Being Surprised by the Unsurprising:

Earnings Seasonality and Stock Returns

Tom Y. Chang*, Samuel M. Hartzmark†, David H. Solomon* and Eugene F. Soltes‡

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Abstract: We present evidence that markets fail to properly price information in seasonal earnings patterns. Firms whose earnings are historically larger in one quarter of the year ("high seasonality quarters") have higher returns when those earnings are usually announced. Analyst forecast errors are more positive in high seasonality quarters, consistent with the returns being driven by mistaken earnings estimates. We show that investors appear to overweight recent lower earnings following a high seasonality quarter, leading to pessimistic forecasts in the subsequent high seasonality quarter. The returns are not explained by announcement risk, firm-specific information, increased volume, or idiosyncratic volatility.

*University of Southern California, †Chicago Booth School of Business ‡ Harvard Business School

Contact at tychang@marshall.usc.edu, samuel.hartzmark@chicagobooth.edu, dhsolomo@marshall.usc.edu and esoltes@hbs.edu respectively. We would like to thank Joey Engelberg, Wayne Ferson, Dick Roll, and seminar participants at the USC Finance Brownbag, Fuller and Thaler Asset Management, the Southern California Finance Conference, and the USC/UCLA/UCI Finance Day.

1. Introduction

A balanced reading of the voluminous literature on market efficiency seems to support the conclusion that markets are neither wholly efficient (that is, correctly pricing absolutely every piece of information) nor wholly inefficient (pricing nothing at all).[1] A natural question arises then as to *what sorts of information* investors are relatively good at incorporating into prices. One can contrast two possible views on this point. A standard information acquisition view posits that investors should do better with signals that are easy to acquire and process – information that is easy to interpret, and that is repeated frequently for each firm in a timely manner, thus allowing ample opportunities for learning. A more behavioral view, however, emphasizes that investors are likely to concentrate on information that is more salient – focal events that attract investor attention. Under an investor inattention view, repeated and well-understood events may be *less* likely to be fully priced, as they are less likely to be focused on.

We examine this question in the context of the information contained in earnings seasonality. The fact that ice cream producers generate more earnings in summer and snow-blower shops generate more earnings in winter would strike most people as obvious to the point of being trite. Earnings seasonality is thus a strong candidate for information whose very obviousness means that it should be easy to process for an unbiased investor, but which may not be salient and attention-grabbing, and thus may not be fully incorporated into prices.

In this paper we present evidence that markets fail to properly price information contained in seasonal patterns of earnings. Some companies have earnings that are consistently higher in one quarter of the year relative to others, which we call a high seasonality quarter. We find that

[1] For a recent examination of the long list of current anomalies, see for instance Pontiff and McLean (2013)

companies earn significant abnormal returns in months when they are likely to announce earnings from a high seasonality quarter.

Consider the example of Borders Books, which traded from 1995 to 2010. Borders Books had a highly seasonal business, with a large fraction of earnings in the 4th quarter, partly as a result of Christmas sales. Out of Borders' 63 quarterly earnings announcements, the 14 largest were all 4th quarter earnings. Not only did these quarters have high levels of earnings, but they also had high earnings announcement returns – the average monthly market-adjusted return for Borders' 4th quarter announcements was 2.27%, compared with -3.40% for all other quarters. Earnings seasonality is a persistent property of the firm's business, and thus an investor could easily forecast when these high returns would occur. We show that the pattern in earnings announcements returns for Borders holds in general for seasonal firms – high earnings announcement returns can be forecast using past information about seasonal patterns in earnings.

To measure earnings seasonality, we rank a company's quarterly earnings announcements over a five year period beginning one year before portfolio formation. We then calculate the average rank in the previous five years of the upcoming quarter. The highest possible seasonality in quarter three, for instance, would be a company where the previous five announcements in quarter three were the largest out of the 20 announcements considered.

A portfolio of companies with expected earnings announcements in the highest quintile of earnings seasonality earns abnormal returns of 65 basis points per month relative to a four factor model, compared with abnormal returns of 31 basis points per month for the lowest seasonality quintile. This difference is statistically significant at the 1% level, and unlike many anomalies it becomes stronger when the portfolio is value weighted (abnormal returns of 55 basis points for the difference portfolio, with a *t*-statistic of 3.14). As the base returns in expected earnings announcement months are generally positive due to the earnings announcement premium (Frazzini and Lamont (2006)), another way of interpreting this finding is that the earnings announcement premium is larger in months when earnings are expected to be higher.

The nature of the earnings seasonality measure makes it unlikely that these returns are driven by seasonal firms having different fixed loadings on risk factors. In the first place, the portfolio of highly seasonal firms does not show higher volatility than the portfolio of low seasonal firms. More importantly, because seasonality is constructed based on the time series of each firm's earnings, if earnings are higher than average in one month then they will be lower than average in other months of the year. As a result, firms tend to cycle through both the long and short sides of the portfolio. To emphasize this point, we redo the analysis limiting the sample to firms that are both in quintile 1 and quintile 5 at some point in the same year (ensuring we are only sorting on time-series variation within each firm) and the results are very similar. In order for risk to explain the results, it must be the case that firms are more risky in months of high seasonality than other months. It is also worth noting that the risk cannot simply be coming from increased exposure to the standard four factors, as the regressions already control for this.

We examine a number of alternative risk-based explanations, and fail to find support for them. Savor and Wilson (2011) argue that the earnings announcement premium is driven by a common earnings announcement risk factor. We show that the seasonality effect is not driven by high seasonality quarters having a greater exposure to a common source of earnings announcement risk – when we include a portfolio of all firms with an earnings announcement, exposure to this factor does not drive the results. Keloharju, Linnainmaa and Nyberg (2013) argue that sorting on past returns at annual intervals can produce time-varying exposure to risk factors. Even though earnings seasonality does explicitly sort on such returns, we show that the abnormal returns are similar when we allow the seasonality difference portfolio itself to have time-varying exposure to standard factors.

We also provide positive evidence of investor mistakes by examining analyst forecast errors. If seasonality returns were only driven by risk, as in a discount rate explanation, it is not clear why the average analyst forecast error would be related to firm seasonality, as such forecasts only relate to cash flows. Instead, we find that analyst forecast errors are more positive in high seasonality quarters, consistent with analysts being more positively surprised. For firms that shift between high and low quintiles of seasonality, the median forecast error in high seasonal quarters is 7% of the overall shift in earnings between high and low seasonal quarters. Thus analysts on average correctly forecast 93% of the seasonal shift in earnings, suggesting that they are underreacting to seasonality, not ignoring it altogether. To the extent that individual investors may either make the same mistakes as analysts, or may simply take analysts' mistaken forecasts at face value, the portfolio returns are consistent with mispricing rather than risk.

We find additional evidence of investor mispricing in our analysis of the daily characteristic adjusted returns around earnings announcements. Specifically, most of the abnormal returns occur in the short event window surrounding the announcement. This pattern is consistent with the analyst results and the hypothesis of predictable investor mistakes. The results also suggest that the returns to seasonality are distinct from the effects of liquidity provision (Johnson and So 2014) as this is mainly a pre-announcement phenomenon. Finally, we do not observe either a drift or a reversal subsequent to the positive returns of the announcement, suggesting the price response is capturing a permanent shift in returns due to information that was not incorporated in the price prior to the announcement.

We hypothesize that the effects of seasonality are a result of investors incorrectly processing patterns in data when forming estimates of future earnings. The availability heuristic (Tversky and Kahneman (1973)) describes the theory that individuals estimate probabilities according to the ease with which instances of an event can be brought to mind. As one example of this, the recency effect describes how individuals are more likely to remember recent information than old information (Murdock Jr (1962), Davelaar et al. (2005)). If an upcoming quarter has high seasonality, this implies that the level of earnings in the three most recent announcements was likely to be lower than the announcement four quarters ago. If investors suffer from a recency effect, they may be more likely to overweight recent lower earnings compared to the higher earnings from the same quarter last year. This would cause them to be overly pessimistic about the upcoming announcement, leading to greater positive surprises. The recency effect is an example of the behavioral view of learning, where older information is less salient even though it is not more difficult to acquire or process.

Consistent with a recency effect, we find that the seasonality effect is larger when earnings in the three most recent announcements (typically 3, 6 and 9 months before portfolio formation) were lower relative to earnings 12 months ago. This suggests that when the recent news has been of a larger decrease in earnings relative to the high seasonal quarter, investors are more pessimistic when the high seasonal quarter arrives. On the other hand, if there are lower earnings *before* the seasonal quarter 12 months ago (typically 15, 18 and 21 months before portfolio formation), this does not generate a spread in returns. This suggests that the recency of low earnings is important in generating underreaction to seasonality. The seasonality effect is not present when the firm has broken an earnings record in the past 12 months, an event which is also likely to make the prospect of continuing good news salient to investors.

Earnings seasonality effects are not explained by other variables that have been associated with the earnings announcement premium. Frazzini and Lamont (2006) argue that the increase in turnover in earnings months drives the earnings announcement premium, and is associated with increased investor attention. While high seasonal months have more turnover than low seasonal months, there is no relationship between the increase in turnover and the returns to seasonality, suggesting that the volume increase does not drive the returns. Barber, George, Lehavy and Trueman (2013) show that earnings announcement returns are related to the increase in idiosyncratic volatility. By contrast, returns to seasonality are similar between firms with high and low expected idiosyncratic volatility, suggesting that the effects are distinct.

In addition, a large literature has examined the time-series properties of earnings to identify what information is properly impounded into prices. We show the result is not driven by the earnings surprise in any of the previous four quarters (Bernard and Thomas (1990)), firm financial condition (as measured by the F_score (Piotroski (2000)), or high accruals (Sloan (1996)). In the internet appendix we show that the seasonality effect does not appear to be due to a tendency of firms to engage in more earnings management in highly seasonal quarters.

We also conduct a number of tests to show that seasonality is not simply proxying for another driver of returns. The returns are not explained by other time-series effects within the firm, including overall return seasonality (Heston and Sadka (2008)), momentum, short-term reversals, or the dividend month premium (Hartzmark and Solomon (2013)). Earnings seasonality is not some general driver of returns, as it does not forecast higher returns outside of earnings months. Seasonality is also unlikely to be proxying for some recent information about the firm, however arising. Seasonality is highly persistent across years, and lagging the measure by up to ten years produces similar results. Earnings seasonality returns are stronger in the first quarter of the year, but are directionally positive in all four quarters. Seasonality predicts returns both within and between industries, and is robust to alternative measures of how seasonal a quarter is.

Overall, our results are consistent with investors underreacting to the information in earnings seasonality. Such information is repeated frequently and is easy to understand and forecast, but it is slow-moving and not very salient. It is, in other words, a 'dog bites man' type of story. Our findings are consistent with information sometimes being incorrectly priced not *despite* the fact that it is obvious, but rather *because* it is obvious.

In addition, our findings point to a broader stylized fact about asset returns, namely that predictably recurring firm events are commonly associated with abnormal returns. Abnormal returns are evident in months forecasted to have earnings announcements, dividends, stock splits, stock dividends, special dividends, increases in dividends, and now, high levels of earnings.[2] Our results are consistent with a generalized underreaction to recurring and predictable events, a fact which is puzzling to many standard finance models.

2. Literature Review

This paper contributes to several literatures in finance. Firstly, it is related to a number of papers that document high returns during recurring and predictable time-series changes within the firm. In addition to the reactions to firm-level events mentioned earlier, firms also have high returns at increments of 12 months (Heston and Sadka (2008)). These findings about recurring events are related to price responses to various one-off changes in prices and volumes, including

[2] The returns in expected earnings announcement months are explored in Beaver (1968), Frazzini and Lamont (2006), Savor and Wilson (2011), and Barber, George, Lehavy and Trueman (2013). Hartzmark and Solomon (2013) document high returns in months with an expected dividend. Bessembinder and Zhang (2014) document high returns for months with stock splits, stock dividends, special dividends, and increases in dividends.

one month returns (Jegadeesh (1990)), 2 to 12 month returns (Jegadeesh and Titman (1993)), 3 to 5 year returns (DeBondt and Thaler (1985), and recent spikes in volume (Gervais, Kaniel and Mingelgrin (2002)). We contribute to this literature by identifying a new anomaly based on repeated and predictable variation in earnings levels.

Second, our paper also contributes to the literature examining underreaction and information processing constraints. A number of papers have documented how prices can react to information with a delay if investors have limited attention. Hirshleifer, Lim and Teoh (2009) document that investors are more likely to underreact to earnings news on days with many competing announcements, consistent with the announcements competing for limited total investor attention. Da, Gurun and Warachka (2013) show that momentum in stock returns is related to the tendency of investors to underreact to information that arrives in small increments. Hirshleifer, Lim and Teoh (2011) argue that models of limited attention can explain post-earnings announcement drift, the accrual anomaly, the profitability anomaly and the cash flow anomaly. Our paper contributes to this literature by showing that an excessive focus on recent events can cause investors to pay insufficient attention to longer term patterns in earnings, giving another basis for attention-related information processing constraints.

