'Tis the Season!
Mood-Based Cross-Sectional Return Seasonality*

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Existing research has documented cross-sectional seasonality of stock returns – the periodic outperformance of certain stocks relative to others during the same calendar month or weekday. We document that relative performance across stocks during the calendar months or weekdays with high aggregate returns (e.g., January, Friday, the best-return month realized in the year, the best-return day realized in a week) tends to *persist* in future calendar months or on weekdays when high aggregate returns are expected (e.g., January, Friday), but *reverse* when low aggregate returns are expected (e.g., September, Monday). We present a model based on investor mood to explain the findings. As a direct test of the model, we use anticipation of an upcoming holiday to identify periodic investor positive mood swings and document strong persistence in the cross-section of stock returns during the two to three days immediately preceding or on a holiday. This pre-holiday seasonality is long lasting, is robust to controlling for a host of firm attributes, is present in foreign equity markets and only among firms with a retail clientele, and tends to reverse in the immediate, post-holiday period. Collectively, this evidence suggests that investor mood swings are important sources of stock return seasonality in the cross section.

[Key Words] Return seasonality, Pre-holiday effect, Investor mood, Retail clientele

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[Key Words] Return seasonality, Pre-holiday effect, Investor mood, Retail clientele

1. Introduction

Although voluminous research over a period of decades has established that the aggregate stock market seasonality,[1] only recently have researchers uncovered seasonality in the cross section of stock returns. Aggregate stock market seasonality refers to the periodic outperformance of market index portfolios. Cross-sectional seasonality refers to the periodic outperformance of certain stocks relative to other stocks in the same calendar month (Heston and Sadka 2008, 2012) or on the same day of the week (Keloharju, Linnainmaa, and Nyberg 2015).

In this paper, we document a broad set of cross-sectional seasonalities where predictable return persistence, or reversal, occurs across different calendar months or weekdays that last for years or months. Specifically, relative performance across stocks during the calendar months or weekdays with high aggregate returns (e.g., January, Friday, the best-return month realized in the year, the best-return day realized in a week) tends to *persist* in future calendar months or on weekdays when high aggregate returns are expected (e.g., January, Friday), but *reverse* when low aggregate returns are expected (e.g., September, Monday). Similarly, relative performance observed during seasonal periods with expected or realized low aggregate returns tends to persist (reverse) during future seasonal periods wherein low aggregate returns are expected to continue (reverse). We provide a theoretical model in which investor mood swings cause periodic optimism or pessimism bias in perceiving signals about common factors in returns and, therefore, lead to seasonal patterns both at the aggregate and cross-sectional levels.

Motivated by the model, we use the anticipation of an upcoming holiday to identify periodic positive mood swings among investors (Fabozzi, Ma, and Briley 1994; Friender and Subrahmanyam 2004; Autore, Bergsma, and Jiang 2015). We present a novel *preholiday cross-sectional seasonality*, wherein relative performance across stocks tends to persist during the pre-holiday period, defined as the two to three trading days immediately prior to or on a holiday, for the next one to ten years. This pre-holiday seasonal effect applies to the same and different holidays, cannot can be explained by firm beta or characteristics, and is observed in foreign equity markets. Further, it is present only among stocks with a retail investor clientele and quickly reverses during the immediate, post-holiday period. By linking cross-sectional return seasonalities in calendar months, on weekdays, and surrounding holidays, our evidence collectively suggests that investor mood swings are important sources of stock return seasonalities.

[1] See Keim (1983), Lakonishok and Smidt (1988), and Kamstra, Kramer, and Levi (2003), among others.

We start the empirical analyses by exploring the seasonal effects related to the month-of-the-year and the day-of-the-week. The month-of-the-year effect refers to the observation that aggregate stock markets tend to do better in certain calendar months (e.g., January) and do worse in other calendar months (e.g., September) (Lakonishok and Smidt 1988). In the cross section, Heston and Sadka (2008, 2010) find that relative performance across stocks tends to persist for years in the same calendar month, which we term the *same-calendar-month cross-sectional persistence effect*. Using Fama-MacBeth regressions, we replicate their finding for January and September and, furthermore, uncover a different kind of month-level persistence. We find that relative performance across stocks during the best-market-return (worst-market-return) month realized in a year tends to persist in subsequent one to ten January (September) months, when good (bad) market performance is expected to continue.[2] We term it the *same-market-state-month cross-sectional persistence effect*. A one-standard-deviation increase in the historical same-calendar-month or same-market-state-month return leads an average 17% or 7% increase in the January and October months during the next ten years.

Moreover, we document new *cross-calendar-month and cross-market-state-month cross-sectional reversal effects*, wherein relative performance in January or the best-market-return month realized in a year (September or the worst-market-return month) tends to *reverse* in subsequent one to ten September (January) months, when good (bad) market performance is expected to reverse. A one-standard-deviation increase in historical different-calendar-month or different-market-state-month return leads an average 8% or 28% return reduction in the subsequent ten January and October months.

