth over the previous eight quarters.
Size	=	Firm size, calculated as the natural log of the market capitalization as of the end of the most recent fiscal quarter for which data are available (in millions).
BM	=	Book-to-market ratio, calculated as book value of equity divided by market value of equity at the end of the most recent fiscal quarter for which data are available.
MOM	=	The buy-and-hold six month stock return ending one month prior to the portfolio formation date.
R_MSUE	=	The decile ranking of *MSUE* based on the distribution for each calendar quarter.
R_SUE	=	The decile ranking of *SUE* based on the distribution for each calendar quarter.
R_Size	=	The decile ranking of *Size* based on the distribution for each calendar quarter.

R_BM	=	The decile ranking of *BM* based on the distribution for each calendar quarter.
R_MOM	=	The decile ranking of *MOM* based on the distribution for each calendar quarter.
ADJ_RET	=	Size-adjusted return over the three-month period beginning in the first month of the calendar quarter that is at least three months subsequent to fiscal quarter-end. The methodology to construct size-adjusted portfolios is based on Barber et al. (1999).

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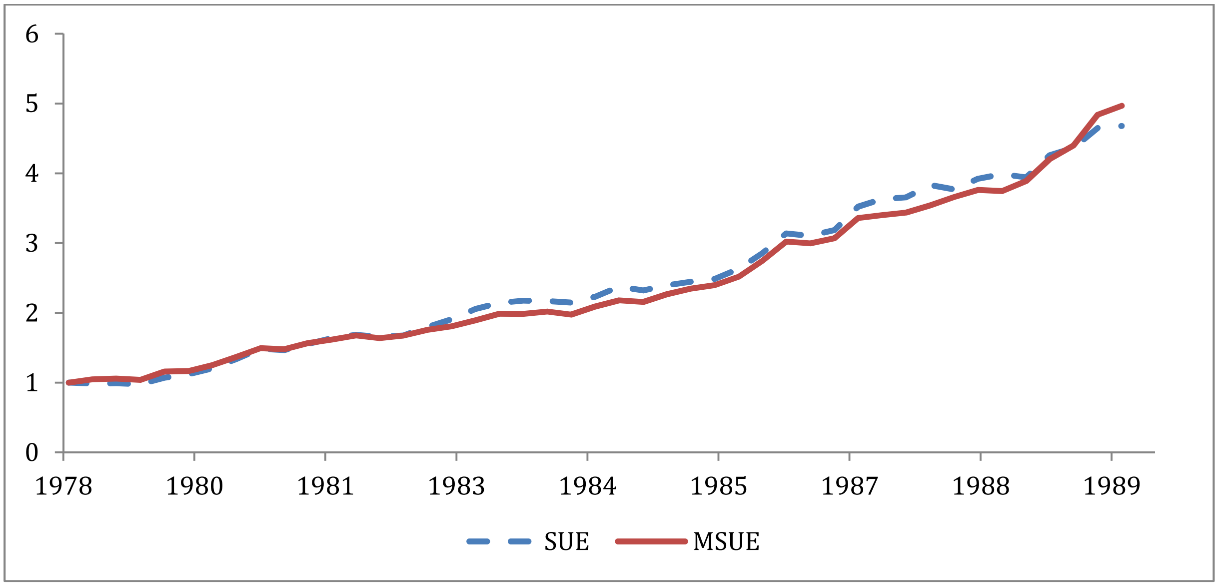
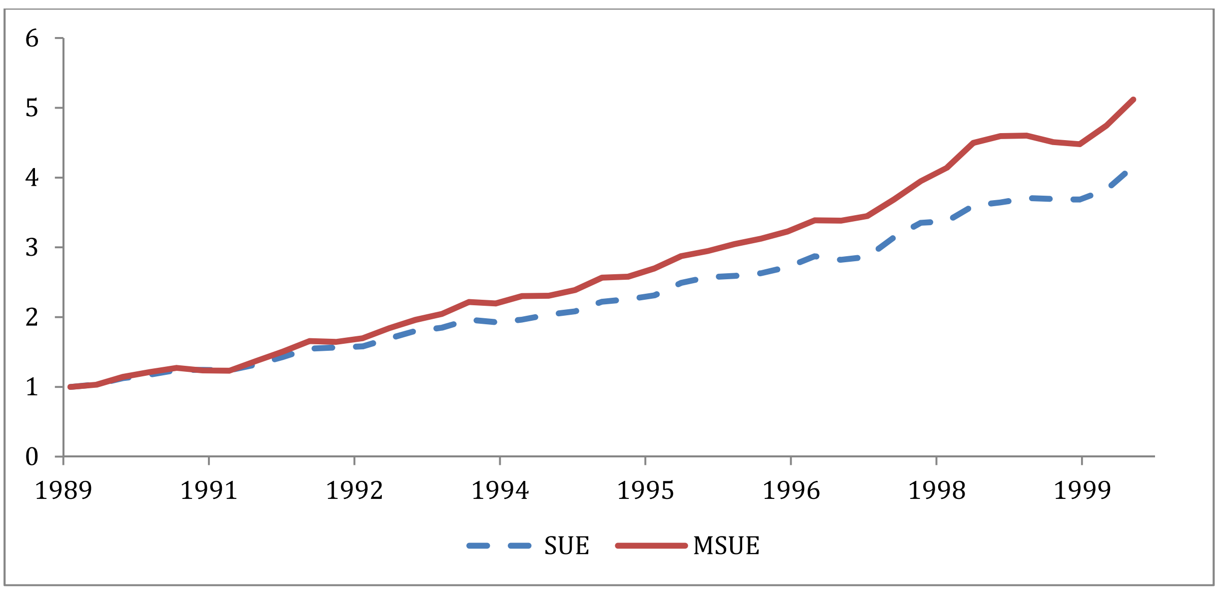
Figure 1 Comparison of hedge returns on *MSUE* and *SUE* strategies.