Finally, this paper is related to the literature that examines how market participants form estimates of firm earnings. A number of papers have explored how markets do not appear to correctly forecast the autocorrelation of earnings news (Bernard and Thomas (1990), Ball and Bartov (1995)). This finding is related to the apparent underreaction to earnings news, evidenced by the post-earnings announcement drift (Ball and Brown (1968), Bernard and Thomas (1989, 1990), among others). Bernard and Thomas (1990) document that the underreaction to earnings is significantly different at the 4th quarter horizon relative quarters 1 to 3. Johnston, Leone, Ramnath and Yang (2012) provide evidence that markets and analysts fail to incorporate predictable periodic changes in the length of firm fiscal quarters, another example of inattention to recurring firm changes. So (2014) shows that firm revisions to earnings announcement dates predict future news and returns. We extend this literature by directly evaluating the market's reaction to long-term patterns in earnings seasonality, and find evidence consistent with mistaken estimates of the effect of seasonal patterns on current earnings.

Most related to the current work, Salomon and Stober (1994) examine the response to earnings surprises depending on the seasonality of firm sales. They find evidence of higher returns around high sales announcements after controlling for the level of the ex-post surprise, and argue that this is due to resolution of uncertainty. We expand on this by examining the asset-pricing implications of seasonality in a portfolio setting using only tradable ex-ante information and controlling for known determinants of returns. We directly examine the role of idiosyncratic risk and find it does not drive the returns, and instead we provide evidence of an alternative explanation, namely biased cash-flow forecasts.

3. Results – Earnings Seasonality and Returns

3.1 Data

The data for earnings come from the Compustat Fundamentals Quarterly File. The data on stock prices come from the Center for Research in Securities Prices (CRSP) monthly stock file. Unless otherwise noted, in our return tests we consider stocks listed on the NYSE, AMEX or NASDAQ exchanges, and consider only common stock (CRSP share codes 10 or 11). We also exclude stocks that have a price less than $5 at the end of the previous month before returns are being measured. The data on analyst forecasts come from the I/B/E/S detail file, and we consider forecasts of quarterly earnings per share. Data on the excess market return, risk-free rate, SMB, HML and UMD portfolios come from Ken French's website.

3.2 Constructing measures of seasonality

To capture the level of earnings seasonality, we wish to measure the extent to which earnings in a given quarter tend to be higher than other quarters. Conceptually, this includes both a question of *how often* earnings are higher in a given quarter, and *by how much* they are higher on average in a given quarter. The main measure we construct prioritizes the first component, counting companies as seasonal if they regularly have high earnings in a given quarter. In the internet appendix we show the effect of measures using the size of the gap in earnings across quarters, and find that both drive returns.

To construct our main measure of predicted seasonality in quarter *t*, we use 5 years of earnings data from quarter *t*-23 to *t*-4. We compute firm earnings per share (excluding extraordinary items) adjusted for stock splits.[3] We then rank the 20 quarters of earnings data from largest to smallest. We require non-missing values for all 20 quarters of earnings in order to construct the measure. The main measure, *EarnRank,* for quarter *t* is taken as the average rank of quarters *t*-4, *t*-8, *t*-12, *t*-16, and *t*-20 – in other words, the average rank of same fiscal quarter taken from previous years. A high value of *EarnRank* means that historically the current quarter of the year has larger earnings than other quarters, while a low rank of *EarnRank* means that the current quarter is low relative to other quarters. A firm whose earnings are randomly distributed will tend to be in the middle of the distribution of *EarnRank.*

[3] The main results of the paper are robust to alternative measures of earnings, such as total earnings, raw earnings per share, earnings per share divided by assets per share, or earnings per share divided by share price.

While there are other ways one could measure seasonality, the current variable has several advantages. Firstly, *EarnRank* is not affected by the existence of negative earnings in some periods, unlike measures that involve percentage changes in earnings. Second, it is relatively invariant to the existence of large outliers in earnings numbers, such as from a single very bad quarter. Third, by ranking earnings over several years, *EarnRank* is less sensitive to trends in overall earnings growth. If each quarter were only ranked relative to other quarters that year, then companies with uniformly growing earnings would appear to have the maximum possible seasonality in the 4^{th} quarter. By contrast, under the current measure, the rankings of the 4^{th} quarters would be 4, 8, 12, 16 and 20, giving an average rank of 12. This is considerably less than the maximum rank of 18, and empirically only 0.35 standard deviations above the median value (11) and 0.45 standard deviations above the mean (10.85). In Table I Panel A, we present summary statistics for the main variables used in the paper.

3.3 Seasonality and the Earnings Announcement Premium

We first examine whether information about earnings seasonality is incorporated into stock prices. To do this, we examine stock returns in months when firms are predicted to have an earnings announcement and sort based on the historical level of seasonality in earnings that quarter. If the market has not fully incorporated the fact that earnings tend to be higher in certain quarters, then the revelation of actual earnings will result in price movements. By contrast, if markets are correctly forecasting the effect of seasonality, then the higher earnings in a given quarter will not result in different stock returns.

Since the timing of an announcement may contain information, such as when a firm delays an earnings announcement due to bad news (Frazzini and Lamont (2006)), we do not condition ex-post on whether a firm has an earnings announcement in the month in question. Instead, we predict whether a firm will have an earnings announcement in the current month, based on whether or not it had an earnings announcement 12 months ago. The portfolio of all stocks predicted to have an earnings announcement has abnormally positive returns, which is the earnings announcement premium in Frazzini and Lamont (2006).

To examine the effects of earnings seasonality, we first condition on the existence of an earnings announcement 12 months ago, and then sort firms into quintiles based on the level of *EarnRank.* As a result, all earnings information is a least 11 months old at the time of portfolio formation. We form portfolios of returns for each quintile of *EarnRank*, using breakpoints calculated from the distribution of *EarnRank* in that month, with quintile 5 being firms where earnings in the upcoming announcement were historically larger than other months. We only include months where the portfolio has at least 10 firms, and in the case of the difference portfolio, where both the long and short leg have at least 10 firms. It is worth emphasizing that due to the earnings announcement premium all of the quintiles of *EarnRank* are predicted to have positive abnormal returns. The main question of interest then is whether seasonality causes larger relative returns.

We consider this question in Table I Panel B. For the equal-weighted portfolio, the highest seasonality quintile earns returns of 175 basis points per months, compared with 146 basis points per month for the lowest seasonality quintile. The gap is larger when value-weighted portfolios are formed, with the high seasonality quintile having returns of 176 basis points per month, compared with 137 basis points per month for the lowest seasonality quintile.

Importantly, the high seasonality portfolio is not more volatile. The low seasonality portfolio actually has the same or a slightly higher standard deviation of monthly portfolio returns (5.28 equal weighted, 5.18 value weighted) than the high seasonality portfolio (5.14 equal weighted, 5.18 value weighted). This militates against some simple risk-based explanations of the difference in portfolio returns, inasmuch as the higher returns to the high seasonality portfolio do not expose the investor to greater volatility. The various snapshots of percentiles from the return distribution do not indicate that the high seasonality portfolio is more exposed to extreme negative returns, such as the crash risk associated with momentum (Daniel and Moskowitz (2013)). The lowest monthly return is -18.0% for the equal-weighted difference portfolio, and -14.9% for the value-weighted difference portfolio (compared with maximums of 10.2% and 18.4% respectively).

Of course, risk is not simply measured by volatility and skewness. It may be that high seasonality firm-months are exposed to other economy-wide risks that investors care about. To test this, we examine the abnormal returns to earnings announcement premium portfolios sorted on earnings seasonality, relative to a four factor model controlling for excess market returns, size, book-to-market (Fama and French (1993)) and momentum (Carhart (1997)). The returns of the earnings seasonality quintile portfolios are regressed on the excess returns of the market, as well as the SMB, HML and UMD portfolios.

The results are presented in Table II. Panel A examines whether the returns to portfolios formed on earnings rank are explained by exposure to standard factors. For equal weighted portfolios, the lowest seasonality quintile has a four factor alpha of 30.6 basis points per month (with a *t*-statistic of 3.35), while the highest seasonality quintile portfolio has an alpha of 65.3 basis points per month (with a *t*-statistic of 6.98). The long-short portfolio has abnormal returns of 34.7 basis points per month, with a *t*-statistic of 3.13. As in Table I, the effects are stronger when value weighted portfolios are used. The low seasonality portfolio has abnormal returns of 35.8 basis points (with a *t*-statistic of 2.77), while the high seasonality portfolio has abnormal returns of 90.9 basis points per month (with *t*-statistic of 6.03). The difference portfolio has abnormal returns of 55.1 basis points per month, with a *t*-statistic of 3.14.

It is worth noting that the effect is driven by the long side of the portfolio. This is unusual among anomalies, where a number of effects are concentrated in the short side (Stambaugh, Yu and Yuan (2012)). Further, the largest distinction is between the highest seasonality quintile and the remainder, with quintiles 1-4 showing similar abnormal returns to each other. The fact that the majority of the anomaly comes from the firms with historically high earnings in the current quarter is something we will return to when examining the possibility of investors being pessimistic about the upcoming high seasonality quarter due to a recency effect.

Secondly, the difference portfolios in Panel A have relatively low loadings on most of the standard factors, having small and statistically insignificant loadings on excess market returns, and UMD, and moderately but negative loadings on SMB and HML (meaning that the portfolio tilts towards somewhat towards large growth firms). These low factor loadings arise because firms with a seasonal pattern in earnings tend to cycle between the two extreme portfolios. For instance, if a firm has unusually high earnings in the March quarter, it is more likely that it will have unusually low earnings in some other quarter (relative to a firm with smooth earnings).

To emphasize this point, in Panel B we form portfolios of firms in the extreme quintiles (1 and 5) which were also in the opposite extreme portfolio within 12 months. In other words, firms are included in the highest quintile of seasonality from 12 months ago (quintile 5) only if they are also in the *lowest* quintile of seasonality either in the three quarters before (e.g. 15, 18 or 21 months ago) or three quarters after (e.g. 9, 6, or 3 months ago). This ensures that any variation in seasonality is only coming from variation within the firm, rather than cross-sectional variation from the types of firms that tend to have high seasonality at some point in time. Because the long and short portfolios cycle through the same set of firms, any fixed loadings on factors will cancel out over time, and only time-varying exposure to factors will remain.

The results are shown in Table II Panel B. The abnormal returns are similar to those in Panel A – the equal-weighted difference portfolio has abnormal returns of 33.5 basis points (*t*-statistic of 2.56) while the value-weighted difference portfolio has abnormal returns of 37.9 basis points (*t*-statistic of 1.88). In addition, the loadings on the factors are small and insignificant in all cases.

These results indicate that the abnormal returns are not driven by fixed loadings on the market, SMB, HML or UMD. In addition, the abnormal returns cannot be explained by high seasonal months having consistently higher loadings on the factors being controlled for (Mkt-Rf, SMB, HML and UMD). For instance, if firms always have a higher market beta in high seasonal months relative to low seasonal months, then the difference portfolio will buy firms in their high beta months and short them in their low beta months. As a result, the difference portfolio will have a positive market beta, but the four-factor regression will control for this, and hence it will not contribute towards the alpha. More generally, because abnormal returns are evident using only within-firm variation, the results are also unlikely to be driven by any fixed loadings on any other omitted factors. The results could however be driven by time-varying exposure to a risk source that we are not measuring, where firms become riskier in high seasonality months relative to low seasonality months. We return to this question in sections 4.1 and 4.4.

3.4 Effect of Earnings Seasonality versus other Seasonal Variables

While the previous table documents that seasonality is associated with abnormal returns relative to a four-factor model, it is possible that by sorting on seasonality we are selecting for some other anomaly that drives returns. Of particular concern are factors that involve predictable changes in the firm over time. These include the dividend month premium (Hartzmark and Solomon (2013)), where firms have abnormally high returns in months when they are predicted to pay a dividend, and return seasonality (Heston and Sadka (2008)), where returns 12, 24, 36, 48 and 60 months ago positively predict returns in the current month. We also examine the effect of other variables known to affect returns – log market capitalization, log book-to-market ratio, momentum (returns from 12 months ago to 2 months ago) and last month's return.

In addition, we wish to examine whether the effect of earnings seasonality is limited to months with a predicted earnings announcement. If high seasonality is associated with a general period of increased exposure to economy-wide risks not specifically related to earnings, then the higher returns may be evident in other months surrounding the high seasonality announcement.