The day-of-the-week effect refers to the observation that aggregate stock markets tend to do better at the end of the week (Friday) and worse at the beginning of the week (Monday) (e.g., French 1980; Lakonishok and Smidt 1988). In the cross section, Keloharju, Linnainmaa, and Nyberg (2015) find that stocks' relative performance on a given weekday persists for subsequent weeks on the same weekday, which we term the *same-weekday cross-sectional persistence effect*. We confirm this finding for Monday and Friday returns, and then show, analogous to the monthly results, that a *same-market-state-weekday return persistence effect* applies: relative performance across stocks on the best-market-return (worst-market-return) day realized in a week tends to persist on subsequent nearly ten Fridays (Mondays), when good (bad) market performance is expected to continue. A one-standard-deviation

[2] The best- or worst-market-return month of a year tends to spread out across the year. They do not tend to coincide with January or September.

increase in historical same-weekday or same-market-state-weekday return leads an average 11% or 10% increase in the subsequent ten Mondays and Fridays.

When market performance is expected to reverse, however, a *cross-weekday* or *cross-market-state-weekday cross-sectional reversal effect* occurs: relative performance across stocks on Friday or the best-market-return weekday realized in a week tends to reverse on subsequent Mondays, and that on Monday or the worst-market-return weekday reverses on subsequent Fridays. At the weekday level, a one-standard-deviation increase in the historical different-weekday or different-market-state-weekday return implies an average 15% or 19% return reduction in the subsequent ten Mondays and Fridays.

Taken together, these seasonal effects suggest that when good market performance continues, stocks that outperform will continue to do so; when bad market performance continues, stocks that underperform will continue to do so; but when market performance is expected to reverse, a cross-sectional return reversal is predicted. These effects are difficult to reconcile with a risk-based story, as predictable, seasonal cross-sectional return reversals require either seasonal, negative risk premiums or seasonal reversals in the cross-section of market betas or factor loadings. Neither is plausible, especially at the daily level. Under a risk-based theory, risk premia have to be positive and risk factor loadings are derived from fundamentals and, therefore, unlikely to frequently reverse across calendar months or weekdays. Instead, we posit that the same-season persistence and cross-season reversal effects are connected, in part, through seasonal investor mood swings. We present a theoretical model to illustrate this idea.

The model is based upon the premise that investor mood swings lead to periodic optimism or pessimism in interpreting information signals about common factors in securities' payoffs. Such investor optimism or pessimism generates factor mispricing, as well as stock mispricing that is inherited from factor mispricing through factor loadings. Such factor mispricing is similar to mispricing derived from sentiment or overconfidence-based behavioral models (Baker and Wurgler 2006, 2007; Daniel, Hirshleifer, and Subrahmanyam 2001; Hirshleifer and Jiang 2010), but here has a direct connection with investor mood states. When factor overpricing (underpricing) is growing, stocks with higher loadings on the factor that is becoming overpriced (underpriced) will earn higher (lower) average returns. Therefore, the history of a stock's seasonal returns will serve as a proxy for its sensitivity to seasonal mood influences and help predict its future average returns under the same, or the opposite, mood states. In other words, our model delivers predictions consistent with both aggregate and cross-sectional return seasonality.[3]

To provide direct tests for the mood-based theory, we document a new pre-holiday cross-sectional seasonal effect, under the premise that upcoming holidays induce positive pre-holiday moods. Employing U.S. data from 1963 to 2012 and thirteen major holidays, we show that historical same-holiday pre-holiday returns across stocks are significant positive predictors of their own future pre-holiday returns in the next one to ten years. A one-standard-deviation increase in the daily pre-holiday return in the prior year leads to an 8.4% increase relative to the average daily pre-holiday return, or 16%-24% increases during a pre-holiday window. The significant predictability persists when the historical pre-holiday returns are lagged by two to ten years, albeit with diminishing impacts over longer annual lags. Alternative measures of historical pre-holiday returns produce similar, or considerably stronger, results. These measures include the five-year moving average of the same-holiday pre-holiday returns, the average pre-holiday return across the thirteen holidays in a year, and the same-holiday pre-holiday return adjusted for the industry median.

We conduct a battery of robustness tests to ensure that the pre-holiday cross-sectional seasonality effect adds to prior research. First, we show that the pre-holiday seasonality is not subsumed or diminished by including the historical same-calendar-month return in the regressions (Heston and Sadka 2008). Second, the pre-holiday seasonality effect remains significant after we exclude the pre-New Year window, suggesting that it is not a repackaging of the turn-of-the-year effect in the cross section (Keim 1983; Doran, Jiang, and Peterson 2012). Third, the pre-holiday cross-sectional seasonality effect survives, and is hardly impacted, after including a host of firm attributes: market beta, firm size, book-to-market equity, past returns at various horizons, and various accounting ratios.[4] Thus, unlike the same-month return persistence effect (Heston and Sadka 2008), the pre-holiday cross-sectional seasonality effect is not explained even in substantial part by return seasonalities associated with a host of firm attributes.[5]

