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Tom Y. Chang
University of Southern California, Marshall School of Business

Samuel M. Hartzmark
Chicago Booth School of Business

David H. Solomon
University of Southern California, Marshall School of Business

Eugene F. Soltes
Harvard Business School

Being Surprised by the Unsurprising:

Earnings Seasonality and Stock Returns

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

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Abstract: We present evidence 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 risk-based explanations, firm-specific information, increased volume, or idiosyncratic volatility.

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

Contact at tychang@marshall.usc.edu, samuel.hartzmark@chicago.booth.edu, dhsolomo@marshall.usc.edu, and esoltes@hbs.edu, respectively. We would like to thank Joey Engelberg, Wayne Ferson, Dick Roll, Kelly Shue, Eric So, Richard Thaler, and seminar participants at Arizona State University, Chicago Booth, DePaul University, Goethe University, the London School of Economics, the University of Mannheim, the University of Michigan, the University of Toronto, the USC Finance Brownbag, the NBER Behavioral Economics Meetings, Fuller and Thaler Asset Management, the Southern California Finance Conference, and the USC/UCLA/UCI Finance Day.

"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 certain 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 such as subtracting off same-quarter earnings from prior years (e.g., Bernard and Thomas (1990)). By contrast, relatively less consideration has been given to how earnings seasonality itself is priced. One likely reason for this divergence is that earnings seasonality appears to be a straightforward concept. 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. Investors have ample opportunities for learning about seasonality, as information on earnings is easily available and repeated frequently for each firm. An expected seasonal change is not "news" in the sense of Samuelson (1965) and should not move prices in an efficient market.

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 proposition that recurring firm events are generally associated with abnormal returns.

Moreover, the apparent simplicity of earnings seasonality is deceptive: while *identifying* seasonal quarters may be easy, calculating a precise seasonal correction for a given firm is rather complicated. Models of seasonal adjustments impose significant structure and are sensitive to a number of ad hoc specification choices. Because earnings seasonality seems straightforward, investors, like academics, pay less attention to it and are unlikely to understand its complexity. A problem that seems easy to solve, but is actually quite difficult, is one that is likely to reveal behavioral biases.

In this paper, we present evidence of abnormal returns consistent with markets failing to properly price information contained in the seasonal patterns of earnings. Some companies have earnings that are consistently higher in one quarter of the year relative to others, which we term 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.

The basic empirical pattern, whereby firms have higher stock returns around earnings announcements covering periods of seasonally higher sales, was documented by Salamon and Stober (1994), with anecdotal mentions as far back as Keynes (1936). Salamon and Stober (1994) argue that the pattern is consistent with a greater resolution of uncertainty in positive seasonal quarters but do not directly test this explanation or consider the possibility of mispricing. Using

[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) 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.

the tools of modern asset pricing, we show that the returns to earnings seasonality have persisted since the initial publication and find that mispricing better explains the patterns in returns.

Consider the example of Borders Books, which traded from 1995 to 2010. Borders had a highly seasonal business, with a large fraction of earnings in the fourth quarter. Out of Borders' 63 quarterly earnings announcements, the 14 largest were all fourth-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' fourth-quarter announcements was 2.27%, compared with -3.40% for all other quarters. Borders' earnings seasonality is a persistent property of its business due in part to increased sales over Christmas. Thus, an investor could easily forecast when these high returns would occur. We show that the pattern in earnings announcements returns for Borders holds in general for seasonal firms: high earnings announcement returns can be forecast using past information about which quarters contain higher than usual earnings.

To construct our main measure of 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 the third quarter, for instance, would be for a company for which the previous five announcements in the third quarter were the largest out of the 20 announcements considered. To make sure the simplicity of our measure is not missing important nuances of seasonality, we also explore more formal structural estimates of seasonality and find, if anything, stronger results. [2]

[2] In the internet appendix we replicate the entire paper using measures of seasonality from a structural seasonal adjustment model.

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 most asset pricing anomalies, it becomes stronger (55 basis points) when the portfolio is value weighted.[3]

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 obtain similar results by sorting a firm's four announcements according to seasonality regardless of the overall level (ensuring that each firm is in each portfolio once per year, generating only time-series variation within the difference portfolio). For risk to explain the results, it must be that firms are more risky in months of positive seasonality. The risk cannot simply come from increased exposure to the standard four factors, as these 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 is not more volatile 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

[3] As expected, earnings announcement months tend to have positive abnormal returns (Frazzini and Lamont (2006)). One interpretation of the main finding of this paper is that the earnings announcement premium is larger in positive seasonality months.

idiosyncratic volatility (as in Barber, George, Lehavy and Trueman (2013)), as seasonality returns are similar between firms with high and low expected idiosyncratic volatility.

We provide positive evidence of investor mistakes by examining analyst forecast errors. If seasonality returns are driven by risk, as in the discount rate explanation of Salamon and Stober (1994), it is not clear why average analyst forecast errors 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, although analysts take seasonality into account, they do not completely correct for seasonal changes. Additionally, in positive seasonality months, analysts' forecasts are also more likely to undershoot predictions from econometric models of earnings seasonality. This reinforces the notion that the biased forecasts are due to analysts not properly accounting for the seasonal shift itself. To the extent that individual investors make the same mistakes, or take analysts' mistaken forecasts at face value, the portfolio returns are consistent with mispricing rather than risk.

If investors are making systematically biased forecasts of earnings, then the returns to earnings seasonality should be concentrated in the period when earnings news is revealed. Examining daily characteristic adjusted returns around earnings announcements, we find that most of the abnormal returns occur in the short event window that surrounds 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 (Barber et al. (2013); Johnson and So (2014)).

We hypothesize that the effects of seasonality are due to investors overweighting recent earnings when forming estimates of future earnings. 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 prior. If investors suffer from a recency effect, whereby recent information is easier to recall than is old information (Murdock (1962), Davelaar et al. (2005)), they will be more likely to overweight recent lower earnings compared to the higher earnings from the same quarter in the prior year.[4] This would cause them to be overly pessimistic about the upcoming announcement and would lead to greater positive surprises. Investors who suffer from a recency effect will not completely ignore information from more than three quarters prior, but recent earnings will be overweighted if more recent events are more salient.

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) are lower than earnings 12 months prior. In contrast, when earnings are lower *before* the seasonal quarter 12 months prior (typically 15, 18, and 21 months before portfolio formation), there is no spread in returns. The seasonality effect is not present when the firm has broken an earnings record in the prior 12 months, an instance of highly salient recent good news. This suggests that recent low earnings make 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 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

[4] Related to the recency effect, 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.