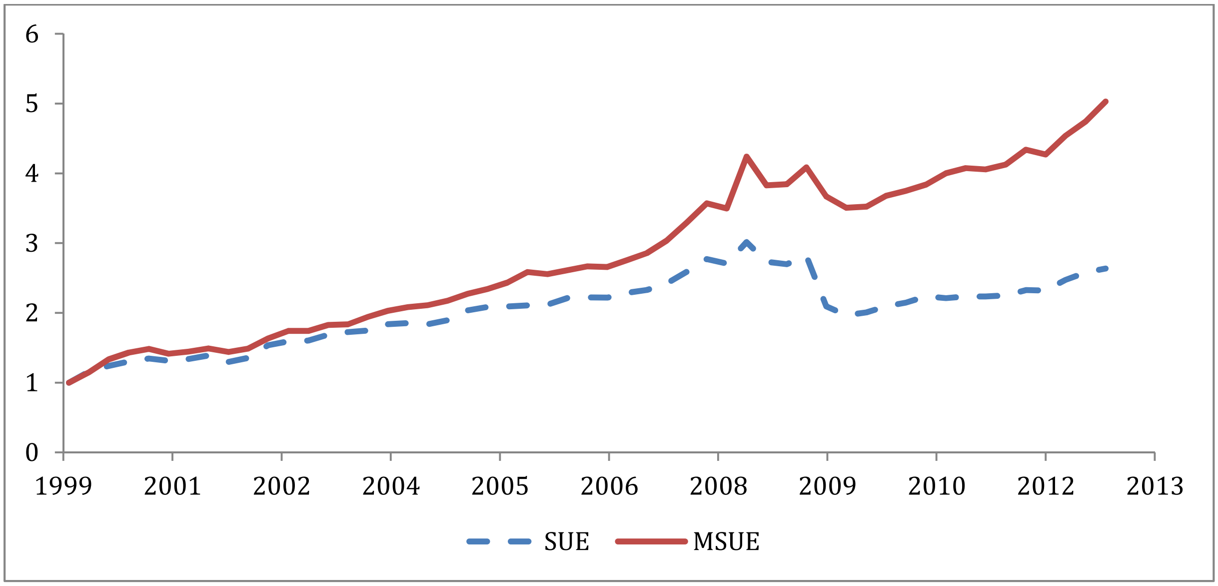
Panel A 1979-1989



Panel B 1990-1999



Panel C 2000-2012



Panel D 1979-2012

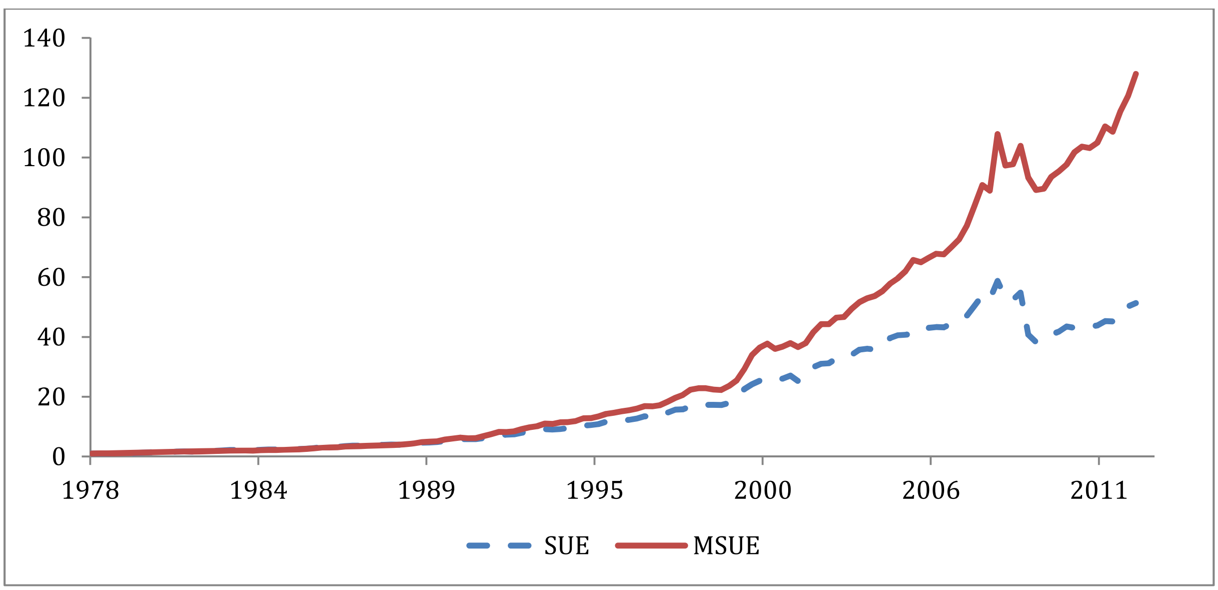


Figure 1 plots the value of a dollar invested at the beginning of three successive sub-periods (Panels A-C) and the full sample (Panel D) in *SUE* (dashed blue line) and *MSUE* (solid red line) hedge portfolios. At the end of each calendar quarter, firms are sorted into deciles based on the value of the sorting variable (*SUE* or *MSUE*). We then form zero-investment hedge portfolios by going long (short) in the highest (lowest) decile of *SUE* and *MSUE*, and we calculate size-adjusted buy-and-hold equal-weighted returns for each portfolio (following the methodology described in Barber et al. (1999)) over the three months subsequent to the portfolio formation date. *MSUE* is standardized unexpected operating profit, calculated as quarterly operating profit per share minus expected operating profit, scaled by the standard deviation of quarterly operating profit growth over the previous eight quarters. Operating profit is defined as revenue minus cost of goods sold and selling, general and administrative expense, as in Ball et al. (2015). Expected operating profit follows a seasonal random walk with drift. The drift term is the average of quarterly operating profit growth over the previous eight quarters. *SUE* is standardized unexpected earnings, calculated as quarterly earnings per share minus expected earnings per share scaled by the standard deviation of quarterly earnings growth over the previous eight quarters, as in Jegadeesh and Livnat (2006). Expected earnings are assumed to follow a seasonal random walk with drift. The drift term is the average of quarterly earnings growth over the previous eight quarters.

Figure 2 Trailing five-year Sharpe ratios for *SUE* and *MSUE* hedge portfolios.

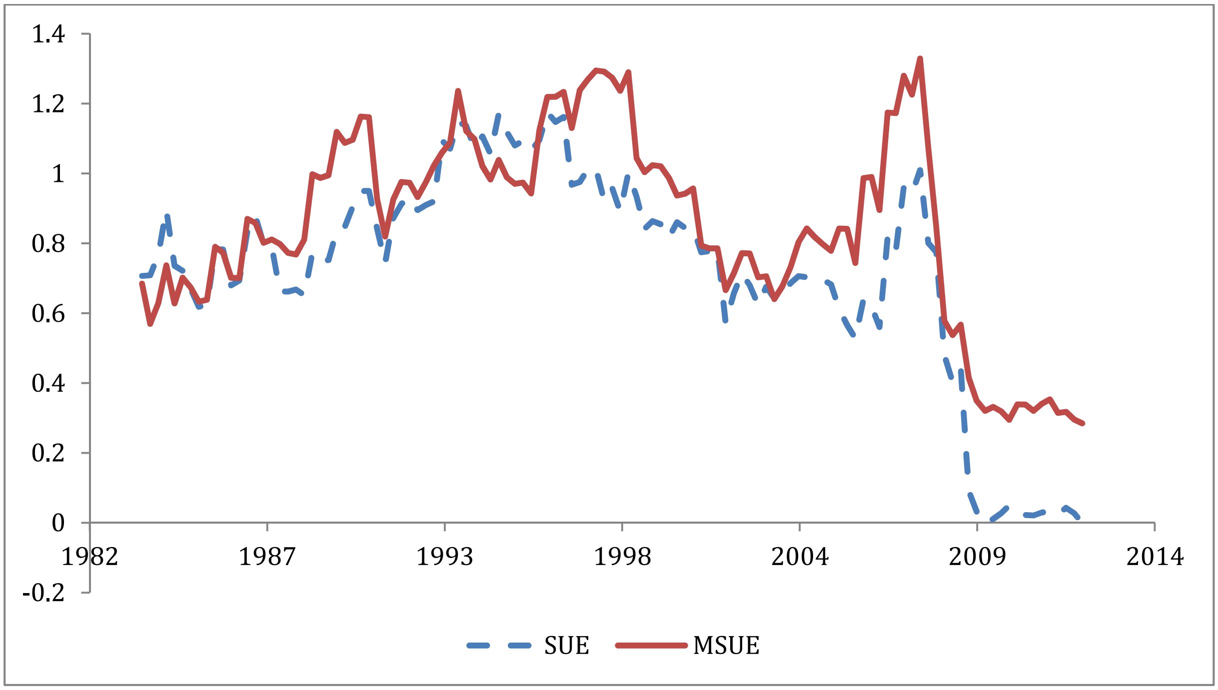
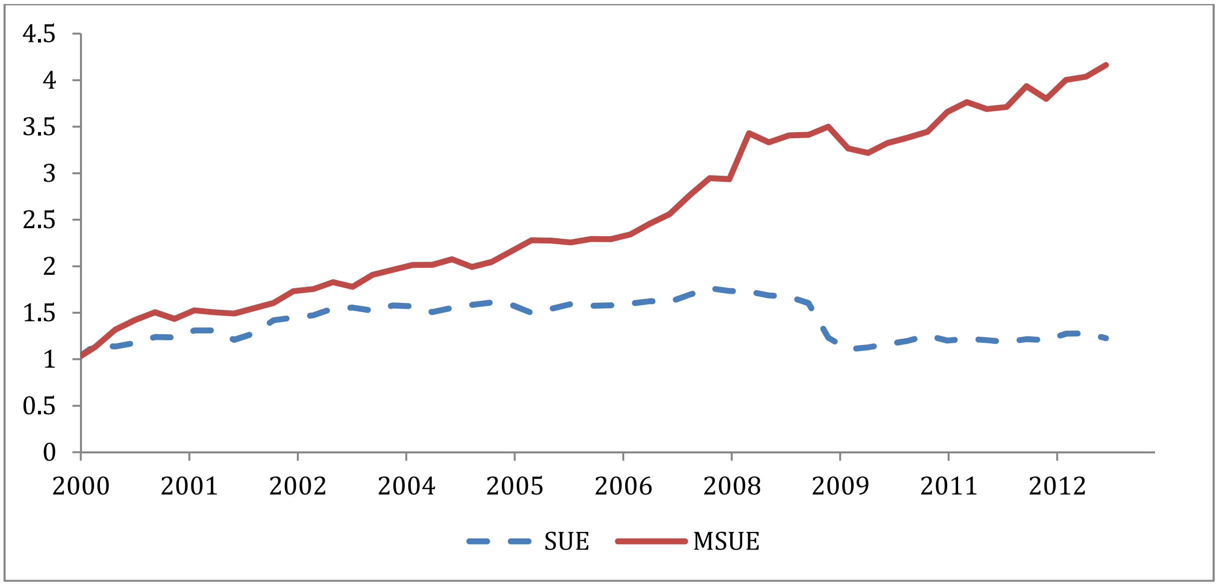


