Being Surprised by the Unsurprising:

Earnings Seasonality and Stock Returns

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

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"Day-to-day fluctuations in the profits of existing investments, which are obviously of an ephemeral and non-significant character, tend to have an altogether excessive, and even an absurd, influence on the market. It is said, for example, that the shares of American companies which manufacture ice tend to sell at a higher price in summer when their profits are seasonally high than in winter when no one wants ice."

-John Maynard Keynes (1936)

Many firms have predictably greater earnings at some points in the year, usually due to the underlying cyclical nature of the firm's business. To avoid misidentifying seasonal patterns as genuine earnings news, the accounting literature has long examined seasonally-adjusted earnings, often by methods like subtracting off same-quarter earnings from prior years (e.g. Bernard and Thomas (1990) among others). By contrast, relatively less consideration has been given to how earnings seasonality itself is priced. One likely reason for this divergence is that correcting for seasonal patterns seems fairly straightforward. 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 thus seems to be tailor-made as an example of an event whose reliability means that it is not news that should move prices in the sense of Samuelson (1965).

Nevertheless, there is a growing body of evidence that many similarly obvious repeating firm events are associated with puzzling abnormal returns. Abnormal returns are evident in months forecasted to have earnings announcements, dividends, stock splits, stock dividends, special dividends, and increases in dividends.[1] Earnings seasonality is thus an interesting test of the

[1] 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)

proposition that recurring firm events are generally associated with abnormal returns. Such a relationship would not be predicted by most information acquisition models, as earnings seasonality is easy to interpret and repeated frequently for each firm, thereby allowing ample opportunities for learning. However, from a behavioral perspective the apparent simplicity of seasonal adjustments can be deceptive: while *identifying* seasonal quarters may be easy, calculating a precise correction for a given firm is more difficult. In addition, repeated events that may appear to be well-understood may be less salient, and thus less likely to attract the careful attention of investors. Consequently, investors may be prone to display biases when making decisions related to such events.

In this paper, we present evidence of abnormal returns consistent with markets failing 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 positive seasonality quarter. We find that companies earn significant abnormal returns in months when they are likely to announce earnings from a positive 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

document high returns in months with an expected dividend. Bessembinder and Zhang (2014) document high returns in months predicted to have stock splits, stock dividends, special dividends, and increases in dividends.

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 (55 basis points) when the portfolio is value weighted.[2]

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. If earnings are higher than average in one month then they will be lower than average in other months of the year, so firms tend to cycle through both the long and short sides of the portfolio. To emphasize this point, we sort a firm's four announcements according to seasonality regardless of the overall level (ensuring each firm appears in each portfolio one month per year, generating only time-series variation within the difference portfolio) and obtain very similar results. In order for risk to explain the

[2] As expected earnings announcement months in general have positive abnormal returns (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.

results, it must be that firms are more risky in months of positive 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 they are controlled for in the regressions.

We examine a number of alternative risk-based explanations, and fail to find support for them. First, the portfolio of positive seasonal firms does not have higher volatility than the portfolio of negative seasonal firms. 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 positive seasonality quarters having a greater exposure to a common source of earnings announcement risk. The returns also do not appear to be driven by increases in idiosyncratic volatility, which Barber, George, Lehavy and Trueman (2013) argue explains earnings announcement returns. Returns to seasonality are similar between firms with high and low expected idiosyncratic volatility, suggesting that the effects are distinct.

We 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 mean analyst forecast errors of cash flows should be related to earnings seasonality. Instead, we find that analyst forecast errors are more positive in positive seasonality quarters. For firms that shift between high and low quintiles of seasonality, the median analyst correctly forecasts 93% of the seasonal shift in earnings and misses 7%. This implies that while analysts take seasonality into account, they do not completely correct for seasonal changes. 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.

When we examine daily characteristic adjusted returns around earnings announcements, we find that most of the abnormal returns occur in the short event window surrounding the announcement. This pattern is consistent with investors and analysts being positively surprised by the earnings news. By contrast, the general returns to earnings announcement months tend to accrue in the pre-announcement period (Johnson and So (2014); Barber et al (2013)).

We hypothesize that the effects of seasonality are a result of investors overweighting (underweighting) recent (year ago) earnings when forming estimates of future earnings. The availability heuristic (Tversky and Kahneman (1973)) describes how individuals estimate probabilities according to the ease with which instances of an event can be brought to mind. Moreover, the recency effect describes how recent information is easier to recall than old information (Murdock Jr (1962), Davelaar et al. (2005)). If an upcoming quarter has positive seasonality, the level of earnings in the three most recent announcements was likely lower than the announcement four quarters ago. If investors suffer from a recency effect, they will 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.

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. In contrast, when earnings are lower *before* the seasonal quarter 12 months ago (typically 15, 18 and 21 months before portfolio formation), this does not generate a spread in returns. The seasonality effect is not present when the firm has broken an earnings record in the past 12 months, another instance of highly salient recent good news. This suggests a recency bias among investors where the recency of low earnings makes investors overly pessimistic about positive seasonal quarters.

We conduct a number of tests to show that seasonality is not simply proxying for other time-series effects within the firm, including overall return seasonality (Heston and Sadka (2008)), momentum (Jegadeesh and Titman (1993)), short-term reversals (Jegadeesh (1990)), or the dividend month premium (Hartzmark and Solomon (2013)). Earnings seasonality effects are not explained by predictable increases in volume (Frazzini and Lamont (2006)), nor are they related to proxies for earnings management. The returns to seasonality survive controlling for other determinants of earnings changes, including past earnings surprises (Bernard and Thomas (1990)), firm financial condition (Piotroski (2000)), and high accruals (Sloan (1996)). 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. Seasonality is highly persistent across years, and lagging the measure by up to ten years produces similar results. The existence of abnormal returns around historically high earnings levels points towards an emerging and puzzling stylized fact about asset returns, namely that predictably recurring firm events tend to be associated with abnormal returns.