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 recent information about the firm. Seasonality is highly persistent across years, and lagging the measure by up to 10 years produces similar results. The existence of abnormal returns around historically high earnings levels points toward 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 excessive focus on recent events, leading to insufficient attention to longer-term patterns in earnings. This contributes to the literature that examines underreaction and information processing constraints, including distraction from competing events (Hirshleifer, Lim and Teoh (2009, 2011)) and underweighting small non-salient increments of information (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 that is consistent with mistaken market estimates of the effect of seasonal patterns on current earnings.

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. In our return tests, we consider the common stock (CRSP share codes 10 or 11) of firms listed on the NYSE, AMEX, or NASDAQ exchanges. We exclude stocks with a price less than $5 or a missing market capitalization at the end of the previous month. The data on analyst forecasts use quarterly earnings per share forecasts from I/B/E/S. 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 *how often* earnings are higher in a given quarter and *by how much* they are higher in a given quarter. The main measure that we construct prioritizes the first component, counting companies as having positive seasonality if they regularly have high earnings in a given quarter.

To construct this measure of predicted seasonality in quarter t, we use five years of earnings data from quarter $t-23$ to $t-4$. We compute firm earnings per share (excluding extraordinary items) adjusted for stock splits.[5] We then rank the 20 quarters of earnings data from largest to smallest. We require non-missing values for all 20 quarters of earnings to construct the measure. The main measure, *earnrank*, for quarter t is the average rank of quarters $t-4$, $t-8$, $t-12$, $t-16$, and $t-20$. This

[5] 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.

is the average rank of the same fiscal quarter as the upcoming announcement 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 value of *earnrank* means that the current quarter typically has lower earnings relative to other quarters. A firm whose earnings are randomly distributed will tend to be in the middle of the distribution of *earnrank*.

Earnrank is relatively simple to construct, easy to replicate, and transparent in what is being measured. In addition, it manages to avoid a number of confounding empirical issues without having to make significant assumptions about the underlying data-generating process. First, *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.[6] In Table I, we present summary statistics for the main variables used in the paper.

Although we use *earnrank* as our main variable of analysis, clearly there are other estimates of seasonality with different strengths and weaknesses. To make sure that the simplicity of *earnrank* is not driving our results due to a lack of precision or through some aspect of the variable's construction, in Section 5, we examine a number of structural estimates of seasonality using variations of the X-12 seasonal adjustment model. The internet appendix replicates all of the tests in the paper using X-12 forecasts. The results are materially similar and, if anything, slightly

[6] If each quarter were ranked only relative to other quarters that year, then companies with uniformly growing earnings would appear to have the maximum possible seasonality in the fourth quarter. By contrast, under the current measure, the rankings of the fourth quarters would be 4, 8, 12, 16, and 20, yielding 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 0.40 standard deviations above the mean (10.85).

stronger.[7] This suggests that the results of the paper are driven by earnings seasonality rather than by the specific choice of how seasonality is measured.

Given that firms tend to either 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.[8] 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 four 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 in Table II indicate that seasonal shifts in earnings are more common for large firms, value firms, old firms, firms with low turnover, and firms with higher accruals. Nearly all of these results are statistically significant at the 1% level when clustered by firm and year. The results are considerably reduced in magnitude when industry fixed effects are added (48 industries from Fama and French (1997)), consistent with industry factors being a significant driver of seasonal patterns in earnings.

The requirement of five years of earnings data to form *earnrank* means that our sample is tilted toward older firms, so the results may not generalize to young firms. This requirement 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 common to both positive and negative seasonality firm/month observations and therefore should not have an

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

[8] 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).

obvious impact on long/short portfolio returns. Second, in terms of the comparison with younger omitted firms, the results presented in Table II imply that the extreme quintiles are more likely to be filled with older firms. As such, firms for which we do not have *earnrank* data are less likely to have large seasonal earnings patterns. In the Internet appendix, we present further details of the variable construction and how this affects the number of observations.

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 accounted for 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.

Because 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 it had an earnings announcement 12 months prior. 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 condition on an earnings announcement 12 months prior and sort firms based on *earnrank.* As a result, all earnings information is at 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 for which earnings in the upcoming announcement were historically larger than other months. We include only months in which the portfolio has at least 10 firms and, in the case of the difference portfolio, in which both the long and short leg have at least 10 firms. Because 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 standard deviation of returns for the negative seasonality portfolio (5.28 equal weighted, 5.18 value weighted) is actually the same or slightly higher than the standard deviation of the positive seasonality portfolio (5.14 equal weighted, 5.18 value weighted). The lack of higher volatility somewhat ameliorates the concern that the returns are driven by differences in risk. The positive seasonality portfolio also does not have more extreme negative returns, such as the crash risk associated with momentum (Daniel and Moskowitz (2013)).

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, and examine the average three-day characteristic-adjusted return over the actual earnings announcement date. The characteristic-adjusted returns are computed similarly to the method in 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 prior (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. As in Table III Panel A, the results indicate that firms with positive seasonality have significantly higher returns than firms with negative seasonality. Consistent with firms switching quintiles, the returns have the opposite sign for the following announcement. They retain the original sign and similar magnitude in four quarters time, when seasonality returns to a similar level.

Although the results presented in Table III indicate that the positive seasonality portfolio is not more volatile or skewed, these are not the only measures of risk. Because positive seasonality firm-months may be more exposed to other economy-wide risks, in Table IV we consider whether the returns to portfolios formed on *earnrank* are explained by exposure to standard factors. We examine portfolios sorted into quintiles of seasonality, and compute abnormal returns relative to a four-factor model (Fama and French (1993), Carhart (1997)). The seasonality portfolio returns are regressed on the excess returns of the market, SMB, HML, and UMD portfolios.

In Table IV Panel A, the lowest seasonality quintile portfolio has a four-factor alpha of 31 basis points per month when equal-weighted (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.[9] 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 noteworthy that the effect is driven by the long side of the portfolio, as a number of effects are concentrated in the short side (Stambaugh, Yu and Yuan (2012)). Further, the largest distinction is between the highest seasonality quintile and the remainder, with quintiles 1–4 showing similarly abnormal returns to each other. The abnormal returns are not monotonic across the quintiles, which is partly due to the fact that firms with little seasonal variation (the middle quintiles) tend to be younger and smaller, yielding different earnings announcement returns. The main variable of interest is the difference between high and low levels of *earnrank,* which is less sensitive to firm characteristics. We will return to the issue of monotonicity shortly.

Second, the difference portfolios in Table IV Panel A have low loadings on the standard factors, with small and statistically insignificant loadings on excess market returns and UMD, and moderate but negative loadings on SMB and HML.[10] These low factor loadings arise because the long and short portfolios are comprised of roughly the same firms at different points in the year.