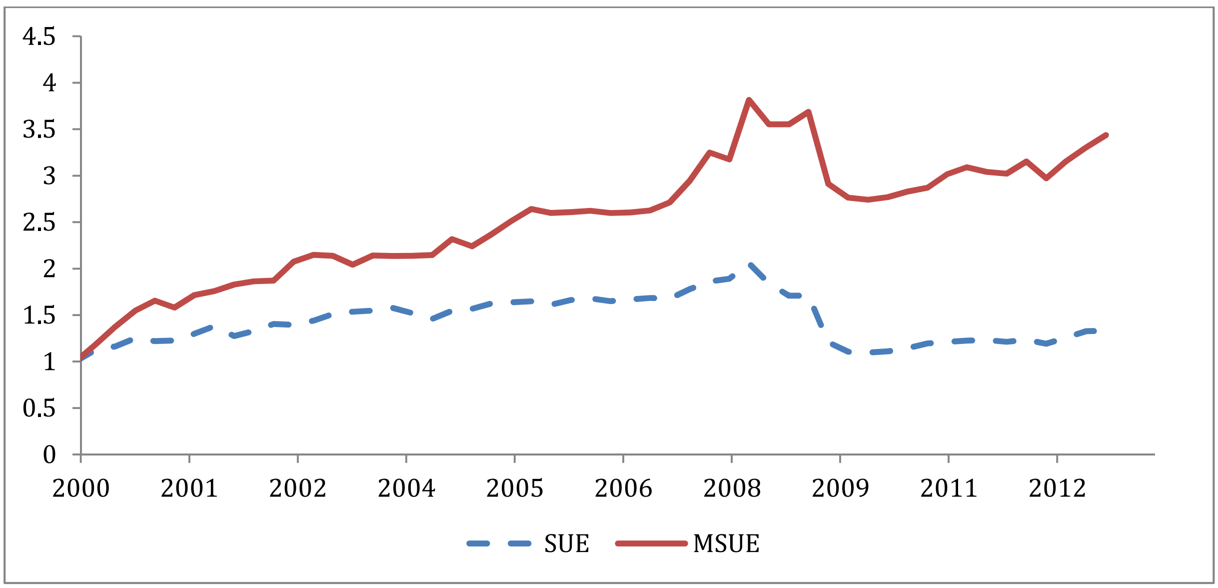
Figure 2 plots trailing five-year Sharpe ratios for *SUE* (dashed blue line) and *MSUE* (solid red line) hedge portfolios. At the end of each calendar quarter, firms are sorted into deciles based on the value of the sorting variable (*SUE* or *MSUE*). We then form zero-investment hedge portfolios by going long (short) in the highest (lowest) decile of *SUE* and *MSUE*, and we calculate size-adjusted buy-and-hold equal-weighted returns for each portfolio (following the methodology described in Barber et al. (1999)) over the three months subsequent to the portfolio formation date. *MSUE* is standardized unexpected operating profit, calculated as quarterly operating profit per share minus expected operating profit, scaled by the standard deviation of quarterly operating profit growth over the previous eight quarters. Operating profit is defined as revenue minus cost of goods sold and selling, general and administrative expense, as in Ball et al. (2015). Expected operating profit follows a seasonal random walk with drift. The drift term is the average of quarterly operating profit growth over the previous eight quarters. *SUE* is standardized unexpected earnings, calculated as quarterly earnings per share minus expected earnings per share scaled by the standard deviation of quarterly earnings growth over the previous eight quarters, as in Jegadeesh and Livnat (2006). Expected earnings are assumed to follow a seasonal random walk with drift. The drift term is the average of quarterly earnings growth over the previous eight quarters.

Figure 3 Comparison of mismatched subsample hedge returns of *MSUE* and *SUE* strategies from 2000-2012.