Overall, our results are consistent with investors having an information-processing constraint whereby an excessive focus on recent events leads to insufficient attention to longer term patterns in earnings. This contributes to the literature examining underreaction and information processing constraints, including investors being distracted by other events (Hirshleifer, Lim and Teoh (2009, 2011)) and underweighting small increments of information that are not salient (Da, Gurun and Warachka (2014)).

Our finding that earnings seasonality predicts earnings announcement returns also contributes to the literature on how market participants form estimates of firm earnings. A number of papers document how markets underreact to earnings news (Ball and Brown (1968), Bernard and Thomas (1989,1990)), form mistaken forecasts of earnings autocorrelation (Bernard and Thomas (1990), Ball and Bartov (1996)), fail to fully price changes in earnings announcement dates (So (2014)) and miss predictable shifts in fiscal quarter lengths (Johnston, Leone, Ramnath and Yang (2012)). We extend this literature by showing evidence consistent with mistaken market estimates of the effect of seasonal patterns on current earnings.

Most related to the current work, Salomon and Stober (1994) find evidence of higher returns in quarters with seasonally higher sales (after controlling for ex-post earnings news), which they argue is due to resolution of uncertainty. In our paper, we explore the asset-pricing implications of seasonality in greater detail, show portfolio returns based on tradable ex-ante information which survive controlling for known determinants of returns. We also directly test 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.

2. Analysis – Earnings Seasonality and Returns

2.1 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 or a missing market capitalization value 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.

2.2 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 having positive seasonality 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.[3]

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.[4] 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 as the upcoming announcement, 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

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

[4] 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.

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*.

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.[5] In Table I, we present summary statistics for the main variables used in the paper.

Given that firms either tend to cycle between extreme quintiles (if they have seasonal shifts in earnings) or stay within the middle quintiles (if they have stable earnings), a question arises as to which firms have seasonal patterns in general.[6] In Table II we take as the dependent variable the change in *earnrank* between a firm's highest and lowest announcement over the calendar year (for firms with 4 announcements). We then examine how this varies with stock characteristics from the previous year – log market capitalization, share turnover, log book-to-market ratio, accruals (Sloan 1996) and the log of firm age.

The results are presented in Table II. They indicate that seasonal shifts in earnings are more common for large firms, value firms, old firms, low turnover firms, and firms with higher accruals. All of these results are statistically significant at the 1% level when clustered by firm and year

[5] 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 4th quarter. By contrast, under the current measure, the rankings of the 4th 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).

[6] Transition probabilities for *earnrank* are reported in the internet appendix, and confirm that firms tend to either cycle between extreme quintiles or stay in the middle of the distribution. The most likely transition from quintile 1 is to quintile 5 and vice versa (33.0% and 33.1% of cases, respectively).

(although market capitalization loses significance when date and industry fixed effects are added). All these results are considerably reduced in magnitude when industry fixed effects are added (using dummies for 48 industries from Fama and French (1997)), consistent with industry factors being a significant driver of seasonal patterns in earnings.

The requirement of 5 years of earnings data to form *earnrank* means that our sample will be tilted somewhat towards older firms, so the results may not generalize to young firms who lack sufficient data to compute *earnrank*. This is unlikely to drive our results, for several reasons. First, the main examination of return differences is between firms in the extreme quintiles, so the characteristics in Table II are likely to be common to both positive and negative seasonality firm/month observations, and hence should not obviously impact long/short portfolio returns. Second, in terms of the comparison with younger omitted firms, Table II implies that the extreme quintiles are more likely to be filled with older firms, so firms for which we do not have *earnrank* data are less likely to have large seasonal earnings patterns.

Most importantly, the conditioning on firm survival occurs entirely in the period before returns are measured, meaning that the one-month measured returns should be an unbiased sample of the relevant firms over the month in which returns are measured (with delisting returns accounting for firms that disappear during that month). In this respect, the results are not driven by the problems with long-horizon conditioning discussed in Kothari, Sabino and Zach (2005).

2.3 Seasonality and the Earnings Announcement Premium

We first examine whether information about earnings seasonality is fully incorporated into stock prices. 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); So (2014)), 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 based on *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 market 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. Since the earnings announcement premium predicts that portfolios sorted on *earnrank* will have positive abnormal returns in general, the main question is whether positive seasonality causes larger returns relative to negative seasonality.

We consider this question in Table III Panel A. 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. Importantly, the positive seasonality portfolio is not more volatile. The negative 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 positive seasonality portfolio (5.14 equal weighted, 5.18 value weighted). The lack of higher volatility ameliorates some of the concern that the difference in portfolio returns is driven by differences in risk. In addition the various snapshots of percentiles from the return distribution do not indicate that the positive seasonality portfolio is more exposed to extreme negative returns, such as the crash risk associated with momentum (Daniel and Moskowitz (2013)).[7]

In Table III Panel B, we examine the announcement returns to seasonality in a panel setting. We again sort firms into quintiles based on their level of *earnrank* for the upcoming announcement to examine the average 3-day characteristic-adjusted return over the actual earnings announcement date. The characteristic-adjusted returns are computed similar to Daniel, Grinblatt, Titman and Wermers (1997) by subtracting the returns of a value-weighted portfolio matched on quintiles of market capitalization, ratio of book value of equity to market value of equity (book to market ratio) and cumulative stock return from 2 to 12 months ago (momentum). We compute the return for the upcoming announcement and the subsequent four announcements. We compare whether the returns in quintile 5 are significantly different from those in quintile 1 by taking observations from these two quintiles and regressing returns on a dummy variable for quintile 5, clustering by firm and date (equivalent to a *t*-test but allowing for clustering).

As in Table III Panel A, we find that firms in the positive seasonality quintile have significantly higher returns than firms in the negative seasonality quintile. Consistent with firms

[7] 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).

being likely to switch quintiles, these returns have the opposite sign for the following announcement. In addition, they retain the original sign and similar magnitude in four quarters time, when the seasonality will be back to a similar level.