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[9] In untabulated results, the abnormal returns to the difference portfolio are larger when using more extreme values of *earnrank.* Sorting portfolios based on the top and bottom 10% of *earnrank* produces equal-weighted alphas of 44.6 basis points (*t*-statistic of 2.99), and sorting at 5% produces abnormal returns of 62.9 basis points (*t*-statistic of 3.44).
[10] As a robustness check, we compute the time series changes in factor loadings between positive and negative seasonal months using daily betas calculated as in Lewellen and Nagel (2006). The changes in betas are generally negative and small (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. Lewellen and Nagel (2006) argue that asset pricing models using time-varying betas have difficulty explaining some basic stylized facts of security returns.

To emphasize this point, we form portfolios by sorting only on within-firm variation in *earnrank* over a year. Specifically, for each firm with 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*. Because all information is at least 12 months old, this ranking is computable by an investor before the start of the year over which returns are measured. The resulting portfolios include each firm in each of the four portfolios for one month per year. Any variation in seasonality is only from variation within the firm, rather than cross-sectional variation from the types of firms that have positive seasonality at some point in time. The long and short portfolios cycle through the same set of firms. Thus, fixed loadings on factors will cancel out, 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 of Panel A: 33 basis points equal-weighted (with a *t*-statistic of 3.40) and 66 basis points value-weighted (with a *t*-statistic of 3.91). When this within-firm variation is examined, the alphas are monotonic across the four announcements.[11]

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 example, if firms have a higher market beta in positive seasonal months, then the difference portfolio buys firms in their high beta months and shorts them in their low beta months. The difference portfolio will have a positive market beta, but the four-factor regression controls for this, and it will not contribute to the alpha. Controlling for different factor loadings is important, as firms have different betas around earnings announcements (Ball and Kothari (1991)).

[11] Four categories, rather than five quintiles, are used as the split is now across the four earnings quarters each year.

More generally, because abnormal returns are evident using only within-firm variation, the results also are not driven by fixed loadings on any other omitted factors.[12] The results could still be driven by time-varying exposure to risks that we are *not* measuring (e.g., something other than the market, SMB, HML, or UMD), with firms in positive seasonality months being riskier than the same firms in negative seasonality months. We return to this issue in Sections 3.1 and 3.4.

Figure 1 presents a plot of the annual returns to the long-short portfolios examined in Table IV. The results show that the returns to the strategy have become larger and more consistently positive since Salamon and Stober (1994) first documented the effect. From 1973 to 1994, the annual returns were, on average, 1.46% equal weighted and 3.70% value weighted, as compared to the 1995–2013 period, when they were 7.89% equal weighted and 13.44% value weighted. This is in contrast to the result in McLean and Pontiff (2016) that anomalies generally decline after their publication. In the internet appendix, we find that the seasonality returns are not significantly related to the sentiment index of Baker and Wurgler (2006). This is consistent with Stambaugh, Yu and Yuan (2012), who find that the correlation between sentiment and anomaly returns is driven by the short leg of the portfolio, but the long leg of anomaly portfolio returns (which drives the overall returns in this instance) shows no correlation with sentiment.

2.4 Effect of Earnings Seasonality versus other Seasonal Variables

While Table IV 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)),

[12] We continue to utilize the main univariate sorting on *earnrank* throughout the paper to better fit the intuition behind our hypotheses, which rely on the existence of a meaningful level of seasonal variation to begin with.

whereby firms have abnormally high returns in months when they are predicted to pay a dividend, and return seasonality (Heston and Sadka (2008)), whereby returns 12, 24, 36, 48, and 60 months prior 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, momentum, and last month's returns. Finally, we examine whether earnings seasonality predicts returns outside of predicted earnings announcement months. If positive seasonality earnings months merely coincide with a general period of increased exposure to economy-wide risks, then higher returns may be evident in other months surrounding a positive seasonality announcement.

In Table V we test these possibilities by examining the effect of earnings seasonality using Fama and Macbeth (1973) cross-sectional regressions. In Columns 1–4, we consider only the cross-section of firms with a predicted earnings announcement in the current month, meaning they had an earnings announcement 12 months prior. The *earnrank* variable shows univariate significant predictive ability, with a coefficient of 0.034 and a *t*-statistic of 2.78. A one standard deviation increase in seasonality (2.85) corresponds to an increase in returns 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, including those without a predicted earnings month. Here, 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 afterward). Column 5 is the all-firm equivalent of the univariate regression, including only seasonality, a predicted earnings dummy, and the interaction between the two. The regression shows that seasonality affects returns only in predicted earnings months, with a significant effect 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

Although the results presented in Subsections 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, by contrast, is property of a firm's underlying business model and, as such, should be persistent across time.[13]

To test whether firm-specific information explains our results, in Table VI we lag the *earnrank* measure over different lengths of time. In Panel A we consider the effects of seasonality from the same quarter of the year, but using various lagged multiples of 12 months to a period of 10 years. This retains the seasonality prediction for the current quarter but omits increasing amounts of recent earnings news, so that any correlated information is more stale. Although this test is necessarily conditioned on firms having a longer time series of data, the selection effect is

[13] The timing of earnings announcements is strongly persistent over time (Frazzini and Lamont (2006)), which is important because our test is a joint test of the persistence of seasonality and earnings announcement months.

equal between the long and short legs of the portfolio. Thus, 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 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. [14]

In Panel B, we consider another prediction of delayed response to firm-specific earnings information. If our results are driven by seasonality in earnings, then *earnrank* will positively predict returns for the same quarter as the measure but not similarly predict returns for other quarters. If seasonality effects were driven by a slow response to correlated earnings news (e.g., earnings growth, post-earnings announcement drift), the effect should be similar when *earnrank* is lagged at other multiples of 3 months and, indeed, ought to be stronger for horizons of 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 firm-specific information flows common to recent earnings announcements.

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

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

3.1 Earnings Announcement Risk and Analyst Forecast Errors

Perhaps the most standard potential explanation for higher expected returns in positive seasonality months is that they represent compensation for risk. This is related to the argument presented in Salamon and Stober (1994), whereby high seasonal quarters involve more resolution of uncertainty, which could come from either systematic or idiosyncratic factors. Although Salamon and Stober (1994) do not distinguish between these two cases, we test both possibilities and find that neither explains the returns.

The first way that announcement risk could explain the results is if seasonality were associated with greater exposure to a systematic announcement risk factor, whereby announcements that represent more of the firm's earnings generate a larger exposure to this factor. This systematic announcement risk must be separate from exposure to market returns over the month, as the four factor regressions already control for different market betas across the long (positive seasonal) and short (negative seasonal) portfolios. In addition, the results in Table IV indicate that firms do not have significantly higher market betas in positive seasonality months relative to negative seasonality months, and the findings in Table III Panel A indicate that the positive seasonality portfolio does not have more volatility than the negative seasonality portfolio.