We test these possibilities in Table III by examining the effect of earnings seasonality using Fama Macbeth cross-sectional regressions – in each month, we run a cross-sectional regression of stock returns on stock characteristics, then the time-series average and *t*-statistic associated with each of the regression coefficients is computed. We consider two versions of the regression. In columns 1-4, we consider only the cross-section of firms that had an earnings announcement 12 months ago, and thus are predicted to have an earnings announcement in the current month. The *EarnRank* variable shows a significant predictive ability in a univariate specification, with a coefficient of 0.034 and a *t*-statistic of 2.78. Since the standard deviation of *EarnRank* is 2.85, this means that a one standard deviation in seasonality corresponds to an increase in returns during earnings months of 9.6 basis points. When additional controls are included in column 2 for predicted dividends, Heston and Sadka (2008) seasonality, log market cap, log book-to-market, momentum and one-month reversal, the coefficient is unchanged at 0.034 with a *t*-statistic of 2.95. The results are similar in columns 3 and 4 when the percentile value of *EarnRank* is used instead of the raw value.

In columns 4-8 we consider the cross-section of all firm-month observations, and include a dummy variable for predicted earnings that we interact with the measure of seasonality. In this specification, seasonality is matched to the predicted earnings month (i.e. 12 months after the measure is formed) and the subsequent two months (13 and 14 months afterwards, respectively). Column 5 is the all-firm equivalent of the univariate regression, including only seasonality, a dummy for predicted earnings, and the interaction between the two. The regression shows that only the interaction of predicted earnings and seasonality shows a significant positive effect, with a coefficient of 0.051 and a *t*-statistic of 3.71. Earnings seasonality has a somewhat negative effect in non-earnings months, although this effect becomes only marginally significant with the inclusion of controls in column 5. The results are again similar if *EarnRank* is measured as a percentile. Seasonality does not seem to be proxying for other drivers of returns, nor does it predict high returns outside of months with a predicted earnings announcement.

3.5 Earnings Seasonality and Delayed Reaction to Firm Specific Information

While the results in subsection 3.3 and 3.4 suggest that the seasonality effect is not proxying for some fixed property of firms, it is possible that seasonality is correlated with other recent firm-specific information that is announced in earnings months. This may relate to some other property of earnings (such as earnings growth or post earnings announcement drift), or any other number of changes in the firm. *EarnRank* is already constructed using 5 years of data and then lagged one year before portfolios are formed, so by its nature it contains information from a long time period, but it is still possible that information flows over this period drive the results.

Rather than trying to control for each possible type of firm-specific information, we test a common prediction of such theories: namely, that firm-specific information should become less relevant over time. As seasonality is a property of the firm's underlying business model, it is likely to be quite persistent over time. In addition, the timing of earnings announcements is strongly persistent over time (Frazzini and Lamont (2006)), meaning that long-term earnings information is still reasonably predictive of the timing of current announcements.

To test whether firm-specific information explains our results, we lag the *EarnRank* measure over different lengths of time. We show this in Table IV. In Panel A, we consider the effects of seasonality from the same quarter of the year, but lagged in various multiples of 12 months when forming portfolios. This retains the prediction of seasonality for the current quarter, but omits more and more of the recent earnings news of the firm. We examine lags of up to ten years. While this restriction conditions on firms having a longer time series of data, the resulting selection effect is equal between the long and short legs of the portfolio, so it should not mechanically increase or decrease the returns to the difference portfolio.

The results show that statistically significant abnormal returns are evident even when using information that is at least 10 years old (i.e. the *EarnRank* measure is computed using information from 10 years to 14 years before the portfolio formation date). The equal-weighted difference portfolio has positive returns that are significant at a 5% level or more at every annual horizon up to 10 years, while the value-weighted portfolio drops below the 5% level only at the 10 year mark. A curious aside is that the main effects actually get slightly larger when lagged two and three years (54-55 basis points equal weighted, 64-68 basis points value-weighted).

In Panel B, we consider another prediction of delayed response to firm-specific earnings information. In particular, if our results are driven by seasonality in earnings, then the *EarnRank* should positively predict returns for the same quarter as the measure, but not have the same results for other quarters. If high seasonality effects were driven by a slow response to some other correlated earnings news (such as earnings growth or post earnings announcement drift), the effect should be similar when lagged at other multiples of 3 months, and indeed ought to be stronger for horizons less than 12 months. When *EarnRank* is lagged 3 months (i.e. using the most recent earnings information), there is no spread in returns. At 6 months the returns are similar when equal weighted but smaller and insignificant when value weighted. At 9 months, the spread is significantly negative when value weighted, but not when equal weighted.

These results are difficult to reconcile with seasonality measuring some firm-specific information flows that are common to recent earnings announcements – earnings information shows persistent effects at long multiples of 12 months (consistent with a seasonality effect), but generates weaker and different patterns at other horizons.

4. Explaining the Seasonality Effect – Risk versus Mistaken Earnings Forecasts

4.1 Earnings Announcement Risk and Analyst Forecast Errors

Perhaps the most standard potential explanation for the higher expected returns in high seasonality months is that they represent compensation for risk. While the regressions in subsections 3.3 suggest that the patterns in returns are not driven by fixed factor loadings, the announcements themselves may cause exposure to risks. Specifically, it is possible that announcing a larger proportion of total annual earnings may make the stock more exposed to announcement risk.

The most obvious way through which announcement risk could explain the results would be if seasonality were associated with greater exposure to a systematic risk factor. This systematic announcement risk must be separate from market returns during that month, as the four factor regressions already control for different market betas across the long (high seasonal) and short (low seasonal) portfolios. For idiosyncratic announcement risk to be associated with higher returns, investors must be somehow prevented from diversifying this idiosyncratic risk away by holding a portfolio of seasonal firms. This is assumed in Barber et al. (2013) (who examine the relationship between idiosyncratic risk and earnings announcement returns) and Johnson and So (2014) (who examine the returns to liquidity provision in the lead-up to earnings announcements). In this view, the higher returns and lower volatility of the portfolio of high seasonal firms is not actually obtainable by the investor, as they can only hold some subset of the firms (and thus face idiosyncratic risk). Whether or not investors are so constrained is a separate question, and one beyond the scope of this paper. We return to the question of whether idiosyncratic risk can explain the seasonality effect in section 5.1.

Table I Panel B indicates that the portfolio of highly seasonal firms does not have more volatile returns than the portfolio of low seasonal firms. While this does not conclusively rule out a greater exposure to particular sources of risk, it does suggest that any systematic risk exposure is being offset by lower risk exposure elsewhere such that the overall volatility is not different.

Nonetheless, systematic risk factors related to earnings announcements are not implausible. Savor and Wilson (2011) argue that there is a systematic component to earnings announcement risk, and that the portfolio of firms with expected earnings announcements represents a priced factor that proxies for the systematic component of earnings announcement risk. If highly seasonal firms have more exposure to this overall earnings announcement risk factor, this could be driving the pattern we document in returns.

We explore this possibility in Table V. The regressions are similar to those in Table II, taking portfolios of firms sorted on earnings rank, but in addition to the standard four factors (excess market return, SMB, HML and UMD) we also include the excess returns of an equal-weighted portfolio of all firms with a predicted earnings announcement that month (EARNRF). This is designed to capture the overall fluctuation in returns for firms announcing earnings that month, thereby proxying for the exposure to announcement risk.

The results indicate that exposure to an overall earnings risk factor does not drive the seasonality effect. The difference in alphas (now a five-factor alpha, including exposure to the overall earnings announcement factor) between high and low seasonality portfolios is still large and significant : 34 basis points in Panel A when equal weighted (with a *t*-statistic of 3.00) and 48 basis points when value weighted in Panel B (with a *t*-statistic of 2.67). These numbers are similar to those in Table II (35 and 55 basis points respectively), indicating that adding in an earnings risk factor does not explain the seasonality effect. This conclusion is reinforced by the fact that the seasonality difference portfolio does not have any significant loading on the earnings risk portfolio in either the equal-weighted or value-weighted tests. In untabulated results, we show that different proxies for earnings risk (such as a value-weighted portfolio of earnings announcement firms, or a difference portfolio between expected announcers and non-announcers) produce similar spreads in abnormal returns.

More broadly, if seasonality returns are driven entirely by compensation for risk, then market participants should not show a more positive average ex post surprise when cash flows are announced. Earnings risk operates only through the discount rate channel – investors require higher returns in high seasonal months because of risk in these months, not because they are more positively surprised on average by cash flows. In the case of earnings, we can test the latter possibility quite cleanly because of the existence of analysts' forecasts of earnings. Since these are only forecasts of cash flows, the mean level of the surprise should not be affected by seasonality under a risk-based explanation. There may be greater variability in forecast errors in months where earnings are larger, but any increase in the mean level of forecast error is *prima facie* evidence that analysts are relatively more pessimistic in months of high seasonality.

In Table VI we test whether analysts tend to be more positively surprised by firm earnings in high seasonality quarters. The unit of observation is at the firm-date level, and the main dependent variable is the forecast error associated with the median quarterly earnings per share forecast, taken over all analysts making forecasts between 3 and 90 days before the earnings announcement.

The measure of forecast error is calculated as (Actual EPS – Forecast EPS) / Price (*t*-3). In columns 1-4 we add controls for the log number of estimates being made, the standard deviation of forecasts (divided by the price three days before the announcement, with the variable set to zero if there is only one analyst), a dummy variable for cases whether there is only one analyst making a forecast, the log market capitalization in the previous month, the log book to market ratio, stock returns for the previous month, stock returns for the previous two to twelve months cumulated, as well as the previous four forecast errors.

In the univariate specification in column 1, the coefficient on *EarnRank* is 0.032, with a *t*-statistic of 11.43 when clustered by firm and day. This shows that the earnings forecast error is more positive when seasonality is high. In columns 2-4 we show that the effect of seasonality survives the addition of firm-level controls, with a coefficient of 0.012 and a *t*-statistic of 5.19 when all firm controls are used. In column 5-7, we add date and firm fixed effects to control for omitted variables related to overall firm differences and time-series changes in the overall analyst mistakes. The effects are substantially similar, indicating that the effect of seasonality on forecast errors is not simply due to the types of firms likely to be highly seasonal or the periods of the sample when high seasonality is more common. Table VI is consistent with investors and analysts being more positively surprised by firm cash flows during high seasonality quarters, and does not support explanations based on earnings risk.

To obtain a sense of the magnitude of these forecast errors, one can compare the forecast error in high seasonal quarters with the overall change in earnings between high and low seasonal quarters. This gives an estimate of the fraction of the overall change in earnings due to seasonality that analysts are missing. To do this, we take firms that were in the highest quintile of seasonality in the current quarter, and were also in the lowest quintile of seasonality at some point in the past 12 months. For each of these firms, we compute the fraction of the seasonal shift that was forecast as follows:

$$Fraction\ Forecast$$
$$= \frac{[High\ Seasonality\ Median\ EPS\ Forecast\ - Low\ Seasonality\ Actual\ EPS]}{[High\ Seasonality\ Actual\ EPS - Low\ Seasonality\ Actual\ EPS]}$$

Among firms that shifted from the low quintile of seasonality to the high quintile of seasonality, the median fraction forecast was 0.93, meaning that analysts correctly forecast 93% of the seasonal shift in earnings but missed 7%. This reinforces the notion that the returns in high seasonal quarters are consistent with an underreaction to information in seasonality, but that this does not imply that seasonality is ignored altogether.

4.2 Daily Returns

To further understand what is driving the returns that we observe in an earnings month, we examine the daily returns surrounding earnings announcements. There are various mechanisms surrounding earnings announcements that have been found to impact returns and each of these suggest the returns will appear in different portions of the month. Barber et al. (2013) and Johnson and So (2014) show that the earnings announcement premium is actually concentrated prior to the earnings announcement itself. Thus if we are capturing a variant of this effect we expect the returns to be concentrated several days before the announcement. The returns at the monthly horizon may also be capturing effects after the initial announcement due to post earnings announcement drift. To the extent that seasonality is proxying for a predictable positive surprise, we expect to see returns concentrated at the announcement itself. While a concentration of returns on the announcement day would also be consistent with a risk explanation, the evidence in Section 3 suggests that this is not the driver of returns.

To test these predictions we examine characteristic-adjusted returns around earnings announcements. Similar to Daniel, Grinblatt, Titman and Wermers (1997) we assign each stock to a quintile based on size, book value, and momentum (using returns from t-20 to t-250). We take the daily return for the stock and subtract the average return for the stocks in the market that match these three quintiles. Where possible we use the filters from DellaVigna and Pollet (2009) to identify the earnings announcement day.

Table VII presents the results and shows that returns are concentrated directly around the earnings announcement itself. The first three columns show the average characteristic returns by day for the highest quintile of seasonality, the lowest quintile and the middle three quintiles. Similar to Barber et al. (2013) we find that the positive abnormal returns surrounding earnings announcements in general begin several days before the earnings announcement itself. These returns contain both the impact of the earnings announcement premium as well as that of seasonality, so in order to see the impact of seasonality further tests are needed.