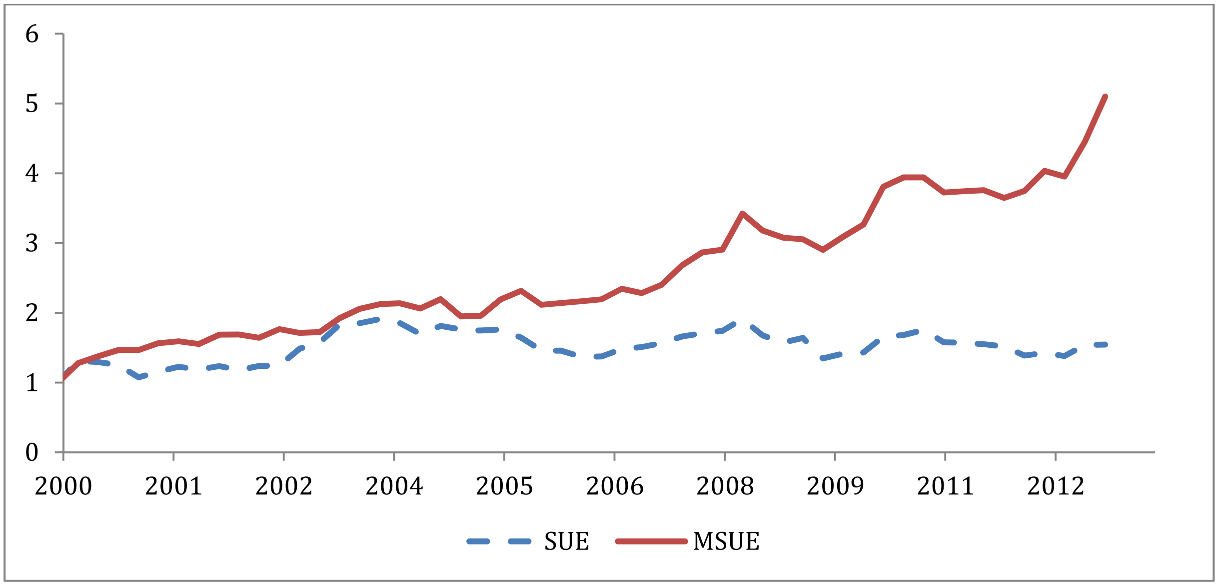
Panel A: Non-overlapping subsample



Panel B: Special items subsample



Panel C: Loss subsample



Panel D: 4th quarter subsample

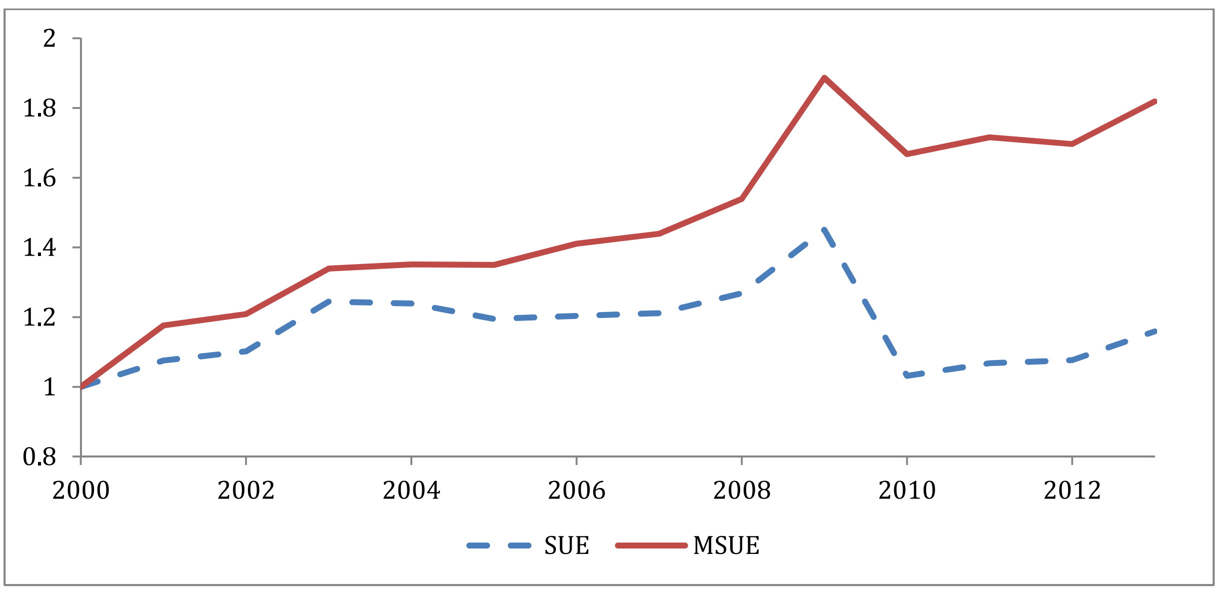


Figure 3 plots excess returns to *SUE* (dashed blue line) and *MSUE* (solid red line) hedge portfolios for four "mismatched" subsamples over the 2000-2012 sub-period. The subsample in Panel A comprises all firm-quarters excluding those with identical extreme calendar quarter decile rankings for *SUE* and *MSUE*. The subsample in Panel B comprises all firm-quarters that report special items (as identified by Compustat). The subsample in Panel C comprises all firm-quarters that report negative income before extraordinary items. The subsample in Panel D comprises all fourth fiscal quarter observations. At the end of each calendar quarter, firms are sorted into deciles based on the value of the sorting variable (*SUE* or *MSUE*). We then form zero-investment hedge portfolios by going long (short) in the highest (lowest) decile of *SUE* and *MSUE*, and we calculate size-adjusted buy-and-hold equal-weighted returns for each portfolio (following the methodology described in Barber et al. (1999)) over the three months subsequent to the portfolio formation date. *MSUE* is standardized unexpected operating profit, calculated as quarterly operating profit per share minus expected operating profit, scaled by the standard deviation of quarterly operating profit growth over the previous eight quarters. Operating profit is defined as revenue minus cost of goods sold and selling, general and administrative expense, as in Ball et al. (2015). Expected operating profit follows a seasonal random walk with drift. The drift term is the average of quarterly operating profit growth over the previous eight quarters. *SUE* is standardized unexpected earnings, calculated as quarterly earnings per share minus expected earnings per share scaled by the standard deviation of quarterly earnings growth over the previous eight quarters, as in Jegadeesh and Livnat (2006). Expected earnings are assumed to follow a seasonal random walk with drift. The drift term is the average of quarterly earnings growth over the previous eight quarters.

Table 1 Sample size by year

Year	# Obs	% of sample
1979	5,396	1.39
1980	6,058	1.56
1981	5,991	1.54
1982	5,875	1.51
1983	5,873	1.51
1984	6,715	1.73
1985	9,066	2.34
1986	9,569	2.46
1987	9,515	2.45
1988	9,110	2.35
1989	9,251	2.38
1990	9,314	2.40
1991	9,457	2.44
1992	10,099	2.60
1993	10,829	2.79
1994	11,668	3.01
1995	12,217	3.15
1996	13,190	3.40
1997	15,106	3.89
1998	15,846	4.08
1999	15,869	4.09
2000	15,655	4.03
2001	14,248	3.67
2002	14,008	3.61
2003	14,190	3.65
2004	14,462	3.72
2005	14,234	3.67
2006	14,248	3.67
2007	14,277	3.68
2008	13,700	3.53
2009	12,999	3.35
2010	13,654	3.52
2011	13,469	3.47
2012	13,091	3.37
All Year	388,249	100

We draw our sample from the CRSP monthly returns database and the Compustat quarterly database for fiscal years spanning 1979 through 2012. We require firms to have stock prices exceeding $1 per share. Following Ball et al. (2014), we require each firm-quarter to have non-missing Compustat data necessary to compute *MSUE* and *SUE* to ensure a consistent sample across our two classes of news measures. *MSUE* is standardized unexpected operating profit, calculated as quarterly operating profit per share minus expected operating profit, scaled by the standard deviation of quarterly operating profit growth over the previous eight quarters. Operating profit is defined as revenue minus cost of goods sold and selling, general and administrative expense, as in Ball et al. (2015). Expected operating profit follows a seasonal random walk with drift. The drift term is the average of quarterly operating profit growth over the previous eight quarters. *SUE* is standardized unexpected earnings, calculated as quarterly earnings per share minus expected earnings per share scaled by the standard deviation of quarterly earnings growth over the previous eight quarters, as in Jegadeesh and Livnat (2006). Expected earnings are assumed to follow a seasonal random walk with drift. The drift term is the average of quarterly earnings growth over the previous eight quarters.

Table 2 Descriptive statistics
Panel A: Descriptive statistics for the variables in the regression

Variable	Mean	Std	25th Pctl	50th Pctl	75th Pctl
MSUE	-0.117	4.095	-2.234	0.037	2.257
SUE	-0.440	5.118	-1.991	-0.046	1.815
ADJ_RET	0.004	0.267	-0.131	-0.014	0.107
SIZE	5.262	2.072	3.742	5.134	6.654
BM	0.704	0.587	0.335	0.569	0.912
MOM	0.089	0.415	-0.145	0.036	0.243

Panel B: Overlap between *MSUE* and *SUE* for each portfolio by sub-period

Decile	1979-1989	1990-1999	2000-2012
1	57.95%	55.22%	51.66%
2	35.85%	35.44%	34.15%
3	28.73%	28.52%	26.91%
4	25.22%	25.16%	24.55%
5	23.50%	24.56%	22.29%
6	24.82%	24.39%	21.81%
7	25.05%	23.39%	21.80%
8	27.66%	26.72%	24.73%
9	34.49%	33.93%	31.65%
10	52.96%	50.69%	47.58%

Panel C: Correlation between different surprises (SUE and MSUE) and future size-adjusted stock returns (*ADJ_RET*) by sub-period.