Furthermore, the mood-based theory offers additional predictions, which we test and find empirical support for. First, we show that pre-holiday returns in the cross section tend to reverse during the immediate, post-holiday trading days, when positive investor mood is expected to recede,

[3] The pre-holiday optimism bias, however, may also apply to firm-specific signals. But this channel is unlikely to produce persistent relative seasonal performances across stocks. See Section 4 for the detailed discussion.
[4] The accounting ratios include leverage, asset growth, accruals, the investment-to-asset ratio, external financing, and net operating assets.
[5] Keloharju, Linnainmaa, and Nyberg (2015) show that two-thirds of the same-month return persistence effect is explained by return seasonality induced by firm characteristics. See Section 2 for discussion.

or reverse, after the holiday. This evidence echoes our earlier evidence on the cross-season reversal effects in the cross section. It suggests that the temporary mispricing caused by positive holiday moods tends to correct rather quickly.

Second, we show that the cross-sectional pre-holiday seasonality effect is observed only among stocks closely held or favored by retail investors, such as small stocks, highly volatile stocks, and stocks with low institutional ownership. This finding suggests a salient role for retail trading in producing the pre-holiday cross-sectional seasonality and supports the notion that retail investors are less sophisticated and may be more prone to mood swings (Grinblatt and Keloharju 2001). This finding is, however, unexplained by the theory based on seasonal common risk factor premiums (Keloharju, Linnainmaa, and Nyberg 2015), which predicts no role for retail trading in explaining return seasonalities.

Lastly, we confirm the presence of the pre-holiday cross-sectional seasonality in the international markets of Canada, United Kingdom, and Japan, where the aggregate pre-holiday seasonality is present (Kim and Park 1994). Using individual stock daily returns from the three countries from 1980 to 2012, we find that the relative pre-holiday return performances across stocks are persistent for the next one to nearly ten years with comparable economic impacts to that in the U.S. market.[6] Thus, our findings provide international confirmation of the existence of the pre-holiday cross-sectional seasonality.

The remainder of the paper is organized as follows: Section 2 provides literature review and motivation. Section 3 reports the empirical results of the seasonal effects related to the month-of-year and the day-of-the-week. Section 4 presents the model based on investor mood and testable predictions regarding pre-holiday seasonality. Section 5 tests for the pre-holiday seasonal effect. Section 6 provides additional evidence for the pre-holiday seasonal effect. Section 7 concludes.

2. Motivation and Contribution

Our paper is motivated by several bodies of existing literature including stock market seasonality, the pre-holiday effect and the investor mood effect on stock returns. We extend the three lines of research and document the same-season persistence effect, the cross-season reversal effect, and the pre-holiday seasonality effect in the cross section.

[6] When each market is studied separately, the effect is statistically weaker than that in the U.S., likely due to a shorter sample period, but the economic impact remains significant.

Earlier studies on stock market seasonality have focused on time-series seasonality at the aggregate level, such as the January effect (Rozeff and Kinney 1976), the Halloween effect (Bouman and Jacobsen 2002), and the seasonal affective disorder (SAD) effect (Kamstra, Kramer, and Levi 2003). Heston and Sadka (2008) are the first to fully explore seasonality in the cross section of monthly stock returns. They present the same-calendar-month cross-sectional persistence effect, wherein stocks with above-average returns in a given month tend to earn above-average returns at annual intervals for up to 20 years. This seasonality pattern is not explained by firm size, industry, earnings announcements, dividends, or fiscal year end.

Keloharju, Linnainmaa and Nyberg (2015) propose a seasonal-risk-premium-based model to explain the same-month cross-sectional persistence effect. Their model shows that seasonalities in individual stock returns are a necessary consequence of seasonalities in common risk factor premiums. Consistent with their model, they show that portfolios of stocks formed by sorts on various firms attributes display return seasonality similar to those displayed by individual stocks and, furthermore, the same-month cross-sectional persistence effect in characteristics-sorted portfolios explains over two-thirds of that in individual stocks. They further document that the same-weekday cross-sectional persistence effect, in which stocks that outperform on a certain weekday continue to do so on the same day-of-the-week for subsequent weeks.

Relative to earnings announcement seasons, Frazzini and Lamont (2006) show that stocks tend to earn a premium during scheduled, earnings announcement months relative to other months of the year. Chang, Hartzmark, Solomon, and Soltes (2015) find that, during the scheduled earnings announcement months, stocks with predictable, seasonally high earnings outperform those with seasonally low earnings. They show that the results are not explained by other time-series effects within the firm, including the same-calendar-month cross-sectional persistence effect by Heston and Sadka (2008), momentum, short-term reversals, or the dividend month premium documented by Hartzmark and Solomon (2013).

Doran, Jiang, Peterson (2012) focus on cross-sectional seasonality in January and examine the cross-sectional return patterns across lottery features between January and other months in the U.S. stock market. They find that lottery-type stocks (low price, high idiosyncratic volatility, and high expected idiosyncratic skewness) outperform their counterparts in January but underperform in other months of the year.