The fourth column in Table VII examines the difference in characteristic adjust return from the top quintile and the bottom quintile of seasonality (similar to the portfolio sorts in Table II). The largest return occurs on the announcement day itself, earning roughly 10 basis points with a t-statistic of 3.37. Adding up the coefficients from t-2 to t+1 yields roughly 26 basis points of returns. Comparing this to the equal weighted portfolio result of 35 basis points in Table II, this suggests that most of the returns due to seasonality are related to the announcement itself. The final column shows regression estimates of daily abnormal returns on earnings seasonality. On each day surrounding an earnings announcement the characteristic-adjusted return is regressed on *EarnRank*. The coefficients that are both economically and statistically significant are clustered around the announcement from *t-2* to *t*+1. The largest effect occurs on the announcement date itself and the second largest occurs on the day after the announcement.

As noted in DellaVigna and Pollet (2009), the recorded announcement dates sometimes contain inconsistencies, so finding an association between seasonality and returns in a short period either side of the recorded announcement date is not inconsistent with the returns being from the announcement itself. By contrast, Johnson and So (2014) document that earnings announcement returns in general are evident further before the announcement (significant up to six days before the announcement date), which they attribute to liquidity provision. The differential returns to seasonality are limited to a shorter period around the announcement, consistent with a predictable positive surprise in earnings occurring in seasonal quarters.

4.2 Underreaction to Seasonality, the Recency Effect and Levels of Recent Earnings

The second broad class of explanation for seasonality affecting stock returns is that markets are underweighting information contained in past seasonality information. If investors do not fully account for the fact that earnings are predictably higher in certain quarters, then they may be positively surprised when upcoming earnings are at high levels. The results in Table VI are consistent with analysts being more positively surprised in high seasonal quarters. Though this does not necessarily mean that other investors are also more surprised, it does suggest the possibility of a common reaction of positive surprise by financial market participants which may be driving the high returns.

As Ball and Bartov (1995) note, finding mistakes in investors' reactions to particular earnings announcements does not mean that investors are ignoring earnings news entirely. The same is true of seasonality – we document that investors are not properly pricing seasonal patterns in earnings, but this does not mean that seasonality is being ignored altogether. Our results also do not require that investors are being especially naïve - the problem of precisely estimating seasonal effects for each firm is far from straightforward. Nonetheless, our results suggest that whatever seasonality correction is being applied is insufficient, leading to predictable patterns in announcement returns.

While underreaction provides a potential explanation distinct from risk, it is somewhat unsatisfying without a further understanding of *why* investors are underreacting. Underreaction as an explanation becomes more compelling if it can be combined with an understanding of the psychological reason for the underreaction. This is particularly important in light of the Fama (1998) critique that apparent underreactions are about as common as apparent overreactions.

In this case, psychology provides a potential basis for the underreaction to earnings seasonality. Tversky and Kahneman (1973) argue that individuals estimate probabilities according to the ease with which instances of the particular event can be brought to mind, which they call the availability heuristic. As a consequence, events which can be easily recalled will be given higher probabilities. Tversky and Kahneman (1973) describe various attributes that may make a particular event more likely to be recalled, one of which is the recency of data. Their theory builds on an earlier literature in studies of memory, which documented a finding known as the serial position effect (Murdock Jr (1962), Davelaar et al. (2005) that individuals have different tendencies to remember items in a list. In particularly, people are more likely to recall the last items (the recency effect) as well as the first item (the primacy effect). Between them, the recency effect and the availability heuristic imply that investors are more likely to recall recent earnings announcements, and more likely to overweight those announcements when forming estimates of the likely distribution of future firm earnings.

Seasonality as we measure it represents a long-run statement about the relative size of earnings in the upcoming quarter relative to other quarters of the year. Mechanically, if the firm has relatively more earnings in the upcoming quarter then it must have relatively less in the other quarters of the year. If the historical pattern in earnings continues as before, then firms in the high seasonality portfolio will typically have announced large earnings 12 months ago, but lower earnings over the subsequent three announcements. If investors suffer from a recency effect, then the three more recent announcements may be more salient when forming expectations of the upcoming earnings announcement. On average this will cause investors to be too pessimistic in highly seasonal quarters.

This explanation generates additional testable predictions. Firms with a high seasonality quarter will *on average* have three recent announcements that are lower than the announcement 12 months ago. Importantly, if the recency effect is driving the seasonality returns, then the returns should be higher when subsequent announcements *actually were lower ex post*. This is the necessary basis for the investor underreaction. If the ex-post news since the high seasonal quarter was actually positive, then a recency effect would not cause investors to be overly pessimistic about the upcoming high seasonal quarter.

We test this prediction in Tables VIII and IX, by examining how the seasonality effect is impacted by recent earnings news. In Table VIII, we examine whether the returns in the seasonality long/short portfolio depend on how much earnings have decreased since the same quarter announcement last year. We form a two-way sort of stocks. The first sort is similar to before − whether or not the firm is above or below the median earnings rank that month. For the second sort, we define a new variable based on the difference between the average of the three most recent earnings announcements before portfolio formation and the announcement 12 months ago (with earnings scaled by firm assets per share). We then split stocks according to whether they are above or below the median of this measure.

Table VIII presents these results. In Panel A, consistent with the predictions of the recency effect, when recent earnings are more negative relative to earnings 12 months ago, the seasonality effect is larger. The long/short seasonality portfolio among firms with lower earnings in the most recent announcements earns abnormal returns of 66 basis points equal weighted and 79 basis points value weighted, both significant at the 1% level. By contrast, the long/short seasonality portfolio has lower returns when implemented among firms whose recent earnings were higher – 28 basis points equal weighted, and 3 basis points value weighted. The double difference is statistically significant at the 1% level for both equal- and value-weighted portfolios. Similar results are obtained (not tabulated) if we instead sort on the gap only between the last earnings announcement and the announcement 12 months ago.

One possible concern with the previous regressions is that by conditioning on low recent earnings we are somehow just selecting for firms that are more seasonal overall. To address this possibility, in Panel B we perform a placebo version of the same regression. We use a similar double sort as before, but for the second sorting variable we compute the gap between the three earnings announcements *before* the announcement 12 months ago. In other words, the gap is computed using announcements that are on average 15, 18 and 21 months before portfolio formation, instead of in Panel A where they are on average 3, 6 and 9 months before portfolio formation. If the recency effect is driving our results, low earnings in this period should not produce the same spread in returns. This double sort produces a gap in returns that is smaller in magnitude, statistically insignificant when value weighted and marginally significant (*t*-stat of 1.69) when equal weighted. This reinforces the conclusion that what matters is the level of the *most recent* earnings, consistent with the predictions of the recency effect.

In Table IX, we consider an alternative measure of when investors are less likely to be pessimistic about upcoming news – when the firm has broken an earnings record in the past 12 months. Since earnings records are a salient indicator of the firm having improved its performance, record high recent earnings are likely to be highly weighted when investors forecast returns, thereby reducing the seasonality effect if it is due to a recency effect. Similar to Table VIII, we sort stocks according to *EarnRank* and whether a previous earnings record has been broken in the past 12 months. To avoid spuriously counting records early in the firm's life, we consider records starting two years after the firm appears in Compustat.

Consistent with recency, we find that the effects of seasonality are significantly higher among firms who have not recently broken a record. The double difference portfolio has abnormal returns of 34 basis points when equal weighted (*t*-statistic of 2.73) and 51 basis points when value weighted (*t*-statistic of 2.26). In addition, the seasonality difference portfolio among firms that have recently broken a record has abnormal returns that are very close to zero (-2 basis points and 2 basis points). These results confirm the view from Table VIII that the seasonality effect is larger when firms have had lower recent earnings.

5. Additional Alternative Explanations

5.1 Increases in Volume and Idiosyncratic Risk

Given the seasonality effect is formed within the set of firms comprising the earnings announcement premium, it is possible that seasonality is driven by the same underlying factors that make returns generally high in this period. Frazzini and Lamont (2006) argue that the returns around earnings announcements are driven by the predictable increase in volume in this period, as firms with historically higher volume in earnings announcement months have higher earnings announcement returns. Barber et al (2013) argue that the earnings announcement premium is associated with increases in idiosyncratic volatility, and that these explain the level of returns. It is possible that high seasonal quarters may have higher returns than low seasonal quarters either due to having higher volume or higher idiosyncratic volatility.

In Table X, we examine the effect of increases in volume on seasonality. We take the same set of earnings announcements from one year ago to six years ago used to form the earnings rank measures, and examine the relative level of trading volume in the upcoming quarter. We form a ratio of the average volume from the past 5 announcements in the same fiscal quarter as the upcoming announcement, divided by the average volume from the 20 announcements starting 12 months ago. This measure is the within-earnings-announcement analogue of Frazzini and Lamont (2006), as it measures whether the current quarter's earnings announcement is likely to have higher volume than other quarters (whereas those authors examine whether earnings announcements as a whole have higher volume than non-earnings months). Similar to Table VIII and IX, we double sort firms into portfolios according to the expected level of the volume in the upcoming quarter and the earnings rank. If the seasonality effect is merely proxying for the increase in volume, we should see a spread when sorting on volume, but not see a spread when sorting on seasonality after controlling for the level of volume increase. If the seasonality effect is exacerbated by trading volume, we should see a higher effect of seasonality for firms that also have a larger increase in volume.

Table X is consistent with neither prediction, and suggests that increases in trading volume do not drive the higher returns in high seasonal months. The seasonality difference portfolio shows similar returns when formed among firms that have a relatively high trading volume in that month or firms that have a relatively low trading volume that month. The double difference portfolio earns 14 basis points when equal weighted and 16 basis points when value weighted, with neither being significant. In addition, the abnormal returns to the seasonality difference portfolio are individually significant for equal weighted low turnover, equal weighted high turnover and value weighted high turnover (with value weighted low turnover on its own being insignificant). Overall, the results suggest that seasonality is not driven by an increase in trading volume during high seasonal months.

We next examine whether increases in idiosyncratic volatility can explain returns to seasonality. If seasonality returns represent compensation for higher idiosyncratic risk, then the expected idiosyncratic volatility of the upcoming announcement should explain the returns to seasonality portfolios. To test this, we compute the daily abnormal idiosyncratic volatility around each earnings announcement as in Barber et al (2013). This involves first regressing daily stock returns on a market model (including three lags) for the hundred days ending eleven days before the announcement. This is used to generate a squared residual return on the announcement day, which is divided by the average squared residual from the hundred day regression period to obtain the announcement period increase in idiosyncratic volatility. We predict the abnormal idiosyncratic volatility in the upcoming quarter by taking the average of the previous five announcements in the same quarter for that firm.

Table XI shows that idiosyncratic volatility does not explain the returns to seasonality. While announcements with higher expected idiosyncratic volatility have higher returns (consistent with Barber et al. (2013)), the returns to the seasonality difference portfolio are similar between high and low expected idiosyncratic volatility and of a comparable magnitude to the univariate sorts. Overall, predictable abnormal idiosyncratic risk does not seem to explain seasonality returns.

5.2 Time-Varying Factor Exposure

As noted earlier, the seasonality difference portfolio is unlikely to be explained by any loadings on risk factors that are constant for each firm in question, as firms tend to cycle through both the long and short legs of the portfolio. In addition, the abnormal returns also cannot be explained by firms having a predictably higher time-varying loading on the factors being controlled for (Mkt-Rf, SMB, HML and UMD) in high seasonal versus low seasonal months.

On the other hand, the abnormal return could be caused by the difference portfolio itself having time-varying loadings on the factors. In other words, high seasonality firms might tend to be high momentum firms in some months, and high value firms in other months. If this were to occur, the regression would *not* control for it, as it estimates a single loading on each factor for all calendar months. Keloharju, Linnainmaa and Nyberg (2013) argue that such a process explains the calendar seasonality in Heston and Sadka (2008). In that setting, a portfolio of firms with high returns 12, 24, 36, 48 and 60 months ago has high returns in the current month. Keloharju, Linnainmaa and Nyberg (2013) show that if there are seasonal patterns in the underlying factors, then this approach may select for time-varying loadings on whatever factor has high expected returns that month, and that this can explain the return seasonality effect.

In the current context, we are not sorting on past returns (which may capture high exposure to many possible factors) but on high earnings, which do not obviously have different time-varying loadings for different factors. Nonetheless, it is still possible that high seasonality firms have higher exposure to factors in ways that vary over the year.

To test whether this is driving our results, in Table XII we run a similar regression to Table II, but allowing for different factor exposures in each month of the year. The regression is:

$$R_{HighEarnRank} - R_{LowEarnRank} = \alpha + \beta_1 * MktRf * Jan + \beta_2 * MktRf * Feb + \ldots + \beta_{12} * MktRf * Dec + \beta_{13} * SMB * Jan \ldots + \beta_{24} * SMB * Dec + \beta_{25} * HML * Jan \ldots + \beta_{36} * HML * Dec + \beta_{37} * UMD * Jan \ldots + \beta_{48} * UMD * Jan + e_t$$

where *Jan* through *Dec* are dummy variables for each of the months of the year. The regression thus estimates a single abnormal return, but allows for month-of-the-year variation in exposure to all of factors. If time-varying loadings are explaining our results, then there should not be abnormal returns once we control for such variation in factor exposure.