Variable	1979-1989	1990-1999	2000-2012
MSUE	0.060	0.039	0.031
SUE	0.056	0.031	0.009

MSUE is standardized unexpected operating profit, calculated as quarterly operating profit per share minus expected operating profit, scaled by the standard deviation of quarterly operating profit growth over the previous eight quarters. Operating profit is defined as revenue minus cost of goods sold and selling, general and administrative expense, as in Ball et al. (2015). Expected operating profit follows a seasonal random walk with drift. The drift term is the average of quarterly operating profit growth over the previous eight quarters. *SUE* is standardized unexpected earnings, calculated as quarterly earnings per share minus expected earnings per share scaled by the standard deviation of quarterly earnings growth over the previous eight quarters, as in Jegadeesh and Livnat (2006). Expected earnings are assumed to follow a seasonal random walk with drift. The drift term is the average of quarterly earnings growth over the previous eight quarters. *ADJ_RET* is the three-month size-adjusted buy-and-hold stock return following the methodology described in Barber et al. (1999). Our return window begins in the first month of the calendar quarter that is at least three months subsequent to fiscal quarter-end. *SIZE* is firm size, calculated as the natural log of the market capitalization as of the end of the most recent fiscal quarter for which data are available (in millions). *BM* is the book-to-market ratio, calculated as book value of equity divided by market value of equity at the end of the most recent fiscal quarter for which data are available. *MOM* is momentum, calculated as the six-month buy-and-hold stock return ending one month prior to the portfolio formation date.

Table 3 Fama-MacBeth regressions of future *MSUE* or *SUE* on current *MSUE* and *SUE* by sub-period

Panel A: Regression of $MSUE_{t+1}$ on R_MSUE_t and R_SUE_t

	1979-1989	1990-1999	2000-2012	Overall
Intercept	-2.782	-2.785	-3.043	-2.883
	(-21.45)	(-32.56)	(-22.28)	(-40.10)
R_MSUE	0.559	0.581	0.616	0.587
	(36.07)	(45.63)	(49.52)	(72.75)
R_SUE	0.035	0.021	0.018	0.025
	(3.64)	(3.08)	(3.33)	(5.72)
Adj R^2	0.174	0.181	0.211	0.190

Panel B: Regression of SUE_{t+1} on R_MSUE_t and R_SUE_t

	1979-1989	1990-1999	2000-2012	Overall
Intercept	-3.084	-3.198	-3.033	-3.098
	(-20.04)	(-28.21)	(-13.89)	(-30.30)
R_MSUE	0.191	0.178	0.230	0.202
	(16.10)	(21.55)	(19.38)	(30.31)
R_SUE	0.423	0.420	0.336	0.389
	(24.54)	(29.37)	(20.73)	(39.12)
Adj R^2	0.135	0.106	0.119	0.120

Table 3 reports results for regressions of one-quarter-ahead *MSUE* (Panel A) and one-quarter-ahead *SUE* (Panel B) on current quarter *R_MSUE* and *R_SUE*. The "*R_*" prefix denotes decile rank transformations performed each calendar quarter for our variables of interest. *MSUE* is standardized unexpected operating profit, calculated as quarterly operating profit per share minus expected operating profit, scaled by the standard deviation of quarterly operating profit growth over the previous eight quarters. Operating profit is defined as revenue minus cost of goods sold and selling, general and administrative expense, as in Ball et al. (2015). Expected operating profit follows a seasonal random walk with drift. The drift term is the average of quarterly operating profit growth over the previous eight quarters. *SUE* is standardized unexpected earnings, calculated as quarterly earnings per share minus expected earnings per share scaled by the standard deviation of quarterly earnings growth over the previous eight quarters, as in Jegadeesh and Livnat (2006). Expected earnings are assumed to follow a seasonal random walk with drift. The drift term is the average of quarterly earnings growth over the previous eight quarters.

Table 4 Future size-adjusted returns for portfolios formed based on *MSUE* and *SUE* by sub-period.

Panel A: Decile portfolio returns based on *MSUE*

Decile	1979-1989	1990-1999	2000-2012	Overall
1	-1.60%	-1.81%	-1.31%	-1.55%
2	-0.79%	-0.97%	-0.42%	-0.70%
3	-0.19%	-0.60%	-0.20%	-0.31%
4	-0.01%	-0.38%	0.28%	-0.01%
5	0.79%	-0.04%	0.51%	0.44%
6	0.73%	0.25%	0.94%	0.67%
7	0.99%	0.66%	0.97%	0.89%
8	1.40%	1.55%	0.95%	1.27%
9	1.83%	1.24%	1.23%	1.43%
10	2.17%	2.42%	1.98%	2.17%
D10-D1	3.77%	4.23%	3.29%	3.72%
	(6.97)	(7.16)	(4.41)	(9.90)

Panel B: Decile portfolio returns based on *SUE*

Decile	1979-1989	1990-1999	2000-2012	Overall
1	-1.46%	-1.61%	-0.64%	-1.19%
2	-1.30%	-1.33%	-0.58%	-1.03%
3	0.03%	-0.98%	-0.31%	-0.40%
4	0.13%	-0.43%	0.28%	0.02%
5	0.62%	0.17%	0.63%	0.49%
6	1.13%	0.19%	0.65%	0.67%
7	1.22%	1.02%	1.20%	1.15%
8	1.34%	1.39%	1.15%	1.28%
9	1.43%	1.84%	1.12%	1.43%
10	2.18%	2.07%	1.42%	1.86%
D10-D1	3.64%	3.68%	2.06%	3.05%
	(6.18)	(7.28)	(2.54)	(7.69)

Table 4 reports three-month buy-and-hold size-adjusted stock returns to portfolios formed on deciles of *MSUE* and *SUE* for the full sample and by sub-period. At the end of each calendar quarter, firms are sorted into deciles based on the value of the sorting variable (*SUE* or *MSUE*). Size-adjusted buy-and-hold returns for each stock are calculated over the three months subsequent to the portfolio formation date, and an equal-weighted mean return is computed for each portfolio. We then form a zero-investment hedge portfolio for each variable by going long (short) in the highest (lowest) decile portfolio, and we compute

Fama-MacBeth t-statistics based on the time-series distribution of the mean hedge portfolio returns. *MSUE* is standardized unexpected operating profit, calculated as quarterly operating profit per share minus expected operating profit, scaled by the standard deviation of quarterly operating profit growth over the previous eight quarters. Operating profit is defined as revenue minus cost of goods sold and selling, general and administrative expense, as in Ball et al. (2015). Expected operating profit follows a seasonal random walk with drift. The drift term is the average of quarterly operating profit growth over the previous eight quarters. *SUE* is standardized unexpected earnings, calculated as quarterly earnings per share minus expected earnings per share scaled by the standard deviation of quarterly earnings growth over the previous eight quarters, as in Jegadeesh and Livnat (2006). Expected earnings are assumed to follow a seasonal random walk with drift. The drift term is the average of quarterly earnings growth over the previous eight quarters.