While Table III indicates that the positive seasonality portfolio does not have higher volatility or skewness, these are not the only (or indeed the most important) measures of risk. It may be that positive seasonality firm-months are exposed to other economy-wide risks that investors care about. To test this, we examine the monthly abnormal returns to portfolios sorted into quintiles of earnings seasonality, relative to a four factor model (Fama and French (1993), 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.

In Table IV, Panel A we examine whether the returns to portfolios formed on *earnrank* are explained by exposure to standard factors. For equal weighted portfolios, the lowest seasonality quintile has a four factor alpha of 31 basis points per month (with a *t*-statistic of 3.35), while the highest seasonality quintile portfolio has an alpha of 65 basis points per month (with a *t*-statistic of 6.98). The long-short portfolio has abnormal returns of 35 basis points per month, with a *t*-statistic of 3.13.[8] As in Table III, the value weighted abnormal returns are larger, with the difference portfolio having an alpha of 55 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

[8] In untabulated results, the abnormal returns to the difference portfolio are larger when sorting on more extreme values of *earnrank.* If firms are sorted into portfolios based on the top and bottom 10% *earnrank*, the equal-weighted difference portfolio has a four-factor alpha of 44.6 basis points (*t*-statistic of 2.99). For the top and bottom 5% of *earnrank*, the abnormal returns are 62.9 basis points (*t*-statistic of 3.44).

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 abnormal returns are not monotonic across the quintiles, however. This is partly due to the fact that firms with little seasonal variation (those in the middle quintiles) tend to be younger and smaller firms which may have different earnings announcement returns for other reasons. The main variable of interest, however, is the difference between high and low levels of *earnrank,* which will be less sensitive to firm characteristics. We return to the question of monotonicity shortly.

Secondly, the difference portfolios in Table IV, 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.[9] These low factor loadings arise because the long and short portfolios tend to comprise many of the same firms at different points in the year, so the difference portfolio has relatively small loadings on fixed firm factors. 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 we form portfolios that sort only on variation in *earnrank* within the same firm over the course of a year. Specifically, for each firm that has four values of *earnrank* in a given year, we rank the firm's four predicted earnings announcements according to whichever had the highest, second highest, second lowest and lowest percentile value of *earnrank* that year.

[9] As a robustness check, we also compute the time series changes in factor loadings between positive seasonal months using and surrounding earnings announcements using daily betas calculated as in Lewellen and Nagel (2006). The changes in betas are generally negative and small in magnitude (between -0.080 and 0.006, depending on the factor in question and the model). This supports the conclusion that positive seasonal months are not more exposed to common factors known to explain returns.

Since all information in *earnrank* is at least 12 months old, this is computable by an investor before the start of the year over which returns are measured. The resulting portfolios now include each firm in each of the four portfolios for one month per year. Hence, any variation in seasonality is only from variation within the firm, rather than cross-sectional variation from the types of firms that tend to have positive 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 of this analysis are shown in Table IV Panel B. The abnormal returns for the difference portfolios are similar to those in Panel A – 33 basis points equal-weighted (*t*-statistic of 3.40) and 66 basis points value-weighted (*t*-statistic of 3.91). One consequence of this within-firm sort is that variations in *earnrank* levels are no longer correlated with variables related to the overall level of seasonal shifts. When this within-firm variation is examined, the alphas are now monotonic across the four announcements.

The results in Table IV indicate that the abnormal returns are not driven by either fixed or time-varying loadings on the market, SMB, HML or UMD. For instance, if firms always have a higher market beta in positive seasonal months relative to negative 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. Controlling for different possible factor loadings is important due to evidence that firms have different betas around earnings announcements (Ball and Kothari (1991)).

More generally, because abnormal returns are evident using only within-firm variation, the results are also not driven by fixed loadings on any other omitted factors. The results could still be driven by time-varying exposure to risk source that we are *not* measuring (e.g. something other than the market, SMB, HML and UMD), with positive seasonality months firms being riskier than negative seasonality months. We return to this question in sections 3.1 and 3.4.

2.4 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, and last month's return. Finally we examine whether earnings seasonality affects returns outside of months with a predicted earnings announcement. If positive 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 positive seasonality announcement.

We test these possibilities in Table V by examining the effect of earnings seasonality using Fama and Macbeth (1973) cross-sectional regressions – in each month, we run a cross-sectional regression of stock returns on stock characteristics, then compute the time-series average and *t*-

statistic associated with each of the regression coefficients. We run 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. These results indicate that seasonality is not simply proxying for other drivers of returns, nor does it predict high returns outside of predicted earnings-months.

2.5 Earnings Seasonality and Delayed Reaction to Firm Specific Information

While the results in subsection 2.3 and 2.4 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, such as earnings growth or post earnings announcement drift. Rather than trying to control separately for all possible sources of such information, we test a common prediction of such models: firm specific shocks should become less relevant over time. Seasonality, on the other hand, is an underlying property of a firm's underlying business model, and as such should be persistent across time.[10]

To test whether firm-specific information explains our results, we lag the *earnrank* measure over different lengths of time. We show this in Table VI. In Panel A, we consider the effects of seasonality from the same quarter of the year, but lagged various multiples of 12 months to a period of 10 years. This retains the seasonality prediction for the current quarter, but omits more and more of the recent earnings news of the firm, hence making any correlated information staler. Note that while this test necessarily conditions on firms having a longer time series of data, the 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 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 when lagged up

[10] The timing of earnings announcements is strongly persistent over time (Frazzini and Lamont (2006)). This is important as our test for the persistence of explanatory power over time is a joint test of the persistence of seasonality and earnings announcement months.

to 10 years, while the value-weighted portfolio drops below the 5% level only at the 10 year mark. Interestingly, the returns get slightly larger when lagged two and three years. [11]

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 *earnrank* should positively predict returns for the same quarter as the measure, but not have the same results for other quarters. If positive 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.

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

3.1 Earnings Announcement Risk and Analyst Forecast Errors

[11] The fact that the big increase comes from excluding earnings information from 12 to 23 months ago suggests that earnings levels at this specific time may have contaminating factors. This is consistent with the fact that abnormally high earnings from 4 quarters ago (roughly 12 months ago) tend to forecast low current month returns, as the post-earnings announcement drift reverses at the 4th quarter horizon (Bernard and Thomas (1990)).