The results indicate that time-varying loadings on standard factors do not explain the seasonality effect. The portfolio of high earnings rank minus low earnings rank earns abnormal returns in this setting of 35 points equal weighted (with a *t*-statistic of 1.97) and 32 basis points when value weighted (*t*-statistic of 2.74). This suggests that the seasonality effect is not proxying for month-of-the-year variation in exposure to known factors.

5.3 Accounting Predictors of Earnings Announcement Returns

A large literature in accounting has examined what information predicts subsequent earnings levels, surprises and announcement returns. Bernard and Thomas (1990) find that past earnings surprises predict the abnormal returns for the next quarter's announcement, with the past three announcement positively predicting earnings surprises and four quarters ago predicting negatively. Piotroski (2000) constructs a measure of fundamental information called the F-score using nine accounting measures that capture variation in profitability, financial leverage and operating efficiency, and shows that this predicts future announcement returns. Sloan (1996) documents that accruals (the gap between earnings recognized this period and cash flows received) show less persistence than cash flows, and are associated with lower future returns.

Seasonality differs conceptually from some of these variables – it is formed based on past levels of earnings, rather than the composition of earnings or changes in earnings, and it makes predictions that differ over each quarter of the year (rather than predicting a general underreaction over a series of subsequent quarters). Nonetheless, we wish to ensure that seasonality is not simply proxying for other known determinants of earnings surprises.

We examine this question in Table XIII. The dependent variable in the regressions is the characteristic adjusted returns from t-1 to t+1 surrounding earnings announcements, and the independent variables include lagged standardized unexpected earnings, lagged forecast errors, the F score, and accruals . The first column shows that simply regressing this measure on *EarnRank* yields positive and significant abnormal returns. The next column adds controls for the earnings surprise from a seasonal random walk model for each of the previous four quarters. The coefficient on *EarnRank* is basically unchanged from the inclusion of these variables, suggesting that the information contained in recent earnings surprises cannot account for the abnormal returns surrounding earnings seasonality. The next column contains an alternative measure of earnings surprise, that of the median analyst SUE for each of the previous four quarters. Again *EarnRank* remains large positive and significant.

The effect of *EarnRank* remains similar in size, or even slightly larger, when we include additional controls for the *F_Score* from Piotroski (2000) (column 4), the decile of accruals as calculated in Sloan (1996) (column 5), and all of the accounting variables in combination (column 6). With no controls, the coefficient on *EarnRank* is 0.026 (with a *t*-statistic of 6.23), while after including all accounting controls, the coefficient on *EarnRank* is 0.038 (with a *t*-statistic of 5.48). Earnings seasonality appears to elicit a distinct response to these accounting variables.

5.4 Robustness

In the Internet Appendix[4], we consider a number of additional robustness checks. We explore whether seasonality returns may be related to earnings management by firms, and find that seasonality does not have a significant relation with a number of proxies for earnings management. We examine the role of industry factors in seasonality, and find that seasonality relative to industry averages has a strong relation to returns, while average industry seasonality has somewhat lower predictive power. We examine whether returns are evident when the level of seasonality is measured by the size of the gap between high and low quarters, rather than the reliability of one quarter being larger than others. We find that earnings rank has a higher impact on returns when the difference between average earnings levels in seasonal versus non-seasonal quarters is higher, consistent with both the reliability and size of seasonal effects playing a role in driving returns. Finally, we examine seasonality returns separately for each calendar quarter of the year, and find the largest returns for the first quarter but directionally positive returns in all four quarters.

6. Conclusion

We document a new finding about earnings returns – that stocks exhibit high earnings announcement returns when historically their earnings are larger than normal. This effect does not appear to be driven by a delayed reaction to firm-specific news or loadings on risk factors, nor is it a general property of earnings news in other quarters. High seasonality quarters also display greater positive surprise by analysts, suggesting the effect is related to mistaken estimates of earnings.

[4] Available online at http://www-bcf.usc.edu/~dhsolomo/seasonality_appendix.pdf

We present evidence that the effect is linked to the tendency of investors to underreact to predictable information in earning seasonality. We hypothesize that investors who suffer from a tendency to overweight recent data may place too much weight on the lower average earnings that follow a high seasonal quarter, causing them to be too pessimistic by the time the high seasonal quarter comes around again. Consistent with this view, the effects of seasonality are larger when earnings since the last high seasonal quarter are at lower levels.

It is worth noting that our findings do not mean that adjusting for seasonality is a trivial task, or that investors are ignoring seasonality altogether. Indeed, the results in this paper would not tell an analyst or investor exactly how they should adjust for seasonality for each firm (other than to adjust more). There are a number of complications, such as firms with a short time-series of data or large overall trends in earnings. Instead, we show that whatever adjustment investors are using is insufficient – the average response to seasonal patterns in earnings is too low.

The results in this paper are consistent with investors being less likely to process information when it is not salient. More surprisingly, our results are consistent with the idea that even when earnings information is widely available and opportunities for learning are frequent, investors may still face other behavioral constraints that prevent them from fully incorporating such information into asset prices. Our results, in combination with other findings in the literature, point to a general but not commonly appreciated stylized fact, namely that predictably recurring firm events tend to be associated with abnormally high returns. The implications of this for behavioral finance are well deserving of future study.

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Table I – Summary Statistics

This table presents summary statistics for the main variables used in the paper. Panel A presents the distribution of firm-level characteristics, included market capitalization (in millions of dollars), the log of the ratio of book value of equity to market value of equity, stock returns in the current month, from 2 to 12 months ago, and the average returns from 12, 24, 36, 48 and 60 months ago ('Return Seasonality', as in Heston and Sadka (2008)). Return variables are also shown separately for months a predicted earnings announcement, defined as when the stock had a quarterly earnings announcement 12 months prior. Earnings rank at each time is calculated by taking 5 years of earnings data and ranking each announcement by the earnings per share (adjusted for stock splits, etc.).The earnings rank variable is formed by taking the average rank of the 5 announcements from the same fiscal quarter as that of the current announcement. In Panel B, we show the returns of portfolios sorted by earnings rank. In all portfolios, the earnings rank measure is lagged 12 months from the return date, meaning that earnings information is taken from one year ago to six years ago, and used to forecast the seasonality for the upcoming predicted announcement. We sort stocks each month into quintiles according to the distribution of earnings rank that month, with quintile 5 corresponding to stocks where the earnings were historically higher than normal in the upcoming quarter and quintile 1 corresponding to stocks with the earnings were historically lower than normal in the upcoming quarter. 'EW' and 'VW' refer to equal-weighted and value-weighted portfolios respectively. The data runs from September 1972 to October 2013.

Panel A - Stock Characteristics

Variable	Mean	Standard Deviation	25th Pctile	Median	75th Pctile	N
All Firms, All Months						
Market Capitalization	1424.18	9354.32	30.00	107.72	475.77	2,460,113
Log Book to Market Ratio	-0.54	0.84	-1.00	-0.47	0.01	1,705,906
Return (%)	1.04	12.93	-5.22	0.38	6.58	2,469,021
Return 2 to 12 months ago (%)	21.80	67.10	-9.65	11.45	37.57	2,246,753
Return Seasonality (%)	1.61	5.90	-1.66	1.21	4.34	1,663,983
Number of Stocks						21,189
Number of Stock*Months						2,469,039
Predicted Earnings Announcement Months						
Earnings Rank	10.85	2.85	9.10	11.00	12.60	302,474
Return (%)	1.14	13.86	-5.75	0.61	7.41	472,442
Return 2 to 12 months ago (%)	22.45	72.47	-10.19	11.55	38.36	470,522
Return Seasonality (%)	1.88	6.47	-1.80	1.42	4.94	372,715
Number of Stocks						14,420
Number of Stock*Months						472,442

Panel B - Summary Statistics for Portfolio Returns													
Weight	**Earnings Rank**	**Avg. Return**	**Std. Dev. Returns**	**Sharpe Ratio**	**Min**	**5%**	**10%**	**25%**	**50%**	**75%**	**90%**	**95%**	**Max**
EW	1 (Low)	1.46	5.28	0.19	-25.84	-7.11	-4.18	-1.36	1.85	4.53	7.29	8.90	23.45
EW	5 (High)	1.75	5.14	0.25	-22.40	-6.57	-4.09	-1.31	2.04	4.98	7.55	9.48	20.88
EW	5 -1	0.29	2.37	0.12	-18.04	-3.26	-2.26	-1.01	0.24	1.60	2.92	3.74	10.20
VW	1 (Low)	1.37	5.18	0.18	-21.91	-6.54	-4.43	-1.51	1.21	4.45	7.31	9.89	22.15
VW	5 (High)	1.76	5.18	0.26	-18.33	-5.89	-4.50	-1.54	1.71	4.66	7.78	10.12	32.15
VW	5 -1	0.39	3.75	0.10	-14.88	-4.94	-3.79	-1.82	0.31	2.36	4.61	6.30	18.44

Table II – Earnings Seasonality and Abnormal Returns

This table presents the abnormal returns to portfolios formed on measures of earnings seasonality. For each stock with a quarterly earnings announcement 12 months ago, we rank earnings announcements from six years ago to one year ago by earnings per share (adjusted for stock splits, etc.). The earnings rank variable is the average rank of the 5 past announcements from the same fiscal quarter as the expected upcoming announcement. We sort stocks each month into quintiles according to the distribution of earnings rank that month, with quintile 5 corresponding to stocks where the earnings were historically higher than normal in the upcoming quarter and quintile 1 being historically lower than normal earnings in the upcoming quarter. 'EW' and 'VW' are equal-weighted and value-weighted portfolios respectively. Abnormal returns under a four factor model are calculated by regressing portfolio excess returns on excess market returns, SMB, HML and UMD from Ken French's website. In Panel A, all firms are included. In Panel B, we examine the top and bottom quintiles only for stocks that were also in the other extreme quintile within 9 months either side of the current month. The data runs from September 1972 to October 2013. The top number is the coefficient, the bottom number in parentheses is the t-statistic, and *, ** and *** denote significance at the 10%, 5% and 1% level respectively.

Panel A - Base Four Factor Regressions

Earnings Rank	(VW) Intercept	(EW) Intercept	MKTRF	SMB	HML	UMD	R2	N
1 (Low)	0.358 ***	0.306 ***	0.948 ***	0.566 ***	0.370 ***	-0.039 *	0.868	492
	(2.77)	(3.35)	(45.68)	(19.27)	(11.71)	(-1.95)		
2	0.159	0.278 ***	1.004 ***	0.701 ***	0.281 ***	-0.025	0.908	492
	(1.24)	(3.37)	(53.52)	(26.36)	(9.83)	(-1.39)		
3	0.452 ***	0.291 ***	1.001 ***	0.686 ***	0.178 ***	-0.041 **	0.904	492
	(2.82)	(3.43)	(51.86)	(25.07)	(6.05)	(-2.19)		
4	0.216 *	0.375 ***	0.986 ***	0.653 ***	0.179 ***	0.031 *	0.912	492
	(1.69)	(4.77)	(55.24)	(25.81)	(6.59)	(1.82)		
5 (High)	0.909 ***	0.653 ***	0.936 ***	0.473 ***	0.292 ***	-0.049 **	0.854	492
	(6.03)	(6.98)	(44.02)	(15.69)	(9.03)	(-2.41)		
5 - 1	0.551 ***	0.347 ***	-0.011	-0.093 ***	-0.077 **	-0.010	0.020	492
	(3.14)	(3.13)	(-0.45)	(-2.61)	(-2.02)	(-0.42)		

Panel B -Portfolios Using Only Within-Firm Variation

Weighting	Earnings Rank	Intercept	MKTRF	SMB	HML	UMD	R2	N
EW	1 (Low)	0.294 ***	0.928 ***	0.523 ***	0.400 ***	-0.048 **	0.819	485
		(2.76)	(38.15)	(15.16)	(10.83)	(-2.06)		
EW	5 (High)	0.632 ***	0.912 ***	0.469 ***	0.347 ***	-0.042 *	0.793	480
		(5.60)	(35.45)	(12.85)	(8.88)	(-1.68)		
EW	5 - 1	0.335 **	-0.015	-0.051	-0.056	0.005	0.006	480
		(2.56)	(-0.50)	(-1.20)	(-1.25)	(0.17)		
VW	1 (Low)	0.414 ***	0.907 ***	0.029	0.074	0.087 ***	0.659	485
		(2.92)	(28.11)	(0.64)	(1.51)	(2.79)		
VW	5 (High)	0.802 ***	0.899 ***	-0.023	0.014	0.055	0.562	480
		(4.60)	(22.66)	(-0.41)	(0.23)	(1.43)		
VW	5 - 1	0.379 *	-0.008	-0.049	-0.065	-0.034	0.003	480
		(1.88)	(-0.16)	(-0.75)	(-0.94)	(-0.77)		

Table III – Fama Macbeth Cross Sectional Regressions Using Earnings Seasonality

This Table presents the results of Fama and Macbeth (1973) cross-sectional regressions that consider the effect of earnings seasonality on stock returns. The main independent variable is earnings rank. For each announcement, we rank earnings announcements from six years ago to one year ago by their earnings per share (adjusted for stock splits, etc.). The earnings rank variable is formed by taking the average rank of the 5 past announcements from the same fiscal quarter as that of the upcoming announcement. This variable is included both as a raw number, and as a percentile of firms that month. Additional controls are included for dummy variables of whether the stock has a predicted earnings announcement, a predicted dividend, Heston and Sadka (2008) Seasonality (the average returns of the stock from 12, 24, 36, 48 and 60 months ago), the log market capitalization from the previous month, the log book to market ratio, the previous month's stock return, and the stock returns from 2 to 12 months ago. Each month, a separate regression is run on the cross-section of stocks using returns as the dependent variable and the control variables as independent variables. The time series of coefficients for each variable is then averaged to give the final coefficient, and the *t*-statistic for the mean of the series of coefficients is reported in parentheses. Columns 1-4 use only firms that had an earnings announcement 12 months ago, while columns 5-8 use all firms. The top number is the coefficient, the bottom number in parentheses is the *t*-statistic, and *, ** and *** denote significance at the 10%, 5% and 1% level respectively.