This paper differs from previous research in several ways. First, we show there exists a general same-season return persistence effect. The cross-section of return persists not only in the same calendar month or on the same weekday, but also between months or weekdays with common market (or mood) states, measured by past and expected future high or low market returns. Second, we uncover the cross-season cross-sectional reversal phenomenon at different frequencies, which links relative performance across stocks during different calendar months or weekdays with opposite market states. This is a unique implication of the mood-based theory, which is not shared by theories based on seasonal risk premiums of common factors. Third, our tests of cross-sectional pre-holiday returns are not confined to a specific calendar month or weekday, but are tied by the common upward mood swings of investors in anticipation of holidays that fall into different calendar months or weekdays.

Our paper also contributes to the extensive research of the pre-holiday effect on stock markets. It is documented that the aggregate stock markets tend to advance on the trading day immediately prior to holidays and the average pre-holiday return is 10 to 20 times bigger than regular daily returns (Ariel 1990; Lakonishok and Smidt 1988). Subsequent research proposes investor mood as a possible explanation for the aggregate pre-holiday effect in the U.S. and international markets (e.g., Fabozzi, Ma, and Briley 1994; Frieder and Subrahmanyam 2004; Bialkowski, Etebari and Wisniewski 2012; Bergsma and Jiang 2015). In contrast to these studies that focus on aggregate returns, we focus on the cross-section of individual stock returns in anticipation of major holidays.

More broadly, our study adds to research that explores how investors' mood affects their financial decision-making. People in a happier mood tend to exhibit greater risk-taking and a higher demand for stocks (Forgas 1995; Kaplanski, Levy, Veld, and Veld-Merkoulova 2015). Investor optimism (pessimism) induced by pleasant (unpleasant) weather conditions positively (negatively) influences stock returns (Saunders 1993; Hirshleifer and Shumway 2003; Goetzmann, Kim, Kumar, and Wang 2015) and positive mood indicators predict subsequent return reversals in stock markets (Karabulut 2013). Using several daily mood measures including the Gallup Mood Survey, Autore, Bergsma, and Jiang (2015) show that an average American experiences uplifted mood swings in the two trading days leading up to major holidays. This evidence suggests that the pre-holiday period is associated with positive investor moods and, therefore, possible optimism biases.

Motivated by these lines of research, we hypothesize that investors' mood swings are an important source of stock market seasonality. As a necessary consequence, mood-driven aggregate market seasonality will be accompanied by cross-sectional seasonalities as the dispersion in factor loadings creates dispersion in the mood influence on individual stocks. Relative performance across stocks persists in the same mood state (positive or negative) but reverses between opposite mood states. In the next sections we present findings related to the same-season and cross-season return seasonality, the mood-based model, and the pre-holiday seasonality.

3. Calendar Month and Weekday Seasonal Effects

3.1. Data

Our U.S. sample includes common stocks traded on the NYSE, AMEX, and NASDAQ from January 1, 1963 to December 31, 2012. U.S. daily stock returns and other trading information are from the Center for Research in Security Prices (CRSP). Stocks that have price under $5 are eliminated from our sample. However, our main results hold if stocks at all price levels are included in the analyses. Accounting data are from Compustat. We report the daily and monthly return summary statistics in Table 1 with variable definitions presented in Appendix A.

[INSERT TABLE 1 HERE]

3.2. Month-of-the-year seasonal effects

Empirical studies show that, historically, the U.S. aggregate stock market generates the highest average returns in January and lowest average returns in September (Lakonishok and Smidt 1988). In the cross section, monthly stock returns exhibit persistent relative performances in the same calendar month year after year (Heston and Sadka 2008). Under the context of the risk-premium-seasonality-based theory by Keloharju, Linnainmaa, and Nyberg (2015), if some common factors have higher premiums in January, stocks that load heavily on such factors will perform better on average in January. Similarly, if some other common factors have lower premiums in September, stocks that load heavily on those factors will perform worse in those months. Factors exhibiting seasonal premiums in different months may overlap or differ.

In contrast, our mood-based theory assumes a common source of aggregate and cross-sectional seasonality: the fluctuation of investor mood. Thus, seasonal effects across different times of year are connected and predicted by each other when investor mood swings in a predictable fashion. Under this mood-based theory, if investors tend to go through a positive mood swing in January and a negative mood swing in September, aggregate stock markets will outperform in January but underperform in September, and relative performance across stocks persists in the same calendar month.

More generally, stocks that outperform in the positive-mood month of the prior years (which may not be January) likely continue doing so in January, when positive investor moods are expected to continue. Similarly, the cross-section of returns in the negative-mood month of the prior years (which may not be September) likely persists in September, when investors probably have downbeat moods. However, relative performance across stocks will reverse when investors switch from positive to negative, or from negative to positive, mood states. This predicts a reversal in the cross-section of returns from January to September, from September to January, and more generally, from the positive-mood month of the prior years to September and from the negative-mood month of the prior years to January.