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 earnings announcement risk factor, this could be driving the returns.

In Table VII we explore this possibility. The regressions are similar to those in Table IV, but, in addition to the standard four factors, we also include the excess returns of an equal-weighted portfolio of firms with a predicted earnings announcement that month (EARNRF). This captures the exposure of each seasonality portfolio 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 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 those in Table IV, indicating that exposure to an earnings risk factor is not a major driver of the seasonality effect. Indeed, the seasonality difference portfolio does not significantly load on the earnings risk portfolio.[15]

If seasonality returns are driven entirely by compensation for risk, then market participants should not be more positively surprised on average in positive seasonal quarters. Earnings risk operates only through the discount rate channel: investors require higher returns in positive seasonal months due to risk in these months, not because average news is more positive. We examine this proposition using analysts' earnings forecasts. These have been argued to be a reasonable proxy for the views of investors (So (2012)), but even without this assumption they are a sample of opinions from informed market participants. There may be greater variability in forecast errors in positive seasonal months, but any increase in the mean forecast error is *prima facie* evidence that analysts are relatively more pessimistic in these months.

[15] In untabulated results, we show that other proxies for earnings risk (e.g., a value-weighted EARNRF or a difference portfolio between expected announcers and non-announcers) produce similar spreads in abnormal returns.

In Table VIII Panel A we test whether analysts are more positively surprised by firm earnings in positive seasonality quarters. Observations are at the firm-date level, and the dependent variable is the median forecast error for quarterly earnings per share, taken over all analysts who make forecasts between 3 and 90 days before the announcement. The measure of forecast error is (Actual EPS – Forecast EPS) / Price ($t-3$). In Table VIII Panel A we regress the panel of firm-date observations of *earnrank* and various controls. In Columns 1–4 we control for the log number of estimates, the standard deviation of forecasts scaled by price three days before the announcement, a dummy variable for if there is only one analyst's 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 2 to 12 months cumulated, and the previous four forecast errors.

The results presented in Table VIII are consistent with analysts being more positively surprised by firm cash flows during positive seasonality quarters. 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 higher. In Columns 2–4 we show that the effect of seasonality survives adding firm-level controls, with a coefficient of 0.012 and a t-statistic of 5.19 when all firm controls are used. In Columns 5–7 we add date and firm fixed effects to control for omitted fixed firm differences and aggregate time-series changes in the analyst mistakes. The effects are very similar in all cases, indicating that the effect of seasonality on forecast errors is not due to particular firm characteristics or time periods. 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 the forecast errors related to seasonality, we 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 missed by analysts. 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 previous 12 months. For these firms, we compute the fraction of the seasonal shift that was forecasted as follows:

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

Among firms that shifted from the lowest to the highest quintile of seasonality, the median fraction forecast was 0.93, meaning that analysts correctly forecasted 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 but not that seasonality is ignored altogether.

Having shown that forecast errors are correlated with seasonality, we also wish to know whether analysts deviate from econometric models of seasonal adjustments. In Table VIII Panel B we estimate such a benchmark using a structural X-12 additive seasonal adjustment model of earnings per share. We discuss the details of the estimation procedure at length in Section 5. We take these estimates and subtract the median analyst's earnings forecast. This yields an estimate not of forecast error but, of whether analysts are more likely to undershoot a formal seasonal adjustment benchmark in periods of positive seasonality.

Table VIII Panel B utilizes this measure and finds similar results. In all specifications, we find coefficients roughly between 0.40 and 0.45, all highly statistically significant. This suggests that, in positive seasonality periods, analysts' forecasts are lower than both actual earnings and a formal seasonal model of earnings forecasts.

The fact that higher returns in positive seasonality months coincide with positive analyst surprises is consistent with both investors and analysts making cash flow mistakes. So (2012) provides evidence that investors overweight analysts' forecasts when forming expectations of earnings, implying that analysts' forecasts are a good proxy for investors' forecasts. The results in So (2012) raise the possibility that investors may be following the mistakes of analysts, but the two groups may also be making independent correlated errors. Both possibilities would be consistent with our results. In the Internet appendix, we show that seasonality returns are larger among firms with analyst coverage, but the difference is only marginally significant.

3.2 Daily Returns

To further understand what is driving the returns that we observe in an earnings month, we examine the daily returns that surround earnings announcements. Barber et al. (2013) and Johnson and So (2014) show that the earnings announcement premium is actually concentrated prior to the earnings announcement itself. If we are capturing a variant of this premium, we expect the returns to be concentrated several days before the announcement. The returns at the monthly horizon also may 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 time of the announcement itself. While a concentration of returns on the announcement day also would 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 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 seasonality returns are concentrated around the earnings announcement itself. The first three columns show the average daily characteristic returns 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 around earnings announcements in general begin several days before the announcement itself.

The fourth column in Table IX examines the difference in characteristic-adjusted returns between the top quintile and the bottom quintile of seasonality. The largest difference in returns occurs on the announcement day itself (9.7 basis points with a *t*-statistic of 3.37). Adding the adjusted returns from $t-2$ to $t+1$ yields roughly 26 basis points of returns. Because this is similar to the equal-weighted portfolio result of 35 basis points in Table III, it suggests that most of the returns due to seasonality come from the announcement itself. Columns 4 and 5 show the equivalent difference in returns for more extreme sorts on *earnrank*. For more extreme cutoffs, the returns are again earned mostly between $t-2$ and $t+1$, but the magnitudes are larger, consistent with the greater level of seasonality. For the top 10% minus the bottom 10%, the sum of the adjusted returns over the four days is roughly 39 basis points. For the top 5% minus the 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 characteristic-adjusted returns on *earnrank*. The coefficients that are both economically and statistically significant are 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 that occurs 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, consistent with the results in Table VIII.

As Ball and Bartov (1996) note, just because investors are making mistakes in forecasting earnings does not mean that they are ignoring earnings news entirely. Similarly, the fact that investors do not seem to be properly pricing earnings seasonality does not mean that seasonality is being ignored altogether. This is reinforced by the analysts' forecasts results presented above in section 3.1. Our results also do not require that investors are being especially naïve, as 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.

Although 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.[16]

Psychology provides a potential mechanism 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

[16] 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 claims of inefficiency are more convincing if they are constrained by testable predictions that relate to specific causes of mispricing.

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 (1962), Davelaar et al. (2005)), whereby individuals are more likely to recall the last items in a list (the recency effect). In the context of baseball, Green and Zwiebel (2015) find that baseball teams overreact to very recent batting performance. 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.[17]

In addition, there are a number of examples that show that, when individuals make decisions in a sequence, behavioral biases due to previously viewed events often manifest themselves with respect to recently viewed observations. For example, in the context of speed dating, men exhibit contrast effects with respect to the most recently observed women but not those further in the past (Bhargava and Fisman (2014)). In the context of earnings announcements, Hartzmark and Shue (2015) demonstrate that firms exhibit contrast effects with respect to announcements from the previous day but, again, not further in the past.