	Only Firm Months with Predicted Earnings				All Firm Months			
	1	2	3	4	5	6	7	8
Earnings Rank (raw)	0.034 ***	0.034 ***			-0.017 **	-0.012 *		
	(2.78)	(2.95)			(-2.22)	(-1.69)		
Earnings Rank (raw) *					0.051 ***	0.042 ***		
Predicted Earnings					(3.71)	(3.24)		
Earnings Rank (Pctile)			0.313 **	0.329 ***			-0.199 **	-0.133 *
			(2.53)	(2.75)			-2.509	(-1.86)
Earnings Rank (Pctile) *							0.512 ***	0.421 ***
Predicted Earnings							(3.67)	(3.18)
Predicted Earnings					-0.156	-0.078	0.146	0.169 *
					(-0.94)	(-0.51)	(1.53)	(1.92)
Predicted Dividend		0.227 ***		0.226 ***		0.281 ***		0.280 ***
		(3.29)		(3.27)		(5.83)		(5.82)
Heston and Sadka (2008)		3.131 ***		3.105 ***		3.275 ***		3.266 ***
Seasonality		(4.11)		(4.05)		(6.03)		(6.01)
Log Market Cap		0.019		0.019		-0.036		-0.036
		(0.54)		(0.55)		(-1.28)		(-1.27)
Log Book to Market		0.408 ***		0.411 ***		0.239 ***		0.238 ***
		(5.04)		(5.09)		(3.75)		(3.74)
Momentum		0.385 **		0.385 **		0.497 ***		0.497 ***
		(2.17)		(2.17)		(3.35)		(3.35)
Return (t-1)		-4.463 ***		-4.471 ***		-3.630 ***		-3.628 ***
		(-8.35)		(-8.35)		(-9.16)		(-9.15)
Avg. R-Sq	0.004	0.064	0.004	0.064	0.005	0.050	0.005	0.050
N	494	492	494	492	494	494	494	494

Table IV – Earnings Seasonality at Different Horizons

This table presents the abnormal returns to portfolios formed on measures of earnings seasonality, lagged at different horizons. The base earnings rank measure considers 5 years of earnings announcements, and ranks each announcement by the earnings per share (adjusted for stock splits, etc.). The earnings rank variable is formed by taking the average rank of the 5 announcements from the same fiscal quarter as that of the expected upcoming announcement. Panel A considers the measure lagged at different multiples of 12 months (so that the seasonality estimates are for the same quarter as the upcoming one). '12' uses data from 1 year ago to 6 years ago, '24' uses data from 2 years to 7 years ago, etc. Panel B considers the measure lagged at different multiples of 3 months, so each stock is still predicted to have an earnings announcement that month, but for multiples other than 12 and 24 the seasonality measure applies to a different quarter than the upcoming announcement. In both cases, stocks are sorted each month into quintiles according to the distribution of earnings rank that month, with quintile 5 corresponding to stocks where the earnings were historically higher than normal in the lagged period and quintile 1 corresponding to stocks with the earnings were historically lower than normal in the lagged period. Abnormal returns under a four factor model are calculated by regressing portfolio excess returns on excess market returns, SMB, HML and UMD from Ken French's website. The top number is the intercept from the four factor regression, and the bottom number in parentheses is the *t*-statistic associated with the intercept. The data runs from September 1972 to October 2013. *, ** and *** denote significance at the 10%, 5% and 1% level respectively.

Panel A - Seasonality at Different Annual Horizons

		Months Lagged									
Weighting	**Earnings Rank**	**12**	**24**	**36**	**48**	**60**	**72**	**84**	**96**	**108**	**120**
EW	1 (Low)	0.306 ***	0.167 *	0.144	0.187 **	0.167 *	0.195 *	0.277 ***	0.244 **	0.290 ***	0.222 **
		(3.35)	(1.89)	(1.61)	(1.99)	(1.66)	(1.92)	(2.84)	(2.30)	(2.83)	(2.04)
EW	5 (High)	0.653 ***	0.709 ***	0.692 ***	0.688 ***	0.642 ***	0.576 ***	0.552 ***	0.558 ***	0.561 ***	0.622 ***
		(6.98)	(7.81)	(7.39)	(7.27)	(6.27)	(5.79)	(5.33)	(5.28)	(5.19)	(5.54)
EW	5 - 1	0.347 ***	0.542 ***	0.548 ***	0.502 ***	0.475 ***	0.381 ***	0.275 **	0.314 ***	0.271 **	0.400 ***
		(3.13)	(4.83)	(4.86)	(4.50)	(4.06)	(3.07)	(2.33)	(2.63)	(2.25)	(3.16)
VW	1 (Low)	0.358 ***	0.218 *	0.173	0.263 *	0.223	0.297 *	0.299 **	0.253 *	0.153	0.321 **
		(2.77)	(1.69)	(1.26)	(1.86)	(1.46)	(1.76)	(2.01)	(1.68)	(0.98)	(1.98)
VW	5 (High)	0.909 ***	0.900 ***	0.810 ***	0.736 ***	0.693 ***	0.796 ***	0.716 ***	0.688 ***	0.665 ***	0.706 ***
		(6.03)	(6.28)	(5.31)	(4.96)	(4.46)	(4.66)	(4.23)	(4.35)	(3.93)	(4.26)
VW	5 - 1	0.551 ***	0.682 ***	0.637 ***	0.473 **	0.470 **	0.500 **	0.418 **	0.435 **	0.513 **	0.385 *
		(3.14)	(4.00)	(3.25)	(2.53)	(2.31)	(2.09)	(2.03)	(2.11)	(2.37)	(1.71)

Panel B - Seasonality at Different Quarterly Horizons									
		Months Lagged							
Weighting	Earnings Rank	3	6	9	12	15	18	21	24
EW	1 (Low)	0.220 ***	0.081	0.317 ***	0.306 ***	0.376 ***	0.138 *	0.460 ***	0.167 *
		(2.68)	(1.01)	(3.94)	(3.35)	(4.45)	(1.69)	(4.88)	(1.89)
EW	5 (High)	0.221 ***	0.425 ***	0.300 ***	0.653 ***	0.153 *	0.399 ***	0.249 ***	0.709 ***
		(2.69)	(5.20)	(3.66)	(6.98)	(1.82)	(4.78)	(2.98)	(7.81)
EW	5 - 1	0.001	0.344 ***	-0.016	0.347 ***	-0.223 **	0.261 ***	-0.211 *	0.542 ***
		(0.01)	(3.53)	(-0.17)	(3.13)	(-2.15)	(2.69)	(-1.93)	(4.83)
VW	1 (Low)	0.461 ***	-0.014	0.673 ***	0.358 ***	0.519 ***	-0.040	0.748 ***	0.218 *
		(3.23)	(-0.10)	(5.06)	(2.77)	(3.26)	(-0.24)	(5.25)	(1.69)
VW	5 (High)	0.388 ***	0.367 **	0.081	0.909 ***	0.359 ***	0.352 **	-0.009	0.900 ***
		(2.92)	(2.17)	(0.63)	(6.03)	(2.93)	(2.21)	(-0.07)	(6.28)
VW	5 - 1	-0.073	0.381	-0.593 ***	0.551 ***	-0.160	0.393 *	-0.757 ***	0.682 ***
		(-0.40)	(1.60)	(-3.28)	(3.14)	(-0.79)	(1.70)	(-4.13)	(4.00)

Table V – Earnings Seasonality and Earnings Announcement Risk

This table examines whether earnings seasonality returns load on a common factor related to earnings announcement risk. Excess returns of portfolios sorted on earnings rank are regressed on excess market returns, SMB, HML and UMD (from Ken French's website), as well as the excess returns of an equal-weighted portfolio of all stocks with an earnings announcement 12 months ago (EARNRF). To form seasonality portfolios, for each stock with a quarterly earnings announcement 12 months ago, we rank earnings announcements from six years ago to one year ago by their earnings per share (adjusted for stock splits, etc.). The earnings rank variable is formed by taking the average rank of the 5 past announcements from the same fiscal quarter as that of the expected upcoming announcement. We sort stocks each month into quintiles according to the distribution of earnings rank that month, with quintile 5 corresponding to stocks where the earnings were historically higher than normal in the upcoming quarter and quintile 1 corresponding to stocks with the earnings were historically lower than normal in the upcoming quarter. In Panel A the seasonality portfolios are equal-weighted, in Panel B they are value weighted. The data runs from September 1972 to October 2013. The top number is the coefficient, the bottom number in parentheses is the *t*-statistic, and *, ** and *** denote significance at the 10%, 5% and 1% level respectively.

Panel A - Equal-Weighted

Earnings Rank	Intercept	MKTRF	SMB	HML	UMD	EARNRF	R2	N
1 (Low)	0.017	-0.065	-0.146 ***	0.180 ***	-0.001	1.039 ***	0.910	492
	(0.22)	(-0.94)	(-2.75)	(6.20)	(-0.06)	(15.11)		
2	0.010	0.064	0.040	0.104 ***	0.010	0.965 ***	0.939	492
	(0.14)	(1.03)	(0.84)	(4.02)	(0.69)	(15.70)		
3	-0.001	-0.021	-0.033	-0.014	-0.002	1.049 ***	0.940	492
	(-0.01)	(-0.35)	(-0.70)	(-0.55)	(-0.15)	(17.12)		
4	0.120 *	0.092	0.024	0.011	0.065 ***	0.917 ***	0.941	492
	(1.81)	(1.56)	(0.54)	(0.45)	(4.57)	(15.69)		
5 (High)	0.361 ***	-0.089	-0.248 ***	0.100 ***	-0.011	1.051 ***	0.899	492
	(4.50)	(-1.24)	(-4.53)	(3.34)	(-0.62)	(14.82)		
5 - 1	0.344 ***	-0.024	-0.102	-0.080 *	-0.010	0.013	0.020	492
	(3.00)	(-0.23)	(-1.30)	(-1.87)	(-0.40)	(0.12)		

Panel B - Value-Weighted

Earnings Rank	Intercept	MKTRF	SMB	HML	UMD	EARNRF	R2	N
1 (Low)	0.232 *	0.544 ***	-0.319 ***	0.042	0.072 **	0.450 ***	0.733	492
	(1.77)	(4.65)	(-3.57)	(0.86)	(2.54)	(3.87)		
2	0.114	0.864 ***	0.020	0.076	0.029	0.162	0.757	492
	(0.86)	(7.33)	(0.23)	(1.54)	(1.01)	(1.38)		
3	0.401 **	0.872 ***	-0.045	-0.170 ***	0.027	0.185	0.697	492
	(2.43)	(5.93)	(-0.40)	(-2.77)	(0.77)	(1.27)		
4	0.134	0.764 ***	-0.126	-0.157 ***	0.083 ***	0.297 **	0.780	492
	(1.02)	(6.53)	(-1.41)	(-3.22)	(2.95)	(2.55)		
5 (High)	0.716 ***	0.205	-0.542 ***	-0.198 ***	0.049	0.695 ***	0.646	492
	(4.72)	(1.52)	(-5.25)	(-3.51)	(1.51)	(5.19)		
5 - 1	0.483 ***	-0.338 **	-0.223 *	-0.240 ***	-0.023	0.245	0.032	492
	(2.67)	(-2.10)	(-1.81)	(-3.56)	(-0.58)	(1.53)		

Table VI – Analyst Forecast Errors and Earnings Seasonality

This Table examines how analyst forecast errors vary with measures of earnings seasonality. The dependent variable is the difference between actual earnings per share and the median analyst forecast of earnings per share, divided by price three days before the announcement. Earnings forecasts are considered if made within 90 days of the announcement date. The main independent variable is earnings rank. For each announcement, we rank earnings announcements from six years ago to one year ago by their earnings per share (adjusted for stock splits, etc.). The earnings rank variable is formed by taking the average rank of the 5 past announcements from the same fiscal quarter as that of the upcoming announcement. Additional controls are included for the log of the number of estimates, for the standard deviation of analyst forecasts scaled by assets per share (set to zero for cases where there is only one analyst), a dummy variable for cases where there is only one forecast, and forecast errors from the previous four announcements. 'Stock Characteristics' includes the log market capitalization from the previous month, the log book to market ratio, the previous month's stock return, and the stock returns from 2 to 12 months ago. Standard errors are clustered by firm and date. The top number is the coefficient, the bottom number in parentheses is the *t*-statistic, and *, ** and *** denote significance at the 10%, 5% and 1% level respectively.