3.2.1 The same-month cross-sectional persistence effect

We first replicate the same-calendar-month cross-sectional persistence effect of Heston and Sadka (2008) for January and September in our sample period. Using the Fama-MacBeth (FMB) regressions, we regress January and September returns across stocks on their historical same-month returns at the 1st to the 10th annual lag:

$$RET_t^{Jan/Sept} = \alpha_{k,t} + \gamma_{k,t} RET_{t-k}^{Jan/Sept} + \varepsilon_t \ , \tag{1}$$

where $k = 1,\dots,10$, $RET_t^{Jan/Sept}$ is the current January or September return in year t for a given stock , and $RET_{t-k}^{Jan/Sept}$ is the historical January or September return in year $t-k$ for the same stock. The monthly estimates of $\gamma_{k,t}$ are averaged across the full sample period to yield the estimate for γ_k, which is reported as the FMB regression coefficient. Such regressions help to assess whether certain stocks tend to repeatedly outperform other stocks during the same calendar month year after year. Heston and Sadka (2008) call the slope coefficient estimate γ_k the "return response" because the coefficient represents the cross-sectional response of returns at one date to returns at a previous date. We follow their language in our discussions hereafter.

Reported in Table 2, Column (1), we observe positive and statistically significant return response on the historical January/September returns for all 10 annual lags. The return responses are large. For example, for the 1st annual lag the return response is 3.24 (t-statistic = 3.75), suggesting a one-standard-deviation (19.26%) increase in the prior same-month return leads to a 62 bps (19.26%×3.24%) increase in the current same-month return, or a nearly 23% increase relative to the mean January/September monthly returns. For the other annual lags, the return response is between 2.02 (8th lag, t-statistic = 2.66) and 3.56 (3rd lag, t-statistic = 5.84), with an average of 2.42, suggesting a one-standard-deviation increases in the historical same-month return elevates the future same-month return by about 17% for at least ten years. Thus, our evidence confirms that the same calendar month returns persist for years in the cross section in a sample including only January and September monthly stock returns.

[INSERT TABLE 2 AND FIGURE 1 HERE]

Next, we expand the same-calendar-month return persistence effect to considering historical months with the same mood state. We measure the past high-mood state using the month with the best aggregate return realized in a year, and the past low-mood state using the month with the realized lowest aggregate return in a year, where aggregate returns are the defined as the equal-weighted CRSP market index portfolio returns in excess of the risk-free rates.[7] Although both fundamental news and mood states may independently drive market returns, the two likely also reinforce each other. Thus, the best-return month is most likely to associate with favorable mood state and the worst-return month most likely to indicate unfavorable mood state.

Using FMB regressions, we employ the relative performance across stocks in these historically high-mood (low-mood) states to forecast the cross-section of returns in subsequent January (September) months, during which high-mood (low-mood) states are expected. Specifically, we regress the current January and September returns ($RET_t^{Jan/Sept}$) across stocks on their own historical return of the prior year in the same-mood month (best-market-return or worst-market-return month, denoted as $RET_{t-k}^{Best/Worst}$), respectively.

$$RET_t^{Jan/Sept} = \alpha_{k,t} + \gamma_{k,t} RET_{t-k}^{Best/Worst} + \varepsilon_t \,, \tag{2}$$

The return responses are reported in Column (2) of Table 2 and plotted in Figure 1A. We obtain positive return responses for all 10 annual lags and six are significant at the 5% level or better. The estimate at the 1st annual lag implies that a one-standard-deviation (22.28%) increase in the return in the best-market-return (worst-market-return) month of the previous year leads to a 29 bps (22.28%×1.39%), or an 11%, increase in the current returns in January (September). Besides the 1st annual lag, the return response is significant at the 3rd lag from lag 2 to lag 5, and then is significance for four of the remaining five lags, including the 10th lag. The relatively weaker results between lag 2 to lag 5 are likely attributed to the long-term reversal effect that exists for lagged three to five year returns documented by De Bondt and Thaler (1985). This evidence supports our conjecture that

[7] In untabulated tests, we replace the equal-weighted CRSP market index returns with value-weighted CRSP return and find qualitatively similar results with slightly weaker statistical significance for this effect. As the cross-sectional regression equally weights individual stocks, the equal-weighted market index can more accurately reflect the collective mood effect for individual stocks than a value-weighted index. In addition, we show in Section 7 that the mood-induced seasonality is stronger among small firms more closely held by individual (mood-prone) investors, further supporting our choice of using the equal-weighted market returns.

cross-sectional returns persist across the same-mood states, which may occur on different calendar months.