Perhaps the most standard potential explanation for the higher expected returns in positive seasonality months is that they represent compensation for risk. While the regressions in sub-section 3.3 suggest that returns are not driven by fixed factor loadings, the announcements themselves may cause exposure to risks.

The most obvious way through which announcement risk could explain the results would be if seasonality were associated with greater exposure to a systematic announcement risk factor, where announcements that represent more of the firm's earnings generate a larger exposure to this 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 (positive seasonal) and short (negative seasonal) portfolios. Table III Panel A indicates that the positive seasonality portfolio does not have more volatility than the negative seasonality portfolio. While this does not rule out greater risk exposure, any systematic risk exposure would need to be 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 VII. The regressions are similar to those in Table IV, taking portfolios of firms sorted on earnings rank, but in addition to the standard four factors we also include the excess returns of an equal-weighted portfolio of all firms with a predicted earnings announcement that month (EARNRF). This captures the overall fluctuation in returns for firms announcing earnings that month controlling for 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 earnings announcement factor) between positive and negative seasonality portfolios is still large and significant: 34 basis points equal weighted in Panel A (with a *t*-statistic of 3.00) and 48 basis points value weighted in Panel B (with a *t*-statistic of 2.67). These numbers are similar to Table IV, indicating that exposure to an earnings risk factor is not a major driver of 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.[12]

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 positive seasonal months because of risk in these months, not because they are more positively surprised on average by cash flows. We examine this proposition using analysts' earnings forecasts. Analysts' earnings estimates have been argued to be a reasonable proxy for the views of investors (e.g. in Brown (1999)), but even without this assumption they represent a potentially informative sample of opinions from a segment of market participants. There may be greater variability in forecast errors in months where earnings are larger, but any increase in the

[12] 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.

mean level of forecast error is *prima facie* evidence that analysts are relatively more pessimistic in months of positive seasonality.

In Table VIII we test whether analysts tend to be more positively surprised by firm earnings in positive seasonality quarters. Observations are at the firm-date level, and the dependent variable is the forecast error from the median quarterly earnings per share forecast, taken over all analysts making forecasts between 3 and 90 days before the announcement.

The measure of forecast error is calculated as (Actual EPS – Forecast EPS) / Price (*t*-3). In Table VIII, we regress the panel of firm-date observations of *earnrank* and various controls. 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 very similar across all 7 columns, 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 positive seasonality is more common. Table VIII is consistent with investors and analysts being more positively surprised by firm cash flows during positive seasonality quarters. In the internet appendix, we show that there is also a significant spread in analyst forecast errors in quarter t+4, consistent with seasonality leading to repeated errors.

To gauge the magnitude of these forecast errors, one can compare the forecast error in positive seasonal quarters with the overall change in earnings across seasonal quarters. This gives an estimate of the fraction of the overall seasonal change in earnings 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 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 lowest to the highest 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 positive seasonal quarters represent an underreaction to seasonality, not that seasonality is ignored altogether.

3.2 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 a proxy 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. We take the daily return for the stock and subtract the average return for a portfolio of stocks matched on being in the same quintile of size, book-to-market, and momentum (using returns from t-20 to t-250).

Table IX 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.

As in Table IV, the effect of seasonality is measured by the difference in returns between firms sorted on seasonality. The fourth column in Table IX examines the difference in characteristic adjust return from the top quintile and the bottom quintile of seasonality. The largest return occurs on the announcement day itself, earning roughly 10 basis points with a t-statistic of 3.37. Adding up the adjusted returns 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 III, this suggests that most of the returns due to seasonality are related to the announcement itself. Columns 4 and 5 show the equivalent difference in returns for more extreme sorts – the top and bottom 10% of *earnrank* in column 5, and the top and bottom 5% in column 6. For more extreme cutoffs, the returns are again mostly earned between t-2 and t+1, but the magnitudes are larger, consistent with the greater level of seasonality. For the top 10% minus bottom 10%, the sum of the 4 days adjusted returns is roughly 39 basis points. For the top 5% minus bottom 5%, the sum from t-1 to t+1 (as t-2 is not significant here) is roughly 47 basis points.

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. The differential returns to seasonality are limited to a short period around the announcement, consistent with a predictable positive surprise in earnings occurring in seasonal quarters.

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

The second class of explanation for seasonality affecting stock returns is that markets are underweighting earnings 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 VIII are consistent with analysts being more positively surprised in positive seasonal quarters. This suggests the possibility of a common positive surprise by financial market participants which drives the high returns.

As Ball and Bartov (1996) 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.

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, and the argument in Kothari (2001) that arguments for inefficiency are more convincing if they are constrained by testable predictions relating to specific causes of mispricing.

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. Tversky and Kahneman (1973) describe various attributes that may make a particular event more likely to be recalled (and thus overweighted in probability forecasts), 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 are more likely to recall the last items in a list (the recency effect). 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 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 higher earnings in the upcoming quarter then it must have relatively lower earnings in the other quarters of the year. If the historical pattern in earnings continues as before, then firms in the positive 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 most 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 positive 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 earnings *actually were lower ex post*. This is the necessary basis for the investor underreaction. If the earnings since the positive seasonal quarter were actually higher than those from 12 months ago, then a recency effect would not cause investors to be overly pessimistic about the upcoming positive seasonal quarter.

We test this prediction in Tables X and XI, by examining how the seasonality effect is impacted by recent earnings levels. In Table X, we examine whether the returns in the seasonality long/short portfolio depend on the difference between recent earnings and those from 12 months ago. We form a two-way sort of stocks. The first sort is whether the firm is above or below the median value of *earnrank* that month. For the second sort, we define a new variable as the difference between the average of the three most recent earnings announcements (typically 3, 6, 9 months ago) and the announcement 12 months ago (with earnings scaled by firm assets per share). We then sort stocks by whether they are above or below the median of this measure.