	Dependent variable is forecast error: earnings per share minus median analyst forecast, divided by price						
Earnings Rank	0.032***	0.023***	0.017***	0.012***	0.013 ***	0.014 ***	0.013 ***
	(11.43)	(9.27)	(7.34)	(5.19)	(5.00)	(5.73)	(5.15)
Log (# Estimates)		0.061***	-0.103***	-0.071***	-0.074 ***	-0.083 ***	-0.096 ***
		(6.13)	(-8.09)	(-6.79)	(-7.04)	(-5.59)	(-6.38)
Forecast Dispersion		-0.443***	-0.423***	-0.300***	-0.296 ***	-0.324 ***	-0.313 ***
		(-16.42)	(-15.37)	(-12.73)	(-12.57)	(-14.18)	(-13.84)
Single Estimate (Dummy)		-0.467***	-0.441***	-0.277***	-0.258 ***	-0.281 ***	-0.258 ***
		(-13.10)	(-12.59)	(-9.64)	(-8.83)	(-8.96)	(-8.30)
Forecast Error (t-1)				0.168***	0.165 ***	0.086 ***	0.082 ***
				(14.74)	(14.25)	(7.15)	(6.81)
Forecast Error (t-2)				0.097***	0.097 ***	0.043 ***	0.044 ***
				(7.48)	(7.22)	(2.97)	(2.91)
Forecast Error (t-3)				0.045***	0.046 ***	-0.001	0.000
				(3.89)	(3.89)	(-0.08)	(0.00)
Forecast Error (t-4)				0.054***	0.053 ***	0.009	0.008
				(4.71)	(4.51)	(0.75)	(0.66)
Stock Characteristics	No	No	Yes	Yes	Yes	Yes	Yes
Date FE	No	No	No	No	Yes	No	Yes
Stock FE	No	No	No	No	No	Yes	Yes
Observations	180,184	180,184	176,508	159,133	159,133	159,133	159,133
R-squared	0.001	0.129	0.143	0.190	0.205	0.242	0.081

Table VII – Daily Characteristic Adjusted Returns Around Earnings Announcements

This Table examines daily characteristic adjusted returns around earnings announcements. Each return takes the company's stock return and subtracts the return of a matched portfolio on quintiles of market-capitalization, book-to-market and momentum. Date *t* is the day of the earnings announcement and the analysis is conducted for 10 trading days before and after the announcement. The first three columns present the average adjusted return for the highest quintile of seasonality, the middle three quintiles of seasonality and the lowest quintile of seasonality. The fourth column shows the difference in returns between the highest and lowest quintile of seasonality. The last column presents the coefficient on a regression of adjusted return on *EarnRank*. Standard errors are clustered by firm and date. The top number is the coefficient, the bottom number in parentheses is the *t*-statistic, and *, ** and *** denote significance at the 10%, 5% and 1% level respectively.

Days from Earnings Annoucnement (t)	High Earnings Rank	Middle Earnings Rank	Low Earnings Rank	(High Earnings Rank) - (Low Earnings Rank)	Regression Coefficient on EarnRank
t-10	-0.003	-0.003	0.015	-0.018	-0.001
	(-0.24)	(-0.49)	(1.39)	(-1.19)	(-0.88)
t-9	0.007	0.010 *	-0.014	0.021	0.001
	(0.65)	(1.66)	(-1.34)	(1.48)	(0.67)
t-8	0.011	0.002	0.010	0.001	0.000
	(1.05)	(0.37)	(0.91)	(0.09)	(0.23)
t-7	0.017	0.009	0.012	0.005	0.001
	(1.60)	(1.45)	(1.10)	(0.34)	(0.73)
t-6	0.026 **	0.008	0.003	0.023	0.002
	(2.48)	(1.26)	(0.31)	(1.60)	(1.21)
t-5	0.010	0.015 **	0.034 ***	-0.025 *	-0.003 **
	(0.90)	(2.23)	(3.26)	(-1.67)	(-2.11)
t-4	0.000	0.020 ***	0.021 **	-0.021	-0.001
	(0.02)	(3.00)	(1.98)	(-1.44)	(-0.73)
t-3	0.030 ***	0.039 ***	0.013	0.017	0.001
	(2.92)	(5.97)	(1.31)	(1.18)	(0.84)
t-2	0.067 ***	0.041 ***	0.030 ***	0.038 **	0.004 **
	(6.26)	(6.20)	(2.75)	(2.56)	(2.52)
t-1	0.122 ***	0.108 ***	0.064 ***	0.058 ***	0.006 ***
	(10.33)	(13.66)	(5.20)	(3.48)	(3.21)
t	0.235 ***	0.136 ***	0.139 ***	0.097 ***	0.013 ***
	(11.06)	(10.72)	(6.86)	(3.37)	(4.40)
t+1	0.072 ***	0.021 **	0.008	0.064 ***	0.007 ***
	(4.96)	(2.31)	(0.55)	(3.35)	(3.60)
t+2	0.001	-0.002	0.005	-0.004	0.000
	(0.05)	(-0.23)	(0.42)	(-0.27)	(-0.15)
t+3	0.014	-0.006	-0.005	0.019	0.002
	(1.34)	(-0.90)	(-0.51)	(1.36)	(1.56)
t+4	0.029 ***	0.009	0.002	0.027 *	0.003 **
	(2.80)	(1.47)	(0.20)	(1.91)	(1.98)
t+5	0.023 **	0.008	0.023 **	0.001	-0.001
	(2.36)	(1.32)	(2.25)	(0.06)	(-0.37)
t+6	0.014	0.022 ***	0.029 ***	-0.015	-0.001
	(1.48)	(3.68)	(2.96)	(-1.13)	(-0.53)
t+7	-0.004	0.013 **	0.008	-0.012	-0.001
	(-0.46)	(2.14)	(0.74)	(-0.87)	(-0.65)
t+8	0.021 **	0.019 ***	0.020 **	0.001	0.000
	(2.13)	(3.11)	(1.99)	(0.06)	(-0.21)
t+9	0.025 ***	0.002	0.000	0.026 *	0.002
	(2.61)	(0.33)	(-0.04)	(1.86)	(1.31)
t+10	0.003	0.013 **	0.016	-0.013	-0.001
	(0.29)	(2.08)	(1.61)	(-1.00)	(-1.02)

Table VIII – Recent Earnings Levels and Earnings Seasonality Abnormal Returns

This table presents the abnormal returns to portfolios sorted on both measures of earnings seasonality and the level of other recent earnings announcements. Stocks are sorted based on whether they are above or below the median earnings rank for that month. The second sorting variable is the gap between recent earnings per share (divided by assets) and earnings from 12 months ago. In Panel A, firms are sorted by the difference between the average earnings the three most recent announcements before portfolio formation (typically, but not always, 3, 6 and 9 months before formation) and the announcement 12 months ago. In Panel B, firms are sorted on the gap between the average of the three earnings announcements before the announcement 12 months ago (typically, but not always, 15, 18 and 21 months before formation) and the level of earnings 3 months ago. Abnormal returns relative to a four factor model are shown for each portfolio, the difference portfolios, and the double difference portfolio. In all cases portfolio excess returns are regressed on excess market returns, SMB, HML and UMD from Ken French's website. In each row, the top number is the intercept from the four factor regression, the middle number in parentheses is the *t*-statistic associated with the intercept, and the bottom number in brackets is the number of portfolio months. The data runs from September 1972 to October 2013. *, ** and *** denote significance at the 10%, 5% and 1% level respectively.

Panel A - Gap Between Recent Earnings and 12 Months Ago

Equal Weighted

Gap Between Earnings (3,6,9) Months Ago and 12 Month Ago	All	Earnings Rank Level 1 (Low)	Earnings Rank Level 2 (High)	2 - 1
All		0.284 ***	0.503 ***	0.219 ***
		(4.24)	(7.39)	(3.15)
		{482}	{482}	{482}
1 (Non-Annual earnings more negative)	0.000	-0.315 ***	0.341 ***	0.655 ***
	(0.00)	(-3.26)	(4.38)	(6.46)
	{481}	{451}	{472}	{451}
2 (Non-Annual earnings more positive)	0.625 ***	0.532 ***	0.826 ***	0.275 ***
	(8.46)	(6.42)	(8.79)	(2.90)
	{481}	{462}	{456}	{455}
2 -1	0.625 ***	0.856 ***	0.473 ***	-0.375 ***
	(8.26)	(7.93)	(5.05)	(-2.90)
	{481}	{451}	{456}	{450}

Value Weighted

Gap Between Earnings (3,6,9) Months Ago and 12 Month Ago	All	Earnings Rank Level 1 (Low)	Earnings Rank Level 2 (High)	2 - 1
All		0.290 ***	0.577 ***	0.287 **
		(3.13)	(5.07)	(2.11)
		{482}	{482}	{482}
1 (Non-Annual earnings more negative)	0.325 ***	-0.093	0.676 ***	0.787 ***
	(2.91)	(-0.65)	(4.96)	(4.06)
	{481}	{451}	{472}	{451}
2 (Non-Annual earnings more positive)	0.376 ***	0.316 ***	0.400 **	0.025
	(3.68)	(2.79)	(2.54)	(0.14)
	{481}	{462}	{456}	{455}
2 -1	0.051	0.481 ***	-0.298	-0.769 ***
	(0.35)	(2.68)	(-1.58)	(-2.93)
	{481}	{451}	{456}	{450}

Panel B - Gap Between Older Earnings and 12 Months Ago				
Equal Weighted				
Gap Between Earnings (15,18,21) Months Ago and 12 Month Ago		**Earnings Rank Level**		
	All	1 (Low)	2 (High)	2 - 1
All		0.284 ***	0.503 ***	0.219 ***
		(4.24)	(7.39)	(3.15)
		{482}	{482}	{482}
1 (Non-Annual earnings more negative)	0.246 ***	-0.122	0.433 ***	0.541 ***
	(3.42)	(-1.14)	(5.33)	(4.89)
	{478}	{451}	{470}	{451}
2 (Non-Annual earnings more positive)	0.393 ***	0.406 ***	0.676 ***	0.278 ***
	(5.82)	(5.20)	(6.90)	(2.72)
	{478}	{463}	{455}	{455}
	0.148 *	0.505 ***	0.249 **	-0.257 *
2 -1	(1.93)	(4.41)	(2.30)	(-1.69)
	{478}	{451}	{455}	{450}

Value Weighted				
Gap Between Earnings (15,18,21) Months Ago and 12 Month Ago		**Earnings Rank Level**		
	All	1 (Low)	2 (High)	2 - 1
All		0.290 ***	0.577 ***	0.287 **
		(3.13)	(5.07)	(2.11)
		{482}	{482}	{482}
1 (Non-Annual earnings more negative)	0.508 ***	0.097	0.647 ***	0.541 ***
	(4.87)	(0.64)	(5.00)	(2.72)
	{478}	{451}	{470}	{451}
2 (Non-Annual earnings more positive)	0.285 **	0.223 *	0.577 ***	0.314
	(2.39)	(1.93)	(3.06)	(1.48)
	{478}	{463}	{455}	{455}
	-0.223	0.194	-0.066	-0.234
2 -1	(-1.53)	(1.00)	(-0.30)	(-0.75)
	{478}	{451}	{455}	{450}

Table IX – Recent Records and Earnings Seasonality Abnormal Returns

This table presents the abnormal returns to portfolios sorted on both measures of earnings seasonality and whether the stock had reached record earnings in the previous 12 months. For each stock with a quarterly earnings announcement 12 months ago, we rank earnings announcements from six years ago to one year ago by their earnings per share (adjusted for stock splits, etc.). The earnings rank variable is formed by taking the average rank of the 5 past announcements from the same fiscal quarter as that of the expected upcoming announcement. Stocks are sorted based on whether they are above or below the median earnings rank for that month. The second sorting variable is whether the stock had record earnings in the previous 12 months. Abnormal returns relative to a four factor model are shown for each portfolio, the difference portfolios, and the double difference portfolio. In all cases portfolio excess returns are regressed on excess market returns, SMB, HML and UMD from Ken French's website. In each row, the top number is the intercept from the four factor regression, the middle number in parentheses is the *t*-statistic associated with the intercept, and the bottom number in brackets is the number of portfolio months. Panel A shows the returns to equal weighted portfolios, while Panel B shows the returns to value weighted portfolios. The data runs from September 1972 to October 2013. *, ** and *** denote significance at the 10%, 5% and 1% level respectively.