3.2.2 The cross-month cross-sectional reversal effect

Next, we test for the cross-sectional reversal effect across opposite mood states. In Column (3) of Table 2 and reported in Figure 1A, we report estimates of regressions of January and September returns ($RET_t^{Jan/Sept}$) across stocks on their own historical different-calendar-month (September and January, respectively) returns ($RET_{t-k}^{Sept/Jan}$).

$$RET_t^{Jan/Sept} = \alpha_{k,t} + \gamma_{k,t} RET_{t-k}^{Sept/Jan} + \varepsilon_t , \tag{3}$$

The estimated return responses are negative for 8 out of 10 lags and significant for 7 out of the 8 negative return responses. In the remaining two cases (lags 7 and 8), the return response is insignificant. Specifically, for the 1st annual lag the return response on the historical different-month return in forecasting current-month return is –3.13 (*t*-statistic = –3.34), suggesting a one-standard-deviation increase in last different-month return leads to a 60 bps (19.26%$\times$3.13%), or a 22%, return reduction in this January/September. This economic impact is about 8% based on the average return response for the ten January and September months. The evidence shows a long-lasting reversal effect takes place across the two months with expected, opposite mood states.

We then expand the test of the reversal effect by identifying past mood states with the historical best- and worst-market-return months. In Column (4), we report the estimates from regressions of the current January and September returns ($RET_t^{Jan/Sept}$) across stocks on their own historical returns in prior years during the opposite-market-state month (worst-market-return or best-market-return months, denoted as $RET_{t-k}^{Worst/Best}$), respectively.

$$RET_t^{Jan/Sept} = \alpha_{k,t} + \gamma_{k,t} RET_{t-k}^{Worst/Best} + \varepsilon_t , \tag{4}$$

The return responses are plotted in Figure 1A. We obtain negative and significant return responses across all 10 annual lags at the 5% level or better. The return responses range from –2.16 (10th lag, *t*-statistic = –2.76) to –5.84 (1st lag, *t*-statistic = –4.43), with an average of –3.51, suggesting that a one-standard-deviation increase in the stock return during the past best (worst) market return month leads to an average 28% return reduction in the next ten September (January) months. Thus, the economic impact is more than triple that from regressions of different-month returns, suggesting a stronger reversal effect when the opposite-mood state is identified based on past market states as opposed to fixed calendar months (January/September).

In untabulated tests, we verify during our sample period 1963-2012 that the aggregate excess return (measured by CRSP equal-weighted index minus the riskfree rate) is indeed on average highest in January, consistent with findings by Lakonishok and Smidt (1998).[8] However, the lowest average aggregate excess return occurs in October, not September. Therefore, in our robustness check presented in Appendix B, we use October in place of September to proxy for low-mood state and find similar effects.

Taken together, our results in Columns (3) and (4) suggest the existence of a strong cross-month reversal effect in the cross-sectional returns, which connects seemingly independent cross-sectional seasonalities across different calendar months with the same or opposite market states.

3.3. Day-of-the-week seasonal effect

Moving to higher frequency return seasonalities, we explore whether the cross-sectional persistence and reversal effects are present across days of the week. French (1980) and Lakonishok and Smidt (1988) show that aggregate stock markets tend to perform the best at the end of the week (e.g., Friday) and the worst at the beginning of the week (Monday).[9] We verify these aggregate seasonal effects during our sample period 1963-2012 using the equal-weighted CRSP market excess returns. In the context of the mood-based theory, consistent Friday market outperformance can be driven by a more uplifted mood of investors in anticipation of weekends while consistent Monday market underpeformance can be due to a more downbeat investor mood upon returning to work on Mondays – the human nature when facing periodic relief, or stress, from work.

In the cross section, Keloharju, Linnainmaa, and Nyberg (2015) find that relative performance across stocks in a given weekday is persistent on the same weekday for months. As an explanation for this weekday seasonal effect, the risk-premium-seasonality-based theory of Keloharju et al. relies on seasonal premiums of common risk factors on different days of the week. In their theory, stocks' persistent relative performances on a certain day-of-the-week are caused by their loadings on factors experiencing seasonally high or low premiums on a given weekday. However, their theory does not explain why markets perform badly on Mondays, but well on Fridays, and nor does it tell how a stock's relative performance on Mondays is connected to its relative performance on Fridays.

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8 Lakonishok and Smidt (1998) show that September has the lowest return using the Dow Jones index return from 1897 to 1986.

9 The end of the week trading day is the open market Saturday prior to 1952.

In contrast, our mood-based theory provides coherent answers to the above questions. Investor mood fluctuations can cause both the aggregate and cross-sectional seasonalities. Relative performance across stocks can persist on the same weekday if the same mood state tends to dominate on that day of the week. More broadly, such return persistence is predicted across weekdays when the same mood state is expected to persist. For instance, relative performance in the best-market-return day of the prior week likely persists on subsequent Fridays, when positive moods are expected to continue. Similarly, relative performance in the worst-market-return day persists on subsequent Mondays, when negative moods continue.

More importantly, the mood-based theory predicts a cross-weekday reversal effect – stocks that perform better on Fridays or positive-mood weekdays will perform worse on subsequent Mondays when investors tend to have negative moods, and vice versa for the relative performances on Mondays or negative-mood weekdays, which are predicted to reverse on subsequent Fridays when positive moods likely prevail. This is a unique prediction that arises when the seasonal effect is driven by predictable mood states across weekdays. This prediction also differs from traditional market microstructure-based explanations for the day-of-the-week effect that relies on systematic shifts in closing prices between the bid and the asked before and after weekends (e.g., Gibbons and Hess 1981), as our predictions apply to more than adjacent Mondays and Fridays.