Table X 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 magnitude of the seasonality effect is larger. The long/short seasonality portfolio among firms with lower earnings in the most recent announcements earns abnormal returns of 65 basis points equal weighted and 76 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 6 basis points value weighted. The double difference portfolio has statistically significant abnormal returns at the 1% level both when equal and value weighted.[13]

One possible concern with the previous results is that by conditioning on low recent earnings we may be selecting 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 use 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

[13] 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.

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 1.67) 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 XI, 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, they are likely to be highly weighted under a recency effect, thereby reducing the effect of seasonality. Similar to Table X, we sort stocks according to *earnrank* and whether a previous earnings record was broken in the past 12 months, counting records from 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 35 basis points when equal weighted (t-statistic of 2.88) and 49 basis points when value weighted (t-statistic of 2.22). 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 3 basis points). These results confirm the view from Table X that the seasonality effect is larger when firms have had lower recent earnings.

Recency also explains the result in Table III Panel B that *earnrank* negatively predicts characteristic-adjusted announcement returns one quarter after the main sort (i.e. lagging by one quarter more than the main specification). This is consistent with them having experienced recently higher earnings due to the positive seasonal quarter just past. This leads to the spread being the opposite of the sort based on 12 month ago values of *earnrank.*

It is worth noting that the recency bias appears to contrast with the explanation in Bernard and Thomas (1990) as to why post-earnings announcement drift reverses at the fourth quarter horizon. They argue that investors place too much weight on earnings surprises from 4 quarters ago, and not enough on earnings surprises from the most recent periods. In the current setting low recent earnings *levels* cause investors to form forecasts that are too pessimistic. This may occur even if the low level of recent earnings does not involve a substantial earnings surprise (e.g. when low earnings are mostly predictable in nature, as indeed seasonality implies that they are). While the empirical results in Bernard and Thomas (1990) are clearly distinct from the results here (*earnrank* predicts returns consistently up to a ten year horizon, for instance), and earnings surprises may lead to different investor responses than earnings levels, the difference in relative weighting of recent versus older earnings is somewhat of a puzzle.

One possibility that may explain the discrepancy is that there are different groups of investors responsible for the mistakes in each case. Battalio and Mendenhall (2005) examine the trades of different groups of investors, and find that the trades of small investors seem to exhibit the mistake described in Bernard and Thomas (1990) of underweighting recent earnings changes. This finding is also consistent with the finding that post-earnings announcement drift is stronger for small firms (Ball and Bartov (1996), Brown and Han (2000)). By contrast, Battalio and Mendenhall (2005) find that large investors do not seem to display this pattern in trades, and trade more in line with the views of analysts, who also do not seem to underweight recent earnings surprises. This is consistent with the results in Ke and Ramalingegowda (2005) and Campbell, Ramadorai and Schwartz (2009) that larger institutional investors are more likely to trade to take advantage of the post-earnings announcement drift.

If larger investors are more likely to be trading based on signals in the most recent three quarters (to take advantage of post-earnings announcement drift), they may be the group ignoring the longer-term seasonal information. This would explain several facts in the current context, namely a) the fact that analysts also make systematic mistakes based on seasonality, and b) the bigger seasonality effects for large firms, who are likely to have more trading by larger investors.

4. Additional Alternative Explanations

4.1 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. The higher idiosyncratic volatility is related to the argument in Ball and Kothari (1991) that earnings announcements have high returns because they resolve investor uncertainty. It is possible that positive seasonal quarters may have higher returns than negative seasonal quarters either due to having higher volume or higher idiosyncratic volatility.

In Table XII, 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 X and XI, 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 seasonality effect after controlling for the level of volume increase.

Table XII suggests that increases in trading volume do not drive the higher returns in positive 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 18 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 positive seasonal months.

We next examine whether increases in idiosyncratic volatility can explain returns to seasonality. 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 relate idiosyncratic risk to earnings announcement returns) and Johnson and So (2014) (who examine liquidity provision in the lead-up to earnings announcements). In this view, the low volatility portfolio of positive seasonal firms is not 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. In the following section we remain agnostic on this issue and instead focus on examining whether there is a relationship between idiosyncratic risk and seasonality returns.

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 XIII 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. Overall, predictable abnormal idiosyncratic risk does not seem to explain seasonality returns.

4.2 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 across 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, positive 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), whereby firms with high returns 12, 24, 36, 48 and 60 months ago have 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 positive seasonality firms have higher exposure to factors in ways that vary over the year.

To test whether this explains our results, in Table XIV we run a similar regression to Table IV, but allow 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.

4.3 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 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 XV. 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 announcement returns 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 forecast error for each of the previous four quarters. Again *earnrank* remains large positive and significant.

The effect of *earnrank* is similar in size 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 the accounting variables in combination (column 6). The coefficient on *earnrank* is 0.026 for the univariate regression (*t*-statistic of 6.23) and 0.038 with all controls (*t*-statistic of 5.48). Earnings seasonality returns are not explained by these accounting variables.

4.4 Robustness

In the Internet Appendix, 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 seasonality returns are higher for firms with analyst coverage, and find that they are directionally higher but that the difference is not significant. We examine whether returns are evident when 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. 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.

5. Conclusion

We document a new finding about earnings returns – that stocks exhibit high returns in months when they are predicted to announce earnings that are historically larger than those of other quarters of the year. This effect does not appear to be driven by risk factors or a delayed reaction to firm-specific news. Positive seasonality quarters also display greater positive surprise by analysts, suggesting the effect is related to mistaken estimates of earnings.

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 positive seasonal quarter, causing them to be too pessimistic by the time the positive seasonal quarter comes around again. Consistent with this view, the effects of seasonality are larger when earnings since the last positive seasonal quarter are at lower levels.

It is worth noting that our findings do not imply 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 (*earnrank*) is calculated at each point in time 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 present the transition probabilities for quintiles of the *earnrank* variable across subsequent earnings announcements for the same firm.