Our measure of seasonality captures the long-run relative size of earnings in the upcoming quarter relative to other quarters. Mechanically, relatively higher earnings in the upcoming quarter imply relatively lower earnings in the other quarters. If the historical pattern in earnings continues as before, then positive seasonality firms will typically have announced large earnings 12 months prior but lower earnings over the subsequent three announcements. If investors suffer from a

[17] This is not the only possible behavioral mistake that investors could make, of course. It is possible, counterfactually, that the seasonal trend itself might be salient to investors and that they overreact to this. To some extent, it is an empirical question whether investors overreact or underreact and, if so, why. Importantly, however, we propose a specific microfoundation for underreaction in the current context, which generates additional testable predictions about the role of recent earnings.

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 prior. Importantly, if the recency effect drives the seasonality returns, then the returns should be higher when subsequent earnings *actually were lower ex-post*. If the more recent earnings were actually higher than those from 12 months prior, then a recency effect would not cause investors to be 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 prior. 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 prior) and the announcement 12 months prior (with earnings scaled by firm assets per share).[18] We then sort stocks by whether they are above or below the median of this measure.

Table X presents these results, which are consistent with the predictions of the recency effect. When recent earnings are more negative relative to earnings 12 months prior, the seasonality effect is larger: 65 basis points equal weighted and 76 basis points value weighted, both significant

[18] 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.

at the 1% level. By contrast, seasonality returns are lower among firms with higher recent earnings: 28 basis points equal weighted and 6 basis points value weighted. The returns of the double difference portfolio are statistically significant at the 1% level.

One possible concern with the previous results is that conditioning on low recent earnings may select 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 prior. In other words, the gap is computed using announcements that are, on average, 15, 18, and 21 months before portfolio formation, instead of in Panel A where they are, on average, 3, 6, and 9 months before portfolio formation. If the recency effect is driving our results, low earnings in this period should not produce the same spread in returns. This double sort produces a gap in returns that is smaller in magnitude, statistically insignificant when value weighted, and marginally significant (with a *t*-statistic of 1.67) when equal weighted. 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 prior 12 months. Since earnings records are a salient indicator of improved firm 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 prior 12 months (excluding the first two years of observations for each firm).

Consistent with recency, we find that the effects of seasonality are significantly higher among firms that have not recently broken a record. The double difference portfolio has abnormal returns of 35 basis points when equal weighted (with a *t*-statistic of 2.88) and 49 basis points when value weighted (with a *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, based on 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 their 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-prior values of *earnrank.*

The recency bias appears to contrast with the explanation in Bernard and Thomas (1990) of why post-earnings announcement drift reverses at the fourth quarter. They argue that investors overweight earnings surprises from four quarters prior and underweight 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 recent earnings do not involve a substantial surprise (e.g., when low earnings are mostly predictable, as seasonality implies that they are). The empirical results in Bernard and Thomas (1990) are clearly distinct from the results here (*earnrank* predicts returns consistently up to a 10-year horizon, for instance). Nonetheless, the difference in relative weighting of recent versus older earnings is somewhat of a puzzle.

One possible explanation is that there are different groups of investors who are 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 is 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 trade more in line with the views of analysts, and neither group seems to underweight recent earnings surprises. Similarly, Ke and Ramalingegowda (2005) and Campbell, Ramadorai and Schwartz (2009) find 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 the most recent three quarters (to take advantage of post-earnings announcement drift), they may be the group that ignores longer-term seasonal information. This would explain several facts, namely (a) analysts also make systematic mistakes based on seasonality and (b) large firms have bigger seasonality effects, and are likely to have more trading by larger investors. This argument is rather speculative, however. On face, the fact that seasonality returns are bigger for large firms is puzzling. Many theories of behavioral mistakes posit that institutional investors are less likely to be biased than retail investors, which would predict bigger anomaly returns for small firms (opposite to what we find).

4. Additional Alternative Explanations

4.1 Increases in Volume and Idiosyncratic Risk

Given that the seasonality effect occurs within the set of predicted earnings firms, the returns may be driven by factors associated with the earnings announcement premium. Frazzini and Lamont (2006) argue that earnings announcement returns are driven by predictable increases in volume, 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 explained by increases in idiosyncratic volatility. 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. Positive seasonal quarters may have higher returns due to having either 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 prior to six years prior, used to form the *earnrank* measures, and examine the relative level of trading volume in the upcoming quarter. We form a ratio of the average volume from the past five announcements in the same fiscal quarter as the upcoming announcement, divided by the average volume from the 20 announcements starting 12 months prior. 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 a statistically insignificant 14 basis points when equal weighted and 18 basis points when value weighted. Overall, the results suggest that seasonality is not driven by an increase in trading volume.

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 investors, as they can hold only some subset of the firms and, thus, face idiosyncratic risk. Whether or not investors are so constrained is a question beyond the scope of this paper. We remain agnostic on this issue and instead focus on examining whether there is a relation 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). We first regress daily stock returns on a market model (including three lags) for the 100 days ending 11 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 100-day regression period to obtain the announcement period increase in idiosyncratic volatility. We predict the firm's abnormal idiosyncratic volatility in the upcoming quarter by taking the average of the previous five announcements in the same quarter. Table XIII shows that idiosyncratic volatility does not explain seasonality returns. Although announcements with higher expected idiosyncratic volatility have higher returns, consistent with Barber et al. (2013), the seasonality difference portfolio returns are similar between high and low expected idiosyncratic volatility. In untabulated results, controlling for expected idiosyncratic volatility in a Fama and Macbeth (1973) regression framework produces similar results: the effect of seasonality is not subsumed by the extra controls. Overall, predictable abnormal idiosyncratic risk does not seem to explain seasonality returns.

4.2 Time-varying Factor Exposure

As noted earlier, the seasonality returns are unlikely to be explained by fixed loadings on risk factors, as firms tend to cycle through both the long and short legs of the difference portfolio. In addition, the abnormal returns cannot be explained by firms having a predictably higher time-varying loading on the factors that are being controlled for (Mkt-Rf, SMB, HML, and UMD). On the other hand, the abnormal returns could be caused by the difference portfolio itself having time-varying loadings on the factors. For example, 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 portfolio 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 prior have high returns in the current month. It is 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 that in 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 the 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 *earnrank* minus low *earnrank* 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 (with a 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.