Table 5 Fama-MacBeth regressions of future *MSUE* or *SUE* on current *MSUE* and *SUE* by sub-period for "mismatched" subsamples

Panel A: Non-overlapping subsamples
Top Panel: Regression of $MSUE_{t+1}$ on R_MSUE_t and R_SUE_t
Bottom Panel: Regression of SUE_{t+1} on R_MSUE_t and R_SUE_t

	1979-1989	1990-1999	2000-2012	Overall
Intercept	-2.740	-2.771	-3.022	-2.857
	(-20.48)	(-31.14)	(-21.34)	(-38.39)
R_MSUE	0.556	0.581	0.615	0.586
	(37.44)	(47.76)	(49.50)	(74.31)
R_SUE	0.032	0.022	0.017	0.023
	(3.20)	(2.90)	(3.02)	(5.20)
Adj R^2	0.144	0.156	0.183	0.162

	1979-1989	1990-1999	2000-2012	Overall
Intercept	-3.022	-3.082	-2.927	-3.003
	(-18.90)	(-28.17)	(12.76)	(-28.27)
R_MSUE	0.185	0.169	0.221	0.194
	(14.85)	(20.50)	(16.98)	(27.48)
R_SUE	0.418	0.410	0.326	0.381
	(25.17)	(30.27)	(20.63)	(39.31)
Adj R^2	0.105	0.082	0.092	0.093

Panel B: Special item subsamples

Top Panel: Regression of $MSUE_{t+1}$ on R_MSUE_t and R_SUE_t

Bottom Panel: Regression of SUE_{t+1} on R_MSUE_t and R_SUE_t

	1979-1989	1990-1999	2000-2012	Overall
Intercept	-2.076	-2.207	-2.885	-2.424
	(-13.04)	(-20.03)	(-20.30)	(-27.89)
R_MSUE	0.523	0.517	0.610	0.555
	(29.96)	(52.42)	(43.01)	(52.92)
R_SUE	-0.032	-0.015	0.012	-0.010
	(-1.84)	(-1.47)	(1.60)	(-1.45)
Adj R^2	0.146	0.151	0.216	0.175

	1979-1989	1990-1999	2000-2012	Overall
Intercept	-2.155	-1.921	-2.582	-2.250
	(-11.92)	(-14.89)	(-10.35)	(-18.78)
R_MSUE	0.343	0.271	0.257	0.289
	(13.04)	(17.36)	(20.64)	(25.83)
R_SUE	0.105	0.122	0.238	0.161
	(3.88)	(7.65)	(14.41)	(12.55)
Adj R^2	0.078	0.054	0.092	0.076

Panel C: Loss subsamples

Top Panel: Regression of $MSUE_{t+1}$ on R_MSUE_t and R_SUE_t

Bottom Panel: Regression of SUE_{t+1} on R_MSUE_t and R_SUE_t

	1979-1989	1990-1999	2000-2012	Overall
Intercept	-1.849	-1.954	-2.409	-2.094
	(-14.46)	(-22.26)	(-20.02)	(-29.92)
R_MSUE	0.550	0.532	0.583	0.557
	(23.62)	(28.37)	(37.94)	(50.21)
R_SUE	-0.044	-0.033	0.002	-0.023
	(-2.40)	(-2.84)	(0.50)	(-2.83)
Adj R^2	0.140	0.140	0.198	0.162

	1979-1989	1990-1999	2000-2012	Overall
Intercept	-2.238	-2.111	-2.258	-2.208
	(-13.94)	(-17.73)	(-13.21)	(-24.53)
R_MSUE	0.304	0.248	0.255	0.269
	(9.51)	(16.99)	(19.27)	(21.74)
R_SUE	0.224	0.222	0.240	0.229
	(6.89)	(11.54)	(16.01)	(17.43)
Adj R^2	0.090	0.070	0.090	0.084

Panel D: Fourth quarter subsamples

Top Panel: Regression of $MSUE_{t+1}$ on R_MSUE_t and R_SUE_t

Bottom Panel: Regression of SUE_{t+1} on R_MSUE_t and R_SUE_t

	1979-1989	1990-1999	2000-2012	Overall
Intercept	-1.765	-1.758	-2.410	-2.009
	(-6.10)	(-11.60)	(-9.75)	(-13.70)
R_MSUE	0.337	0.343	0.472	0.390
	(11.50)	(24.34)	(33.46)	(24.59)
R_SUE	0.050	0.012	0.018	0.027
	(2.04)	(0.74)	(2.29)	(2.71)
Adj R^2	0.088	0.075	0.136	0.103

	1979-1989	1990-1999	2000-2012	Overall
Intercept	-2.078	-1.792	-2.057	-1.986
	(-6.14)	(-12.06)	(-10.34)	(-14.41)
R_MSUE	0.241	0.164	0.259	0.225
	(13.18)	(10.68)	(15.79)	(19.18)
R_SUE	0.172	0.149	0.133	0.150
	(7.89)	(11.05)	(6.83)	(13.60)
Adj R^2	0.081	0.045	0.083	0.071

Table 5 reports results for regressions of one-quarter-ahead *MSUE* (top panels) and one-quarter-ahead *SUE* (bottom panels) on current quarter *R_MSUE* and *R_SUE* for four "mismatched" subsamples. The subsample in Panel A comprises all firm-quarters excluding those with identical extreme calendar quarter decile rankings for *SUE* and *MSUE*. The subsample in Panel B comprises all firm-quarters that report special items (as identified by Compustat). The subsample in Panel C comprises all firm-quarters that report negative income before extraordinary items. The subsample in Panel D comprises all fourth fiscal quarter observations. The "*R_*" prefix denotes decile rank transformations performed each calendar quarter for our variables of interest. *MSUE* is standardized unexpected operating profit, calculated as quarterly operating profit per share minus expected operating profit, scaled by the standard deviation of quarterly operating profit growth over the previous eight quarters. Operating profit is defined as revenue minus cost of goods sold and selling, general and administrative expense, as in Ball et al. (2015). Expected operating profit follows a seasonal random walk with drift. The drift term is the average of quarterly operating profit growth over the previous eight quarters. *SUE* is standardized unexpected earnings, calculated as quarterly earnings per share minus expected earnings per share scaled by the standard deviation of quarterly earnings growth over the previous eight quarters, as in Jegadeesh and Livnat (2006). Expected earnings are assumed to follow a seasonal random walk with drift. The drift term is the average of quarterly earnings growth over the previous eight quarters.

Table 6 Future size-adjusted returns for portfolios formed based on *MSUE* and *SUE* by sub-period for "mismatched" subsamples

Panel A: Non-overlapping subsamples

	1979-1989	1990-1999	2000-2012	Overall
R_MSUE	2.72%	2.87%	2.88%	2.83%
	(4.89)	(5.43)	(4.45)	(8.29)
R_SUE	2.50%	1.63%	0.54%	1.50%
	(4.04)	(3.96)	(0.73)	(4.01)

Panel B: Special item subsamples

	1979-1989	1990-1999	2000-2012	Overall
R_MSUE	3.98%	3.48%	2.61%	3.31%
	(2.92)	(3.90)	(2.86)	(5.35)
R_SUE	1.77%	1.45%	0.76%	1.29%
	(2.00)	(2.07)	(0.90)	(2.71)

Panel C: Loss subsamples

	1979-1989	1990-1999	2000-2012	Overall
R_MSUE	4.96%	3.29%	3.42%	3.88%
	(3.22)	(3.32)	(3.45)	(5.63)
R_SUE	-0.18%	1.03%	1.18%	0.70%
	(-0.12)	(1.18)	(1.00)	(0.99)

Panel D: Fourth quarter subsamples

	1979-1989	1990-1999	2000-2012	Overall
R_MSUE	5.03%	3.03%	5.03%	4.44%
	(5.08)	(1.98)	(2.11)	(4.24)
R_SUE	4.55%	3.09%	1.73%	3.04%
	(6.19)	(2.46)	(0.59)	(2.56)