Panel A - Equal Weighted

Record Within Past Year	Earnings Rank Level: All	1 (Low)	2 (High)	2 - 1
All		0.284 ***	0.503 ***	0.219 ***
		(4.24)	(7.39)	(3.15)
		{482}	{482}	{482}
No Recent Record	-0.130 ***	0.122	0.438 ***	0.316 ***
	(-3.35)	(1.62)	(5.65)	(3.54)
	{493}	{482}	{482}	{482}
Recent Record	0.266 ***	0.570 ***	0.549 ***	-0.020
	(4.56)	(5.52)	(6.09)	(-0.21)
	{492}	{481}	{481}	{481}
Recent - No Recent	0.395 ***	0.450 ***	0.114	-0.336 ***
	(7.45)	(4.13)	(1.19)	(-2.73)
	{492}	{481}	{481}	{481}

Panel B - Value Weighted

Record Within Past Year	Earnings Rank Level: All	1 (Low)	2 (High)	2 - 1
All		0.290 ***	0.577 ***	0.287 **
		(3.13)	(5.07)	(2.11)
		{482}	{482}	{482}
No Recent Record	-0.108 ***	0.055	0.578 ***	0.523 ***
	(-2.76)	(0.50)	(4.93)	(3.49)
	{493}	{482}	{482}	{482}
Recent Record	0.137 ***	0.498 ***	0.513 ***	0.015
	(3.84)	(3.88)	(3.72)	(0.09)
	{492}	{481}	{481}	{481}
Recent - No Recent	0.251 ***	0.445 ***	-0.062	-0.507 **
	(3.70)	(2.66)	(-0.38)	(-2.26)
	{492}	{481}	{481}	{481}

Table X – Increases in Turnover and Earnings Seasonality

This table presents the abnormal returns to portfolios sorted on both measures of earnings seasonality and the average increase in turnover during announcements of the current quarter. Stocks are sorted based on whether they are above or below the median earnings rank for that month. The second sorting variable is the average share turnover in the past 5 announcements from the same fiscal quarter as the upcoming announcement, divided by the average turnover from all announcements in the 5 year period. Abnormal returns relative to a four factor model are shown for each portfolio, the difference portfolios, and the double difference portfolio. In all cases portfolio excess returns are regressed on excess market returns, SMB, HML and UMD from Ken French's website. In each row, the top number is the regression coefficient, the middle number in parentheses is the *t*-statistic, and the bottom number in brackets is the number of portfolio months. Panel A shows the returns to equal weighted portfolios, while Panel B shows the returns to value weighted portfolios. In each row, the top number is the intercept from the four factor regression, the middle number in parentheses is the *t*-statistic associated with the intercept, and the bottom number in brackets is the number of portfolio months. The data runs from September 1972 to October 2013. *, ** and *** denote significance at the 10%, 5% and 1% level respectively.

Panel A - Equal Weighted

Avg Increase in Turnover	Earnings Rank Level: All	1 (Low)	2 (High)	2 - 1
All		0.284 ***	0.503 ***	0.219 ***
		(4.24)	(7.39)	(3.15)
		{482}	{482}	{482}
1 (turnover low this quarter)	0.465 ***	0.375 ***	0.585 ***	0.210 **
	(6.00)	(3.95)	(6.42)	(2.05)
	{425}	{425}	{425}	{425}
2 (turnover high this quarter)	0.362 ***	0.185 *	0.550 ***	0.365 ***
	(4.62)	(1.95)	(5.98)	(3.62)
	{425}	{424}	{425}	{424}
	-0.103	-0.177 *	-0.035	0.142
2 -1	(-1.32)	(-1.67)	(-0.36)	(1.09)
	{425}	{424}	{425}	{424}

Panel B - Value Weighted

Avg Increase in Turnover	Earnings Rank Level: All	1 (Low)	2 (High)	2 - 1
All		0.290 ***	0.577 ***	0.287 **
		(3.13)	(5.07)	(2.11)
		{482}	{482}	{482}
1 (turnover low this quarter)	0.478 ***	0.358 **	0.601 ***	0.244
	(4.12)	(2.46)	(4.12)	(1.25)
	{425}	{425}	{425}	{425}
2 (turnover high this quarter)	0.409 ***	0.188	0.606 ***	0.416 **
	(3.26)	(1.48)	(3.81)	(2.05)
	{425}	{424}	{425}	{424}
	-0.068	-0.166	0.005	0.160
2 -1	(-0.42)	(-0.87)	(0.02)	(0.57)
	{425}	{424}	{425}	{424}

Table XI – Idiosyncratic Volatility and Earnings Seasonality

This table presents the abnormal returns to portfolios sorted on both measures of earnings seasonality and the average level of abnormal idiosyncratic volatility from previous earnings announcements in the same quarter. Stocks are sorted based on whether they are above or below the median earnings rank for that month. The second sorting variable is the average abnormal idiosyncratic volatility that occurred on the day of an earnings announcement 4, 8, 12, 16 and 20 quarters ago. Abnormal returns relative to a four factor model are shown for each portfolio, the difference portfolios, and the double difference portfolio. In Panel A, portfolios are equal weighted while in Panel B portfolios are value weighted. In all cases portfolio excess returns are regressed on excess market returns, SMB, HML and UMD from Ken French's website. In each row, the top number is the intercept from the four factor regression, the middle number in parentheses is the t-statistic associated with the intercept, and the bottom number in brackets is the number of portfolio months. The data runs from September 1972 to October 2013. *, ** and *** denote significance at the 10%, 5% and 1% level respectively.

Panel A -Equal Weighted

Average Abnormal Idiosynchratic Volatility On [t-1] to [t+1]	Earnings Rank Level: All	1 (Low)	2 (High)	2 - 1
All		0.284 ***	0.503 ***	0.219 ***
		(4.24)	(7.39)	(3.15)
		{482}	{482}	{482}
1 (Low Abnormal Idiosynchrativ Vol.)	0.343 ***	0.216 *	0.474 ***	0.292 **
	(3.36)	(1.88)	(3.56)	(2.11)
	{431}	{420}	{422}	{413}
2 (High Abnormal Idiosynchrativ Vol.)	0.748 ***	0.599 ***	0.878 ***	0.282 *
	(8.42)	(5.35)	(7.35)	(1.95)
	{431}	{426}	{430}	{426}
	0.405 ***	0.363 ***	0.431 ***	0.020
2 -1	(3.76)	(2.61)	(2.93)	(0.11)
	{431}	{420}	{422}	{413}

Panel B -Value Weighted

Average Abnormal Idiosynchratic Volatility On [t-1] to [t+1]	Earnings Rank Level: All	1 (Low)	2 (High)	2 - 1
All		0.290 ***	0.577 ***	0.287 **
		(3.13)	(5.07)	(2.11)
		{482}	{482}	{482}
1 (Low Abnormal Idiosynchrativ Vol.)	0.251 *	0.090	0.452 ***	0.373 *
	(1.92)	(0.56)	(2.79)	(1.82)
	{431}	{420}	{422}	{413}
2 (High Abnormal Idiosynchrativ Vol.)	0.752 ***	0.679 ***	0.956 ***	0.291
	(4.63)	(3.92)	(4.60)	(1.17)
	{431}	{426}	{430}	{426}
	0.501 **	0.564 **	0.527 **	-0.058
2 -1	(2.53)	(2.45)	(2.12)	(-0.18)
	{431}	{420}	{422}	{413}

Table XII – Earnings Seasonality and Time-Varying Factor Loadings

This table examines whether earnings seasonality returns can be explained by time-varying loadings on standard factors. Excess returns of portfolios sorted on earnings rank are regressed on excess market returns, SMB, HML and UMD (from Ken French's website), allowing for different loadings in each month of the year. We fit a single abnormal return and 12 loadings on each factor. To form seasonality portfolios, for each stock with a quarterly earnings announcement 12 months ago, we rank earnings announcements from six years ago to one year ago by their earnings per share (adjusted for stock splits, etc.). The earnings rank variable is formed by taking the average rank of the 5 past announcements from the same fiscal quarter as that of the expected upcoming announcement. We sort stocks each month into quintiles according to the distribution of earnings rank that month, with quintile 5 corresponding to stocks where the earnings were historically higher than normal in the upcoming quarter and quintile 1 corresponding to stocks with the earnings were historically lower than normal in the upcoming quarter. . 'EW' and 'VW' refer to equal-weighted and value-weighted portfolios respectively. The top number is the intercept from the four factor regression, and the bottom number in parentheses is the t-statistic associated with the intercept. The data runs from September 1972 to October 2013. *, ** and *** denote significance at the 10%, 5% and 1% level respectively.

Earnings Rank	(VW) Intercept	(EW) Intercept	Factor (MKTRF, SMB, HML, UMD) * Month Controls	(EW) R2	(EW) N
1 (Low)	0.419 ***	0.313 ***	Yes	0.889	492
	(3.02)	(3.30)			
2	0.197	0.269 ***	Yes	0.916	492
	(1.52)	(3.02)			
3	0.292 *	0.260 ***	Yes	0.917	492
	(1.84)	(2.91)			
4	0.128	0.318 ***	Yes	0.929	492
	(0.95)	(3.98)			
5 (High)	0.770 ***	0.632 ***	Yes	0.879	492
	(5.07)	(6.55)			
5 - 1	0.351 **	0.319 ***	Yes	0.156	492
	(1.97)	(2.74)			

Table XIII – Earnings Seasonality and Accounting Variables that Predict Earnings Returns

This table examines whether earnings seasonality returns can be explained by variables from the accounting literature that predict earnings announcement returns. Regressions are run where the dependent variable is the company's stock return with the return of a portfolio matched on quintiles of market-capitalization, book-to-market and momentum. Subtracted from it. The earnings rank variable is formed by taking the average rank of the 5 past announcements from the same fiscal quarter as that of the expected upcoming announcement. Earnings(t-X) –Earnings(t-X-4) denotes the difference in earnings that occurred X quarters ago and that quarter the year prior, winsorised at the 1% and 99% level. Forecast error(t-X) denotes the median analyst's SUE X quarters ago, winsorised at the 1% and 99% level. F-score is calculated as described by Piotroski (2000). Accrual Decile denotes the decile of accruals calculated as in Sloan (1996). The top number is the coefficient, and the bottom number in parentheses is the t-statistic associated with the intercept. The data runs from September 1972 to October 2013. Standard errors are clustered by date and firm and *, ** and *** denote significance at the 10%, 5% and 1%

	Dependent variable is characteristic-adjusted return from t-1 to t+1					
Earnings Rank	0.026 ***	0.027 ***	0.031 ***	0.032 ***	0.030 ***	0.038 ***
	(6.23)	(6.46)	(5.12)	(5.18)	(6.78)	(5.48)
Earnings(t-1)-Earnings(t-5)		0.016				-0.205 ***
		(0.49)				(-3.57)
Earnings(t-2)-Earnings(t-6)		0.092 ***				0.075
		(2.78)				(1.32)
Earnings(t-3)-Earnings(t-7)		-0.093 ***				-0.134 **
		(-2.85)				(-2.54)
Earnings(t-4)-Earnings(t-8)		-0.188 ***				-0.077
		(-5.95)				(-1.46)
Forecast Error (t-1)			-1.504			-0.153
			(-0.62)			(-0.05)
Forecast Error (t-2)			0.391			2.188
			(0.16)			(0.72)
Forecast Error (t-3)			-2.884			-4.037
			(-1.19)			(-1.33)
Forecast Error (t-4)			-5.465 **			-5.154 *
			(-2.48)			(-1.84)
F_Score				-0.063 ***		-0.030 *
				(-4.63)		(-1.87)
Accrual Decile					-0.047 ***	-0.045 ***
					(-7.27)	(-4.55)
Constant	0.018	0.011	0.003	0.359 ***	0.244 ***	0.376 ***
	(0.38)	(0.23)	(0.04)	(3.77)	(3.97)	(3.19)
Observations	273,665	273,665	155,075	153,473	226,286	123,860
R-squared	0.0001	0.0004	0.0003	0.0003	0.0005	0.0009