It is difficult to rule out all possible variations on risk-based explanations that involve time-varying expected returns. One way of interpreting our results is that if earnings seasonality is in fact proxying for a risk exposure, then there is a considerable puzzle as to how to measure the risks that underlie the predictability of returns based on earnings seasonality.

4.3 Accounting Predictors of Earnings Announcement Returns

A large literature in accounting has examined what variables predict earnings surprises and announcement returns. Bernard and Thomas (1990) show that positive earnings surprises predict high abnormal returns for the next three quarters' announcements and low abnormal returns for the fourth quarter. Piotroski (2000) constructs a measure 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) are associated with lower future returns. Seasonality may be proxying for these 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 *earnrank* positively and significantly predicts announcement 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 when these variables are included, suggesting that seasonality is not just proxying for recent earnings surprises. Column 3 uses median analyst forecast errors as an alternative measure of past earnings surprises. Again, *earnrank* remains positive and significant. The effect of *earnrank* is similar when controlling for the *F-score* from Piotroski (2000) (Column 4), the decile of accruals as in Sloan (1996) (Column 5), and all the accounting variables in combination (Column 6). 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 are related to earnings management by firms and find that seasonality does not have a significant relation with the various 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 less predictive power. Finally, we examine seasonality returns separately for each calendar quarter of the year and find the largest returns in the first quarter but directionally positive returns in all four quarters.

5. Alternative Measures of Seasonality

Our results so far measure seasonality using *earnrank*, which is simple, easy to replicate, and necessitates a minimum of assumptions. *Earnrank* is designed to reliably identify seasonal quarters without making the parametric assumptions necessary to estimate the size of the seasonal term. In this section, we explore alternative measures based on time-series modeling techniques designed to forecast the size of the seasonal trend (rather than its reliability). While both measures broadly identify similar seasonal firms and quarters, it seems likely that both aspects should contribute to the effect. Consistent with this, in untabulated results, taking the intersection of both size and reliability measures produces stronger results. The results are similar across all of our measures, suggesting that our findings are not due to specific modeling assumptions.

The estimates of seasonality in this section are based on the X-12 seasonal adjustment model used by the U.S. Census Bureau. The X-12 model is based on an autoregressive integrated moving average (ARIMA) framework (Findley et al. (1998)). The model estimates the seasonal component of earnings relative to a time-trend, adjusts for the presence of outliers, and chooses the optimal moving average to measure seasonal components. In addition to the assumptions underlying the ARIMA model, a number of additional modeling decisions must be made.

One such assumption is whether to model the seasonal relation as additive (e.g., earnings are $10 million more in the fourth quarter) or multiplicative (e.g., earnings are 20% higher in the fourth quarter). For many firms, it seems that seasonality should be modeled as multiplicative. If a firm doubles in size, it seems likely that the point estimate of seasonality will not stay a consistent additive component but will double in size as well. Nonetheless, multiplicative X-12 models can be used only when the entire series is positive. Because this is not the case for any firm that experiences negative earnings, we model seasonal earnings terms using additive models and scale by different variables to adjust for changes in firm size: earnings per share, earnings divided by share price, and earnings divided by assets. We also examine seasonal components for both sales and revenue, which are never negative and thus can be estimated using the multiplicative model, which we think is the superior modeling choice.

Finally, there is the choice of how many lags to consider for the seasonal terms. We use five years of data to form our estimates, and our baseline estimates take the average of the seasonal term for all five past observations of the upcoming quarter. We find similar results if we simply use the seasonal term forecast just for the upcoming quarter.[19]

Table XVI presents alphas from portfolios that sort on a variety of X-12 estimates. The alphas are from the strategy going long firms in the top quintile and short firms in the bottom quintile of seasonality. Recall from Table IV that sorting on *earnrank* produced alphas of 35 basis points when equal weighted and 55 basis points when value weighted. The first three columns utilize an additive X-12 model of earnings per share, earnings/price, and earnings to assets. Equal-weighted estimates range from 29 to 37 basis points, and value-weighted estimates range from 59 to 87 basis points. Using our preferred multiplicative model on revenue and sales, we find equal-weighted alphas from 34 to 35 basis points and value-weighted alphas of 62 to 71 basis points.

In the internet appendix, we repeat the entire analysis presented in this paper, utilizing the multiplicative model based on sales. The results are similar and slightly stronger in some cases. This suggests that, while more complicated estimates of seasonality can improve returns, most of the variation in returns is evident even when using the simple *earnrank* measure.

6. Conclusion

Stocks exhibit higher returns in months when they are predicted to announce seasonally larger earnings. This effect does not appear to be driven by risk factors or a delayed reaction to

[19] The large number of non-obvious modeling choices required to implement these models reinforces the conclusion that estimating seasonal adjustments is quite complicated and is something that investors may plausibly get wrong.

firm-specific news. Positive seasonality quarters also display greater positive surprise by analysts, suggesting that the returns are 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 ignore seasonality altogether. Indeed, the results would not tell an analyst or investor exactly how much to adjust for seasonality for each firm. Instead, we show that whatever seasonal adjustment investors are using does not fully account for seasonal shifts.

The results in this paper are consistent with investors being less likely to process information when it is not salient. 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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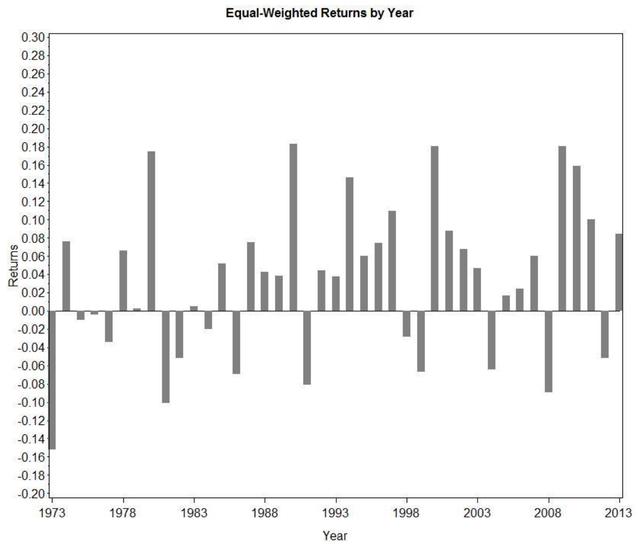
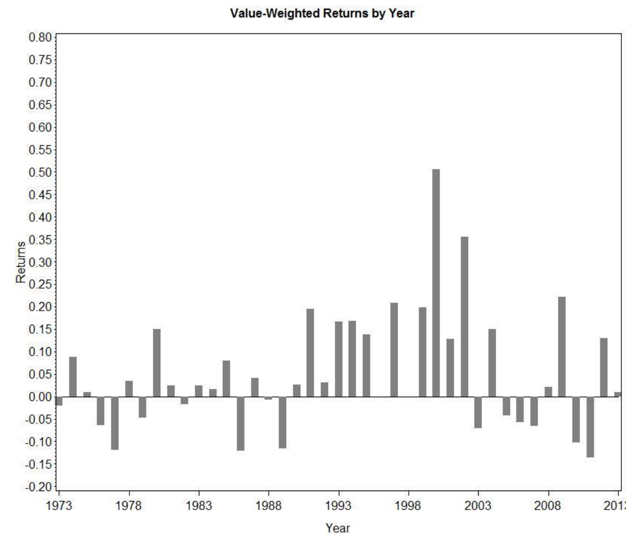
Figure I – Annual Returns to Seasonality Difference Portfolio