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

Table II – Determinants of Annual Seasonality Shifts

This table examines which characteristics predict whether a firm will display higher annual seasonal variation in earnings. The dependent variable is the annual difference between the maximum and minimum value of *earnrank*, the main measure of earnings seasonality. At each point, we examine 5 years of earnings data and ranking each announcement by the earnings per share (adjusted for stock splits, etc.).The *earnrank* variable is formed by taking the average rank of the 5 announcements from the same fiscal quarter as that of the current announcement. We then explain this annual variation in *earnrank* using stock characteristics from the previous year – the December log market capitalization and share turnover, the log of the ratio of book value of equity to market value of equity, the firm's annual accruals from last year (Sloan (1996)), and the log of the firm's age. Fixed effects for year and industry (using 48 dummy variables from Fama and French (1997)) are included where noted. Standard errors are clustered at the year and firm level.

Dependant variable is the difference in Earnrank between highest and lowest announcement over next year			
Log Market Cap	0.098***	0.129***	0.031*
	(4.18)	(5.77)	(1.80)
Log Book-to-Market	0.391***	0.396***	0.155***
	(7.80)	(8.05)	(4.36)
Accruals	1.094***	0.952***	0.542***
	(3.84)	(3.60)	(3.08)
Turnover	-0.306***	-0.251***	-0.157***
	(-9.32)	(-7.84)	(-7.58)
Log Age	0.576***	0.552***	0.417***
	(9.79)	(9.60)	(9.51)
Date FE	No	Yes	Yes
Industry FE	No	No	Yes
Observations	86,624	86,624	85,846
R-squared	0.050	0.058	0.262

Table III – Earnings Seasonality and Stock Returns

This table examines portfolio and firm-level returns and analyst forecast errors according to 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. In Panel A, we present summary statistics for portfolio returns of stocks in the highest and lowest quintiles of *earnrank*. The Sharpe Ratio is the mean returns in excess of the risk-free rate, divided by the standard deviation of returns. In Panel B, we examine 3 day characteristic-adjusted returns around the upcoming earnings announcement (i.e. sorting on *earnrank* values from the same fiscal quarter in the previous year), and over the subsequent four quarters. For each firm, the 3-day returns have subtracted from them the returns of a matching portfolio of firms sorted on market capitalization, book-to-market ratio and momentum (cumulative returns from 12 months ago to 2 months ago), similar to Daniel, Grinblatt, Titman and Wermers (1997). In Panel B, we test for whether the average returns are different between quintile 1 and quintile 5 by considering only firms in those two quintiles, and regression returns on a dummy variable for quintile 5, with standard errors clustered by firm and date. 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 - 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

Panel B - Earnings Announcement Returns Over Following Qtrs

Earnrank Quintile	**3-day Earnings Characteristic-Adjusted Return** Qtr t	Qtr t+1	Qtr t+2	Qtr t+3	Qtr t+4
1	0.174	0.382	0.290	0.234	0.196
2	0.197	0.270	0.264	0.268	0.230
3	0.191	0.214	0.281	0.196	0.227
4	0.244	0.177	0.223	0.245	0.262
5	0.416	0.156	0.226	0.292	0.385
5-1 *t*-stat, double clustered	4.32***	-4.00***	-1.16	1.00	3.18***

Table IV – Earnings Seasonality and Stock 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. We compute abnormal returns under a four factor model (Fama and French (1993), Carhart (1997)) by regressing portfolio excess returns on excess market returns, SMB, HML and UMD from Ken French's website. In Panel A, all firms with a predicted earnings announcement are included, sorting into quintiles based on the *earnrank* variable that month. In Panel B, we examine firms with four values of *earnrank* in the current year, and rank the four announcements according to where they placed the firm in the distribution of *earnrank* in the month in question. In other words, portfolio 4 buys whichever earnings announcement has the highest relative value of *earnrank* for the given firm that year, and portfolio 1 has the lowest value of *earnrank*. 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 - Within-Firm Four Factor Regressions													
Firm-Level Earnrank	**Weighting**	**Intercept**		**MKTRF**		**SMB**		**HML**		**UMD**		**R2**	**N**
1 (lowest Earnrank that year)	EW	0.259	***	0.978	***	0.549	***	0.335	***	-0.062	***	0.899	489
		(3.19)		(53.11)		(21.03)		(11.93)		(-3.49)			
2	EW	0.357	***	0.963	***	0.548	***	0.290	***	-0.051	***	0.900	489
		(4.49)		(53.32)		(21.42)		(10.54)		(-2.90)			
3	EW	0.379	***	0.957	***	0.580	***	0.258	***	-0.046	***	0.915	489
		(5.16)		(57.43)		(24.57)		(10.14)		(-2.88)			
4 (highest Earnrank that year)	EW	0.592	***	0.970	***	0.506	***	0.266	***	-0.051	***	0.893	489
		(7.20)		(51.92)		(19.14)		(9.36)		(-2.85)			
4 - 1	EW	0.333	***	-0.009		-0.043		-0.069	**	0.011		0.012	489
		(3.40)		(-0.40)		(-1.35)		(-2.03)		(0.49)			

Firm-Level Earnrank	**Weighting**	**Intercept**		**MKTRF**		**SMB**		**HML**		**UMD**		**R2**	**N**
1 (lowest Earnrank that year)	VW	0.163		0.992	***	0.013		-0.021		0.083	***	0.770	489
		(1.36)		(36.44)		(0.33)		(-0.51)		(3.16)			
2	VW	0.291	**	1.040	***	0.001		0.032		0.044		0.714	489
		(2.02)		(31.75)		(0.01)		(0.65)		(1.40)			
3	VW	0.344	***	1.009	***	-0.003		0.017		0.055	**	0.799	489
		(3.10)		(40.09)		(-0.09)		(0.44)		(2.26)			
4 (highest Earnrank that year)	VW	0.822	***	0.935	***	0.058		-0.119	**	0.046		0.709	489
		(5.96)		(29.88)		(1.32)		(-2.50)		(1.53)			
4 - 1	VW	0.659	***	-0.057		0.046		-0.098	*	-0.037		0.010	489
		(3.91)		(-1.48)		(0.84)		(-1.68)		(-1.00)			