3.3.1 The same-weekday cross-sectional persistence effect

We test the above predictions related to the day-of-the-week effect using FMB regressions. We first replicate the same-weekday persistence effect for Monday and Friday stock returns:

$$RET_t^{Fri/Mon} = \alpha_{k,t} + \gamma_{k,t} RET_{t-k}^{Fri/Mon} + \varepsilon_t \, . \tag{5}$$

We plot the return responses in Figure 1B. Consistent with findings by Keloharju, Linnainmaa, and Nyberg (2015), Column (1) in Table 3 shows that historical same-weekday returns across stocks are strong positive predictors of their subsequent same-weekday returns except for the 1st lag, which has a positive but insignificant return response. The return responses of the other 9 lagged same-week returns range from 0.20 (10th weekly lag, *t*-statistic = 2.70) to 0.47 (5st weekly lag, *t*-statistic = 6.04) and are all statistically significant at the 1% level. The insignificance at the 1st lag is also observed by Keloharju et al., owing to the short-term reversal at the monthly frequency

(Jegadeesh 1990).[10] Across the ten weekly lags, the average return response is 0.30, implying a one-standard-deviation increase in the daily Monday or Friday return leads to an 11% increase in the same-weekday return for the next ten weeks. Untabulated tests show that the predictive power of the same-weekday return persists for at least 50 weeks. Thus, our evidence confirms persistent relative performances across individual stocks for a given day-of-the-week.

[INSERT TABLE 3 HERE]

We extend the same-weekday persistence effect to the same-market-state persistence effect. We use the best-market-return day of the week to proxy for positive-mood states and the worst-market-return day of the week to proxy for negative-mood states. Then we test whether cross-sectional performance in prior positive (negative) market states persists on subsequent Fridays (Mondays), when the same-market state is predicted.

$$RET_t^{Fri/Mon} = \alpha_{k,t} + \gamma_{k,t} RET_{t-k}^{Best/Worst} + \varepsilon_t \, . \qquad (6)$$

Column (2) of Table 3 and Figure 1B report the estimates. We observe positive and significant or marginally significant return responses from the 2[rd] to the 10[th] lag, while the return response is negative and marginally significant for the 1[st] weekly lag, again owing to the one-month short-term reversal effect. The average return response is 0.24, implying a comparable economic impact (10%) to that of the same-weekday persistence effect during the subsequent ten weeks. Again, untabulated tests show this effect persists for more than 50 weeks. That is, we identify strong cross-sectional return persistence effects across the same-mood weekday, and such effects last for weeks and months.

3.3.2 The cross-weekday cross-sectional reversal effect

To test for the cross-sectional reversal effect at the daily frequency, we regress Friday or Monday returns across stocks on their different-weekday returns (Monday or Friday, respectively) in prior weeks.

$$RET_t^{Fri/Mon} = \alpha_{k,t} + \gamma_{k,t} RET_{t-k}^{Mon/Fri} + \varepsilon_t \, . \qquad (5)$$

As reported in Column (3) of Table 3 and plotted in Figure 1B, we observe mostly significant, negative return responses for the first 6 weekly lags, and negative yet insignificant return responses for the remaining 4 lags. The most negative return response occurs for the 1[st] weekly lag,

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[10] Keloharju, Linnainmaa, and Nyberg (2015) show that past daily returns tend to be negatively related to future daily returns in the subsequent four weeks, except for the same-weekday returns, which is much less negative or slightly positive.

–2.16 (t-statistic = –14.13), implying a one-standard-deviation increase in the past week-day (Friday or Monday) return leads to 83% (= –2.16×3.06%/0.08) return reduction on subsequent different-weekday (Monday or Friday) of the following week. The economic impact reduces to about 15% when we average the return response across the ten weekly lags. These estimates suggest that significant cross-weekday return reversals exist for subsequent six weeks.

Interestingly, a stronger reversal effect is observed across opposite market states. We regress Monday (Friday) returns ($RET_t^{Fri/Mon}$) across stocks on their historical returns on the best-market-return (worst-market-return) day of the prior week ($RET_{t-k}^{Worst/Best}$), when the market or mood state is opposite.

$$RET_t^{Fri/Mon} = \alpha_{k,t} + \gamma_{k,t} RET_{t-k}^{Worst/Best} + \varepsilon_t \,. \tag{8}$$

We plot the return responses in Figure 1B. The return responses reported in Column (4) of Table 3 are negative and significant at the 1% level for all 10 weekly lags, suggesting that the reversal effect is long lasting. At the 1st weekly lag, the return response estimate is –1.38 (t-statistic = –12.31), smaller than the 1st lag return response (–2.16) from the cross-weekday reversal effect in Column (3). However, the return responses from the 2nd to the 6th lags are similar in Columns (3) and (4), but those in the remaining 4 lags (from the 7th to the 10th) in Column (4) are two to three times larger than those in Column (3). In other words, when investor mood switches between opposite states in a predictable way, a strong cross-sectional return reversal is in turn predicted. This different-mood-weekday reversal effect is longer lasting than that based on the different-weekday reversal effect.