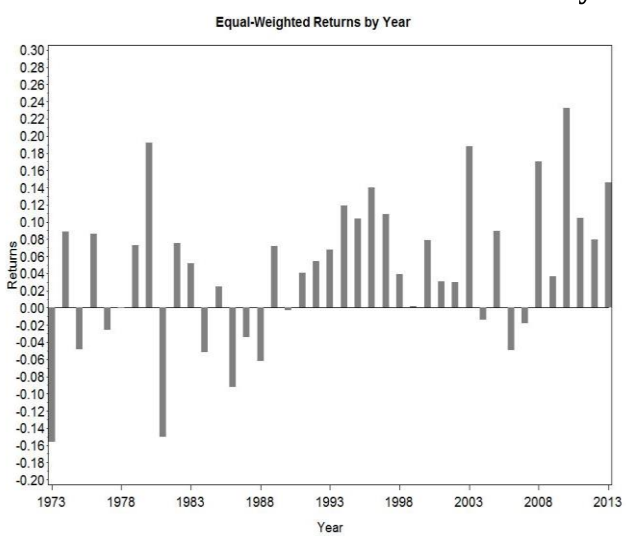
This figure presents the annual returns to portfolios of stock returns formed by sorting on earnings seasonality levels. Panel A presents results using *earnrank*, while Panel B uses the x-12 seasonal adjustment algorithm using five years of prior sales. Each month, all firms with an earnings announcement from 12 months prior are sorted according to the earnings seasonality measure (average rank of past earnings in Panel A and historical percentage increase in sales in Panel B) from the same fiscal quarter as that of the upcoming announcement. The portfolio returns are the average stock return for firms in the top quintile of seasonality (largest increase in sales/earnings) minus firms in the bottom quintile of seasonality (largest decrease in sales/earnings). The portfolios in the left column are equal weighted, while those on the right are value weighted. The annual returns over each calendar year are plotted in the figure.

Panel A – Seasonality measured using *earnrank*





Panel B – Seasonality measured using *X-12 Seasonal Adjustment*



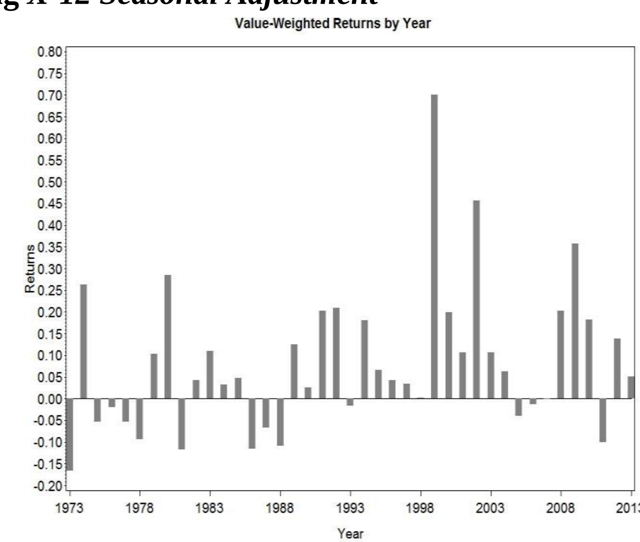


Table I – Summary Statistics

This table presents summary statistics for the main variables used in the paper. Panel A presents the distribution of firm-level characteristics, including market capitalization (in millions of dollars), the log of the ratio of book value of equity to market value of equity, stock returns in both the current month and 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 also are shown separately for months with 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 five years of earnings data and ranking each announcement by the earnings per share (e.g., adjusted for stock splits). The earnings rank variable is formed by taking the average rank of the five announcements from the same fiscal quarter as that of the current announcement.

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	2.87	9.10	11.00	12.60	335,680
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 shows 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 values of *earnrank*, the main measure of earnings seasonality. At each point, we examine five years of earnings data and rank each announcement by the earnings per share (e.g., adjusted for stock splits). The *earnrank* variable is formed by taking the average rank of the five 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 provides portfolio and firm-level returns according to 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 (e.g., adjusted for stock splits). The earnings rank variable is the average rank of the past five 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 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 three-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 three-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 run from October 1972 to September 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% levels, 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 (e.g., adjusted for stock splits). The earnings rank variable is the average rank of the past five 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 run from October 1972 to September 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% levels, 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 (e.g., adjusted for stock splits). The earnings rank variable is formed by taking the average rank of the past five 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% levels, 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 Ann.					(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 Ann.							(3.67)	(3.18)
Predicted Earnings Ann.					-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 five years of earnings announcements and ranks each announcement by the earnings per share (e.g., adjusted for stock splits). The earnings rank variable is formed by taking the average rank of the five 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 one year ago to six years ago, '24' uses data from two years to seven years ago, etc. Panel B considers the measure lagged at different multiples of three 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 that of 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 where 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 run from October 1972 to September 2013. *, **, and *** denote significance at the 10%, 5%, and 1% levels, 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 presents the findings on 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 (e.g., adjusted for stock splits). The earnings rank variable is formed by taking the average rank of the past five 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 where the earnings were historically lower than normal in the upcoming quarter. In Panel A, the seasonality portfolios are equal weighted, and in Panel B, they are value weighted. The data run from October 1972 to September 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% levels, 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 shows how analyst forecast errors vary with measures of earnings seasonality. In Panel A, the dependent variable is the difference between actual earnings per share and the median analyst forecast of earnings per share, divided by the 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 past five 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. In Panel B, the analysis is similar, but the dependent variable is the difference between an x-12 additive model seasonal forecast of earnings per share (adjusted for stock splits) and the median analyst forecast (in other words, how much the analysts undershoot relative to a formal seasonal model of earnings). 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% levels, respectively.