Table V – 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 VI – 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 VII – 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 VIII – 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. We regress the panel of firm-level forecast errors on *earnrank* and other controls. 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 IX – 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 through sixth columns shows the difference in returns between the highest and lowest 20% of *earnrank*, the highest and lowest 10% and the highest and lowest 5%, respectively. The last column presents the coefficient from 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 Announcement (t)	*Earnrank Percentile Groupings*			*Earnrank Differences*			*EarnRank*
	Top 20%	20th-80th Percentile	Bottom 20%	Top 20% - *Bottom 20%*	Top 10% - *Bottom 10%*	Top 5% - *Bottom 5%*	Regression Coefficient
t-10	-0.003	-0.003	0.015	-0.018	-0.014	-0.023	-0.001
	(-0.24)	(-0.49)	(1.39)	(-1.19)	(-0.74)	(-0.88)	(-0.88)
t-9	0.007	0.010 *	-0.014	0.021	-0.004	0.017	0.001
	(0.65)	(1.66)	(-1.34)	(1.48)	(-0.18)	(0.67)	(0.67)
t-8	0.011	0.002	0.010	0.001	-0.006	0.014	0.000
	(1.05)	(0.37)	(0.91)	(0.09)	(-0.34)	(0.57)	(0.23)
t-7	0.017	0.009	0.012	0.005	0.019	0.049 **	0.001
	(1.60)	(1.45)	(1.10)	(0.34)	(1.02)	(1.97)	(0.73)
t-6	0.026 **	0.008	0.003	0.023	0.028	0.007	0.002
	(2.48)	(1.26)	(0.31)	(1.60)	(1.52)	(0.28)	(1.21)
t-5	0.010	0.015 **	0.034 ***	-0.025 *	-0.024	-0.034	-0.003 **
	(0.90)	(2.23)	(3.26)	(-1.67)	(-1.28)	(-1.34)	(-2.11)
t-4	0.000	0.020 ***	0.021 **	-0.021	0.002	0.030	-0.001
	(0.02)	(3.00)	(1.98)	(-1.44)	(0.09)	(1.12)	(-0.73)
t-3	0.030 ***	0.039 ***	0.013	0.017	-0.002	0.002	0.001
	(2.92)	(5.97)	(1.31)	(1.18)	(-0.13)	(0.10)	(0.84)
t-2	0.067 ***	0.041 ***	0.030 ***	0.038 **	0.043 **	0.027	0.004 **
	(6.26)	(6.20)	(2.75)	(2.56)	(2.23)	(1.05)	(2.52)
t-1	0.122 ***	0.108 ***	0.064 ***	0.058 ***	0.063 ***	0.120 ***	0.006 ***
	(10.33)	(13.66)	(5.20)	(3.48)	(2.95)	(4.21)	(3.21)
t	0.235 ***	0.136 ***	0.139 ***	0.097 ***	0.171 ***	0.179 ***	0.013 ***
	(11.06)	(10.72)	(6.86)	(3.37)	(5.22)	(4.06)	(4.40)
t+1	0.072 ***	0.021 **	0.008	0.064 ***	0.112 ***	0.171 ***	0.007 ***
	(4.96)	(2.31)	(0.55)	(3.35)	(3.68)	(4.13)	(3.60)
t+2	0.001	-0.002	0.005	-0.004	0.006	0.013	0.000
	(0.05)	(-0.23)	(0.42)	(-0.27)	(0.28)	(0.49)	(-0.15)
t+3	0.014	-0.006	-0.005	0.019	0.020	0.026	0.002
	(1.34)	(-0.90)	(-0.51)	(1.36)	(1.04)	(1.00)	(1.56)
t+4	0.029 ***	0.009	0.002	0.027 *	0.015	0.022	0.003 **
	(2.80)	(1.47)	(0.20)	(1.91)	(0.79)	(0.87)	(1.98)
t+5	0.023 **	0.008	0.023 **	0.001	-0.004	-0.002	-0.001
	(2.36)	(1.32)	(2.25)	(0.06)	(-0.23)	(-0.09)	(-0.37)
t+6	0.014	0.022 ***	0.029 ***	-0.015	0.004	-0.043 *	-0.001
	(1.48)	(3.68)	(2.96)	(-1.13)	(0.20)	(-1.75)	(-0.53)
t+7	-0.004	0.013 **	0.008	-0.012	0.022	-0.006	-0.001
	(-0.46)	(2.14)	(0.74)	(-0.87)	(1.19)	(-0.24)	(-0.65)
t+8	0.021 **	0.019 ***	0.020 **	0.001	0.005	-0.002	0.000
	(2.13)	(3.11)	(1.99)	(0.06)	(0.26)	(-0.08)	(-0.21)
t+9	0.025 ***	0.002	0.000	0.026 *	0.003	-0.010	0.002
	(2.61)	(0.33)	(-0.04)	(1.86)	(0.20)	(-0.43)	(1.31)
t+10	0.003	0.013 **	0.016	-0.013	0.010	0.010	-0.001
	(0.29)	(2.08)	(1.61)	(-1.00)	(0.55)	(0.42)	(-1.02)

Table X – 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	**Earnings Rank Level** All	1 (Low)	2 (High)	2 - 1
All		0.270 ***	0.496 ***	0.226 ***
		(4.18)	(7.60)	(3.31)
		{493}	{493}	{493}
1 (Non-Annual earnings more negative)	0.004	-0.312 ***	0.340 ***	0.651 ***
	(0.06)	(-3.29)	(4.55)	(6.54)
	{492}	{462}	{483}	{462}
2 (Non-Annual earnings more positive)	0.604 ***	0.511 ***	0.806 ***	0.277 ***
	(8.46)	(6.39)	(8.77)	(2.98)
	{492}	{473}	{467}	{466}
	0.600 ***	0.831 ***	0.457 ***	-0.368 ***
2 -1	(8.04)	(7.81)	(4.95)	(-2.88)
	{492}	{462}	{467}	{461}