Table 6 reports three-month buy-and-hold size-adjusted stock returns to portfolios formed on deciles of *MSUE* and *SUE* for four "mismatched" subsamples. The subsample in Panel A comprises all firm-quarters excluding those with identical extreme calendar quarter decile rankings for *SUE* and *MSUE*. The subsample in Panel B comprises all firm-quarters that report special items (as identified by Compustat). The subsample in Panel C comprises all firm-quarters that report negative income before extraordinary items. The subsample in Panel D comprises all fourth fiscal quarter observations. At the end of each calendar quarter, firms are sorted into deciles based on the value of the sorting variable (*SUE* or *MSUE*). Size-adjusted buy-and-hold returns for each stock are calculated over the three months subsequent to the portfolio formation date, and an equal-weighted mean return is computed for each portfolio. We then form a zero-investment hedge portfolio for each variable by going long (short) in the highest (lowest) decile portfolio, and we compute Fama-MacBeth t-statistics based on the time-series distribution of the mean hedge portfolio returns. *MSUE* is standardized unexpected operating profit, calculated as quarterly operating profit per share minus expected operating profit, scaled by the standard deviation of quarterly operating profit growth over the previous eight quarters. Operating profit is defined as revenue minus cost of goods sold and selling, general and administrative expense, as in Ball et al. (2015). Expected operating profit follows a seasonal random walk with drift. The drift term is the average of quarterly operating profit growth over the previous eight quarters. *SUE* is standardized unexpected earnings, calculated as quarterly earnings per share minus expected earnings per share scaled by the standard deviation of quarterly earnings growth over the previous eight quarters, as in Jegadeesh and Livnat (2006). Expected earnings are assumed to follow a seasonal random walk with drift. The drift term is the average of quarterly earnings growth over the previous eight quarters.

Table 7 Changes in the proportion of shares held by transient institutional investors responding to matching information in earnings news

Panel A: D = 1 if *RSUE* and *RMSUE* are both in top and bottom decile

	1979-1989	1990-1999	2000-2012	Overall
Intercept	-0.6008	-1.3694	-1.1798	-1.0689
	(-10.64)	(-22.25)	(-13.47)	(-21.03)
*D*R_SUE*	0.0185	0.0063	0.0121	0.0122
	(1.93)	(0.75)	(1.42)	(2.40)
R_SUE	0.0118	0.0194	0.0118	0.0141
	(2.18)	(3.24)	(2.24)	(4.42)
D	-0.0026	-0.0214	0.0004	0.0090
	(-0.06)	(-0.34)	(0.75)	(0.29)
R_SIZE	-0.0139	-0.0303	-0.0075	-0.0164
	(-1.56)	(-3.40)	(-0.51)	(-2.34)
R_BM	0.0176	0.0138	0.0219	0.0182
	(3.18)	(2.35)	(3.88)	(5.50)
R_MOM	0.1482	0.3112	0.2682	0.2464
	(18.76)	(52.87)	(30.98)	(33.64)
Adj R^2	0.047	0.104	0.072	0.075

Panel B: D = 1 if special items equals zero

	1979-1989	1990-1999	2000-2012	Overall
Intercept	-0.6208	-1.3618	-1.1745	-1.0703
	(-9.30)	(-22.78)	(13.14)	(-20.74)
*D*R_SUE*	-0.0016	0.0064	0.0091	0.0052
	(-0.18)	(0.81)	(1.09)	(1.06)
R_SUE	0.0168	0.0191	0.0116	0.0154
	(2.39)	(3.12)	(2.04)	(4.31)
D	0.0473	-0.0636	-0.0216	-0.0144
	(1.05)	(-1.23)	(-0.45)	(-0.51)
R_SIZE	-0.0140	-0.0302	-0.0071	-0.0162
	(-1.59)	(-3.38)	(-0.48)	(-2.32)
R_RBM	0.0172	0.0139	0.0221	0.0181
	(3.07)	(2.37)	(3.88)	(5.45)
R_MOM	0.1486	0.3109	0.2681	0.2463
	(18.65)	(53.02)	(30.90)	(33.68)
Adj R^2	0.048	0.104	0.072	0.075

Table 7 reports results for tests of whether transient institutional investors use matching information to extract stronger SUE signals around earnings announcement (adapted from the model in Ke and

Ramalingegowda (2006)). In Panel A, we use an indicator variable *D* that equals 1 when *SUE* and *MSUE* are in the same extreme decile, zero otherwise. In Panel B, we use an indicator variable *D* that equals 1 when *SUE* is in an extreme decile and no special items are reported, zero otherwise. The dependent variable is Δ*Transient*, which is the change in the percentage of shares owned by transient institutions over the calendar quarter in which earnings are announced. The "*R_*" prefix denotes decile rank transformations performed each calendar quarter for our variables of interest. *MSUE* is standardized unexpected operating profit, calculated as quarterly operating profit per share minus expected operating profit, scaled by the standard deviation of quarterly operating profit growth over the previous eight quarters. Operating profit is defined as revenue minus cost of goods sold and selling, general and administrative expense, as in Ball et al. (2015). Expected operating profit follows a seasonal random walk with drift. The drift term is the average of quarterly operating profit growth over the previous eight quarters. *SUE* is standardized unexpected earnings, calculated as quarterly earnings per share minus expected earnings per share scaled by the standard deviation of quarterly earnings growth over the previous eight quarters, as in Jegadeesh and Livnat (2006). Expected earnings are assumed to follow a seasonal random walk with drift. The drift term is the average of quarterly earnings growth over the previous eight quarters. *SIZE* is firm size, calculated as the natural log of the market capitalization as of the end of the most recent fiscal quarter for which data are available (in millions). *BM* is the book-to-market ratio, calculated as book value of equity divided by market value of equity at the end of the most recent fiscal quarter for which data are available. *MOM* is momentum, calculated as the six-month buy-and-hold stock return ending one month prior to the portfolio formation date.

Table 8 Future size-adjusted hedge returns based on levels of operating profit (OP) and earnings (IB) by sub-period

	1979-1989	1990-1999	2000-2012	Overall
OP	5.45%	4.22%	4.39%	4.68%
	(6.53)	(3.10)	(3.00)	(6.37)
IB	5.00%	3.87%	2.79%	3.82%
	(5.69)	(3.13)	(1.95)	(5.34)

Table 8 reports three-month buy-and-hold size-adjusted stock returns to portfolios formed on deciles of *OP* and *IB* for the full sample and by sub-period. At the end of each calendar quarter, firms are sorted into deciles based on the value of the sorting variable (*OP* or *IB*). Size-adjusted buy-and-hold returns for each stock are calculated over the three months subsequent to the portfolio formation date, and an equal-weighted mean return is computed for each portfolio. We then form a zero-investment hedge portfolio for each variable by going long (short) in the highest (lowest) decile portfolio, and we compute Fama-MacBeth t-statistics based on the time-series distribution of the mean hedge portfolio returns. *OP* is the level of operating profit, calculated as quarterly operating profit scaled by average total assets. Operating profit is defined as revenue minus cost of goods sold and selling, general and administrative expense, as in Ball et al. (2015). *IB* is the level of earnings, calculated as quarterly earnings before extraordinary items scaled by average total assets.