Panel A - Seasonality and Analyst Forecast Errors							
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

Panel B - Difference Between Seasonal EPS Forecasts and Analyst Forecasts							
Dependent variable is time-series seasonal forecast of earnings minus median analyst forecast, divided by price							
Earnings Rank	0.187***	0.180***	0.156***	0.151***	0.155 ***	0.137 ***	0.137 ***
	(25.43)	(25.43)	(24.62)	(23.48)	(23.49)	(22.19)	(21.86)
Log (# Estimates)		0.089***	-0.248***	-0.192***	-0.147 ***	-0.005	0.056 *
		(4.04)	(-8.98)	(-7.40)	(-5.87)	(-0.18)	(1.95)
Forecast Dispersion		-0.328***	-0.270***	-0.064**	-0.051 *	-0.109 ***	-0.081 ***
		(-8.31)	(-7.24)	(-2.28)	(-1.90)	(-5.00)	(-3.72)
Single Estimate (Dummy)		-0.467***	-0.455***	-0.225***	-0.139 ***	-0.195 ***	-0.064
		(-8.81)	(-9.00)	(-4.58)	(-2.77)	(-3.85)	(-1.23)
Forecast Error (t-1)				0.339***	0.336 ***	0.348 ***	0.338 ***
				(17.87)	(17.76)	(17.41)	(17.07)
Forecast Error (t-2)				0.213***	0.209 ***	0.230 ***	0.221 ***
				(13.93)	(13.40)	(14.37)	(13.77)
Forecast Error (t-3)				0.053***	0.053 ***	0.066 ***	0.064 ***
				(4.16)	(4.13)	(5.09)	(4.78)
Forecast Error (t-4)				0.034***	0.032 **	0.055 ***	0.050 ***
				(2.58)	(2.43)	(4.61)	(4.09)
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	177,878	177,878	174,380	157,558	157,558	157,558	157,558
R-squared	0.011	0.041	0.066	0.133	0.147	0.212	0.118

Table IX – Daily Characteristic Adjusted Returns around Earnings Announcements

This table provides 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 show 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% levels, respectively.

Days from Earnings Annoucnement (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 (divided by assets) and earnings from 12 months ago. In Panel A, firms are sorted by the difference between the average earnings in 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 12 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 run from September 1972 to September 2013. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Panel A - Gap Between Recent Earnings and 12 Months Ago

Equal Weighted

Gap Between Earnings (3,6,9) Months Ago and 12 Month Ago	All	**Earnings Rank Level** 1 (Low)	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	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 (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	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 (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}
	0.139 *	0.493 ***	0.244 **	-0.250 *
2 -1	(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	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 (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}
	-0.200	0.200	-0.030	-0.205
2 -1	(-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 past five 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 run from September 1972 to September 2013. *, **, and *** denote significance at the 10%, 5%, and 1% levels, 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 five announcements from the same fiscal quarter as the upcoming announcement, divided by the average turnover from all announcements in the five-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 run from September 1972 to September 2013. *, **, and *** denote significance at the 10%, 5%, and 1% levels, 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 run from September 1972 to September 2013. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Panel A -Equal Weighted

Average Abnormal Idiosyncratic Volatility On [t-1] to [t+1]	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 (Low Abnormal Idiosyncratic Vol.)	0.343 ***	0.216 *	0.474 ***	0.292 **
	(3.36)	(1.88)	(3.56)	(2.11)
	{431}	{420}	{422}	{413}
2 (High Abnormal Idiosyncratic 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 Idiosyncratic Volatility On [t-1] to [t+1]	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 (Low Abnormal Idiosyncratic Vol.)	0.251 *	0.090	0.452 ***	0.373 *
	(1.92)	(0.56)	(2.79)	(1.82)
	{431}	{420}	{422}	{413}
2 (High Abnormal Idiosyncratic 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 provides the findings on 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 past five 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 where 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 run from October 1972 to September 2013. *, **, and *** denote significance at the 10%, 5%, and 1% levels, 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 presents the findings on 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 minus the return of a portfolio matched on quintiles of market capitalization, book-to-market, and momentum. The earnings rank variable is formed by taking the average rank of the past five 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, winsorized at the 1% and 99% levels. Forecast error(t−X) denotes the difference between actual earnings and the median analyst forecast from X quarters ago, winsorized at the 1% and 99% levels. 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 coefficient. The data run from October 1972 to September 2013. Standard errors are clustered by date and firm, and *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	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

Table XVI – Alternative Measures of Earnings Seasonality and Stock Returns

This table presents the returns to earnings seasonality portfolios using alternative measures of the seasonal earnings component estimated over the past five years of earnings data for each firm. The seasonal component is estimated using the Census Bureau's x-12 seasonal adjustment algorithm. The term 'Add.' means that an additive seasonal term is estimated (e.g., earnings are higher by 20c per share), which is used when the earnings series can take on negative values. The term 'Mult.' means that a multiplicative seasonal term is estimated (e.g., sales are higher by 20%), which is used when the series can be only zero or positive. The 'Measure' row refers to the units being used to forecast the seasonal term. '5 year avg' means that the average value of the seasonal term in that quarter over the past five years is used, while '1 year forecast' uses just the estimated seasonal term for the upcoming quarter. We sort stocks each month into quintiles according to the distribution of earnings seasonality 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. Abnormal returns from each regression are shown, with *t*-statistics in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Model		x-12 Add. 5 yr avg	x-12 Add. 5 yr avg	x-12 Add. 5 yr avg	x-12 Mult. 5 yr avg	x-12 Mult. 5 yr avg	x-12 Mult. 1 yr forecast
Measure		Earnings Per Share	Earnings / Price	Earnings / Assets	Revenue	Sales	Sales
Weighting	**Portfolio**						
EW	1 (Low)	-0.057	0.185 **	0.209 **	0.189 **	0.193 **	0.203 **
		(-0.66)	(2.01)	(2.34)	(2.11)	(2.17)	(2.28)
EW	5 (High)	0.315 ***	0.548 ***	0.494 ***	0.531 ***	0.545 ***	0.541 ***
		(3.73)	(6.18)	(5.86)	(6.02)	(6.25)	(5.96)
EW	5 - 1	0.372 ***	0.363 ***	0.285 **	0.342 ***	0.352 ***	0.338 ***
		(3.39)	(3.11)	(2.48)	(3.05)	(3.15)	(2.94)
VW	1 (Low)	-0.051	0.071	0.235	0.245 *	0.194	0.223
		(-0.39)	(0.46)	(1.53)	(1.71)	(1.37)	(1.57)
VW	5 (High)	0.536 ***	0.937 ***	0.877 ***	0.869 ***	0.900 ***	0.882 ***
		(4.07)	(5.78)	(5.49)	(5.73)	(6.01)	(5.94)
VW	5 - 1	0.587 ***	0.866 ***	0.643 ***	0.624 ***	0.706 ***	0.659 ***
		(3.20)	(4.31)	(3.15)	(3.31)	(3.79)	(3.56)