Value Weighted

Gap Between Earnings (3,6,9) Months Ago and 12 Month Ago	**Earnings Rank Level** All	1 (Low)	2 (High)	2 - 1
All		0.269 ***	0.557 ***	0.288 **
		(3.00)	(5.05)	(2.16)
		{493}	{493}	{493}
1 (Non-Annual earnings more negative)	0.306 ***	-0.098	0.642 ***	0.757 ***
	(2.81)	(-0.70)	(4.86)	(3.96)
	{492}	{462}	{483}	{462}
2 (Non-Annual earnings more positive)	0.359 ***	0.287 ***	0.405 ***	0.060
	(3.61)	(2.62)	(2.61)	(0.34)
	{492}	{473}	{467}	{466}
	0.053	0.456 **	-0.258	-0.702 ***
2 -1	(0.37)	(2.58)	(-1.37)	(-2.71)
	{492}	{462}	{467}	{461}

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		0.270 ***	0.496 ***	0.226 ***
		(4.18)	(7.60)	(3.31)
		{493}	{493}	{493}
1 (Non-Annual earnings more negative)	0.240 ***	-0.126	0.427 ***	0.539 ***
	(3.44)	(-1.20)	(5.45)	(4.95)
	{489}	{462}	{481}	{462}
2 (Non-Annual earnings more positive)	0.379 ***	0.390 ***	0.665 ***	0.284 ***
	(5.84)	(5.19)	(6.98)	(2.83)
	{489}	{474}	{466}	{466}
2 -1	0.139 *	0.493 ***	0.244 **	-0.250 *
	(1.84)	(4.38)	(2.29)	(-1.67)
	{489}	{462}	{466}	{461}

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		0.269 ***	0.557 ***	0.288 **
		(3.00)	(5.05)	(2.16)
		{493}	{493}	{493}
1 (Non-Annual earnings more negative)	0.477 ***	0.071	0.616 ***	0.535 ***
	(4.70)	(0.48)	(4.89)	(2.73)
	{489}	{462}	{481}	{462}
2 (Non-Annual earnings more positive)	0.278 **	0.205 *	0.582 ***	0.337
	(2.40)	(1.85)	(3.15)	(1.62)
	{489}	{474}	{466}	{466}
2 -1	-0.200	0.200	-0.030	-0.205
	(-1.39)	(1.05)	(-0.14)	(-0.67)
	{489}	{462}	{466}	{461}

Table XI – 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	All	Earnings Rank Level: 1 (Low)	2 (High)	2 - 1
All		0.270 ***	0.496 ***	0.226 ***
		(4.18)	(7.60)	(3.31)
		{493}	{493}	{493}
No Recent Record	-0.130 ***	0.112	0.439 ***	0.327 ***
	(-3.48)	(1.53)	(5.84)	(3.72)
	{504}	{493}	{493}	{493}
Recent Record	0.255 ***	0.553 ***	0.529 ***	-0.024
	(4.58)	(5.46)	(6.06)	(-0.25)
	{503}	{492}	{492}	{492}
Recent - No Recent	0.385 ***	0.443 ***	0.092	-0.350 ***
	(7.40)	(4.12)	(0.98)	(-2.88)
	{503}	{492}	{492}	{492}

Panel B - Value Weighted

Record Within Past Year	All	Earnings Rank Level: 1 (Low)	2 (High)	2 - 1
All		0.269 ***	0.557 ***	0.288 **
		(3.00)	(5.05)	(2.16)
		{493}	{493}	{493}
No Recent Record	-0.113 ***	0.045	0.564 ***	0.519 ***
	(-2.95)	(0.41)	(4.92)	(3.53)
	{504}	{493}	{493}	{493}
Recent Record	0.121 ***	0.469 ***	0.495 ***	0.026
	(3.74)	(3.74)	(3.70)	(0.15)
	{503}	{492}	{492}	{492}
Recent - No Recent	0.240 ***	0.426 ***	-0.066	-0.492 **
	(3.58)	(2.59)	(-0.40)	(-2.22)
	{503}	{492}	{492}	{492}

Table XII – 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		0.270 ***	0.496 ***	0.226 ***
		(4.18)	(7.60)	(3.31)
		{493}	{493}	{493}
1 (turnover low this quarter)	0.457 ***	0.364 ***	0.582 ***	0.217 **
	(6.12)	(3.95)	(6.59)	(2.16)
	{436}	{436}	{436}	{436}
2 (turnover high this quarter)	0.346 ***	0.164 *	0.537 ***	0.373 ***
	(4.57)	(1.78)	(6.05)	(3.74)
	{436}	{435}	{436}	{435}
	-0.111	-0.187 *	-0.044	0.143
2 -1	(-1.45)	(-1.78)	(-0.46)	(1.10)
	{436}	{435}	{436}	{435}

Panel B - Value Weighted

Avg Increase in Turnover	Earnings Rank Level: All	1 (Low)	2 (High)	2 - 1
All		0.269 ***	0.557 ***	0.288 **
		(3.00)	(5.05)	(2.16)
		{493}	{493}	{493}
1 (turnover low this quarter)	0.451 ***	0.338 **	0.576 ***	0.238
	(4.05)	(2.39)	(4.09)	(1.24)
	{436}	{436}	{436}	{436}
2 (turnover high this quarter)	0.390 ***	0.163	0.589 ***	0.425 **
	(3.19)	(1.31)	(3.79)	(2.13)
	{436}	{435}	{436}	{435}
	-0.061	-0.172	0.014	0.175
2 -1	(-0.38)	(-0.92)	(0.07)	(0.63)
	{436}	{435}	{436}	{435}

Table XIII – 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]	All	**Earnings Rank Level** 1 (Low)	2 (High)	2 - 1
All		0.270 ***	0.496 ***	0.226 ***
		(4.18)	(7.60)	(3.31)
		{493}	{493}	{493}
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]	All	**Earnings Rank Level** 1 (Low)	2 (High)	2 - 1
All		0.269 ***	0.557 ***	0.288 **
		(3.00)	(5.05)	(2.16)
		{493}	{493}	{493}
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 XIV – 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 XV – 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