Table 9 Future size-adjusted hedge returns for portfolios formed based on MSUE and SUE by different subsamples by each decade

Low Volatility

	1979-1989	1990-1999	2000-2012	Overall
MSUE	3.41%	3.63%	2.77%	3.23%
	(5.82)	(5.63)	(4.28)	(8.88)
SUE	3.93%	3.08%	2.27%	3.05%
	(6.19)	(4.96)	(3.07)	(7.69)

Medium Volatility

	1979-1989	1990-1999	2000-2012	Overall
MSUE	4.14%	4.08%	2.53%	3.51%
	(7.08)	(4.94)	(2.80)	(7.56)
SUE	3.97%	3.69%	1.51%	2.94%
	(6.13)	(5.64)	(1.46)	(5.97)

High Volatility

	1979-1989	1990-1999	2000-2012	Overall
MSUE	4.28%	4.65%	3.98%	4.28%
	(4.83)	(5.21)	(3.60)	(7.49)
SUE	3.15%	4.45%	1.06%	2.74%
	(3.24)	(4.85)	(0.90)	(4.41)

Table 9 reports three-month buy-and-hold size-adjusted stock returns to portfolios formed on deciles of *MSUE* and *SUE* by ex ante earning volatility tercile group for the full sample and by sub-period. Firms are sorted into tercile groups each calendar quarter based on whether ex ante earnings volatility is low, medium or high. Ex ante earnings volatility is calculated as the variance of income before extraordinary items scaled by average assets over the previous eight quarters, following Cao and Narayanamoorthy (2012). At the end of each calendar quarter, firms are sorted into deciles based on the value of the sorting variable (*SUE* or *MSUE*). Size-adjusted buy-and-hold returns for each stock are calculated over the three months subsequent to the portfolio formation date, and an equal-weighted mean return is computed for each portfolio. We then form a zero-investment hedge portfolio for each variable by going long (short) in the highest (lowest) decile portfolio, and we compute Fama-MacBeth t-statistics based on the time-series distribution of the mean hedge portfolio returns. *MSUE* is standardized unexpected operating profit, calculated as quarterly operating profit per share minus expected operating profit, scaled by the standard deviation of quarterly operating profit growth over the previous eight quarters. Operating profit is defined as revenue minus cost of goods sold and selling, general and administrative expense, as in Ball et al. (2015). Expected operating profit follows a seasonal random walk with drift. The drift term is the average of quarterly operating profit growth over the previous eight quarters. *SUE* is standardized unexpected earnings, calculated as quarterly earnings per share minus expected earnings per share scaled by the standard deviation of quarterly earnings growth over the previous eight quarters, as in Jegadeesh and Livnat (2006). Expected earnings are assumed to follow a seasonal random walk with drift. The drift term is the average of quarterly earnings growth over the previous eight quarters.

Table 10 Fama-MacBeth regressions of future returns on *MSUE* and *SUE* and control variables by sub-period

	1979-1989	1990-1999	2000-2012	Overall
Intercept	0.012	0.002	0.004	0.006
	(0.51)	(0.09)	(0.16)	(0.42)
R_MSUE	0.016	0.016	0.021	0.179
	(4.32)	(3.88)	(3.27)	(6.07)
R_SUE	0.017	0.020	0.008	0.015
	(4.15)	(5.61)	(1.99)	(6.21)
R_SIZE	-0.001	-0.003	-0.010	-0.005
	(-0.04)	(-0.20)	(1.95)	(-0.57)
R_BM	0.016	0.012	0.023	0.017
	(1.52)	(0.76)	(-0.63)	(2.41)
R_MOM	0.020	0.031	0.005	0.017
	(2.12)	(2.74)	(0.31)	(2.31)
Adj R^2	0.044	0.026	0.031	0.034

Table 10 reports results for Fama-MacBeth regressions of three-month buy-and-hold raw stock returns on *MSUE* and *SUE* and control variables for the full sample and by sub-period. The "*R_*" prefix denotes decile rank transformations performed each calendar quarter for our variables of interest. *MSUE* is standardized unexpected operating profit, calculated as quarterly operating profit per share minus expected operating profit, scaled by the standard deviation of quarterly operating profit growth over the previous eight quarters. Operating profit is defined as revenue minus cost of goods sold and selling, general and administrative expense, as in Ball et al. (2015). Expected operating profit follows a seasonal random walk with drift. The drift term is the average of quarterly operating profit growth over the previous eight quarters. *SUE* is standardized unexpected earnings, calculated as quarterly earnings per share minus expected earnings per share scaled by the standard deviation of quarterly earnings growth over the previous eight quarters, as in Jegadeesh and Livnat (2006). Expected earnings are assumed to follow a seasonal random walk with drift. The drift term is the average of quarterly earnings growth over the previous eight quarters. *SIZE* is firm size, calculated as the natural log of the market capitalization as of the end of the most recent fiscal quarter for which data are available (in millions). *BM* is the book-to-market ratio, calculated as book value of equity divided by market value of equity at the end of the most recent fiscal quarter for which data are available. *MOM* is momentum, calculated as the six-month buy-and-hold stock return ending one month prior to the portfolio formation date.

Table 11 Other robustness checks

Panel A: MSUE based on gross profit (sales minus cost of goods sold)

	1979-1989	1990-1999	2000-2012	Overall
MSUE	4.01%	4.11%	3.03%	3.66%
	(6.37)	(7.71)	(4.13)	(9.64)
SUE	3.64%	3.68%	2.06%	3.05%
	(6.18)	(7.28)	(2.54)	(7.69)

Panel B: Scaled by total assets

	1979-1989	1990-1999	2000-2012	Overall
MSUE	5.16%	4.57%	3.32%	4.28%
	(6.57)	(6.62)	(4.22)	(9.62)
SUE	4.84%	4.17%	2.07%	3.58%
	(6.84)	(5.94)	(2.41)	(7.80)

Panel C: Four equally spaced sub-periods

	1979-1986	1987-1994	1995-2003	2004-2012	Overall
MSUE	3.63%	4.62%	4.05%	2.68%	3.72%
	(5.52)	(6.66)	(5.58)	(3.08)	(9.90)
SUE	3.76%	3.81%	3.58%	1.20%	3.05%
	(5.27)	(6.49)	(5.05)	(1.21)	(7.69)

Panel D: Three-day returns around next earnings announcement

	1979-1989	1990-1999	2000-2012	Overall
MSUE	1.30%	0.95%	0.78%	1.00%
	(10.61)	(7.93)	(5.58)	(12.89)
SUE	1.22%	0.56%	0.27%	0.66%
	(9.88)	(3.75)	(1.66)	(7.10)

Table 11 reports three-month buy-and-hold size-adjusted stock returns to portfolios formed on deciles of *MSUE* and *SUE* under various specifications. Panel A defines *MSUE* as news in gross profit (sales minus cost of goods sold). Panel B scales news variables by total assets at quarter-end. Panel C employs four equally spaced sub-periods. Panel D uses three-day cumulative market-adjusted stock returns centered over the subsequent quarter's earnings announcement. At the end of each calendar quarter, firms are sorted into deciles based on the value of the sorting variable (*SUE* or *MSUE*). Size-adjusted buy-and-hold returns for each stock are calculated over the three months subsequent to the portfolio formation date, and an equal-weighted mean return is computed for each portfolio. We then form a zero-investment hedge portfolio for each variable by going long (short) in the highest (lowest) decile portfolio, and we compute Fama-MacBeth t-statistics based on the time-series distribution of the mean hedge portfolio returns. *MSUE* is standardized unexpected operating profit (except in Panel A, where it is gross profit), calculated as quarterly operating profit per share minus expected operating profit, scaled by the standard deviation of quarterly operating profit growth over the previous eight quarters. Operating profit is defined as revenue minus cost of goods sold and selling, general and administrative expense, as in Ball et al. (2015). Expected operating profit follows a seasonal random walk with drift. The drift term is the average of quarterly operating profit growth over the previous eight quarters. *SUE* is standardized unexpected earnings, calculated as quarterly earnings per share minus expected earnings per share scaled by the standard deviation of quarterly earnings growth over the previous eight quarters, as in Jegadeesh and Livnat (2006). Expected earnings are assumed to follow a seasonal random walk with drift. The drift term is the average of quarterly earnings growth over the previous eight quarters.