Overall, the evidence in Tables 2 and 3 is consistent with the notion that relative stock performance tends to persist when same mood states continue but reverse when opposite mood states are expected to occur across the cycle of calendar months or days of the week. Taken together, the evidence from the cross-month and cross-weekday reversal effects suggests that investor mood swings may explain broad return seasonality related to the month-of-the-year and day-of-the-week effects.

4. Model and Hypotheses

This section presents a model to illustrate how investor mood may induce return seasonality at the aggregate level and in the cross section. The mathematical details of the model are reported in Appendix C to maintain our paper's focus on empirical tests. Here we illustrate the basic setups and intuition of the model to deliver testable hypotheses.

The model considers an economy with two groups of investors. One group is subject to the influence of mood, referred to as *mood-prone investors* (*M*), and the other group is not, referred to as *rational investors* (*R*). For tractability, we assume that *M* investors are risk neutral and *R* investors are risk averse so equilibrium price is set by *M* investors. There are four dates, 0, 1, 2, and 3. At date 0, investors are endowed with asset holdings, and asset payoffs following a known, multi-factor structure. At date 1, *M* investors are in a neutral mood and price the assets rationally based on a set of factor signals. At date 2, *M* investors are in a positive mood and, thus, perceive another set of factor signals with an optimism bias. At date 3, conclusive factor signals arrive and mispricing is corrected. We also consider a variant of date 2, in which *M* investors are subject to a negative mood influence to contrast and connect with the effect of a positive mood influence.

We show that at date 2, if *M* investors have a positive mood, factors signals are misperceived with an optimism bias and factor overpricing occurs. While the aggregate market experiences positive abnormal returns, stocks with higher sensitivities to the overpriced factors experience greater abnormal returns than stocks with lower sensitivities. In contrast, if at date 2 *M* investors are under a negative mood, they perceive factor signals with a pessimism bias, leading to negative abnormal returns at the aggregate level. In the cross section, stocks with higher sensitivities to the underpriced factors are more underpriced and exhibit lower abnormal returns. In either case, mispricing at the aggregate and firm levels is corrected at date 3.

In other words, the mood-based model predicts the rise of both aggregate and cross-sectional return seasonalities from predictable shifts in investor mood even when factor signals are randomly distributed. When a positive investor mood repeats, aggregate markets experience positive returns and cross-sectional returns persist. When a negative mood repeats, aggregate markets have negative abnormal returns and cross-sectional returns still persist. However, when investor moods switch from positive to negative, or from negative to positive, cross-sectional returns reverse. These predictions explain why aggregate and cross-sectional seasonal effects occur together, and why cross-sectional returns persist during the same-mood season but reverse cross different-mood seasons. In absence of the mood influence on investors' perception about factor signals, random factor signals do not produce predictable, seasonal aggregate returns, nor the predictable, seasonal return persistence or reversal in the cross section.

One possible concern is that the pre-holiday optimism bias may also apply to firm-specific signals. This is likely. However, if the same degree of pre-holiday optimism applies across all stocks, this channel alone produces no persistent relative seasonal performances across stocks unless identical, seasonal signals are repeatedly realized across stock, which contradicts the basic premise of random signals. If, however, investors apply a different, persistent, and firm-specific degree of optimism across stocks, stocks with a higher degree of investor optimism will on average outperform during the pre-holiday period. However, such an assumption does not explain the linkage of cross sectional seasonality with aggregate seasonality.

While our findings related to seasonalities in calendar months or on weekdays support the mood-based theory, yet, an alternative, possibly more direct, approach to test the mood-based theory is to explore return seasonalities when investors are predicted to experience mood fluctuations. We identify such predictable mood fluctuations using the anticipation of holiday celebrations.

Anticipation of holidays has an intuitive, direct connection with positive investor mood. Consistent with the idea of a positive pre-holiday mood effect, it is well established that aggregate stock markets have significantly higher average returns during the pre-holiday periods (Fields 1934; Lakonishok and Smidt 1988; Pettengill 1989; Ariel 1990; Frieder and Subrahmanyam 2004). There is also recent evidence that pre-holiday firm announcements of various major corporate events are associated with more positive, or less negative, reactions than otherwise-similar announcements made on ordinary days, suggesting that investors exhibit a pre-holiday optimism bias in valuing information signals (Autore, Bergsma, and Jiang 2015)

Furthermore, major holidays fall in different calendar months and on different weekdays. Thus, traditional hypotheses for stock market seasonality, which involve information disclosure (Damodaran 1989; Peterson 1990), liquidity (Chordia, Roll, and Subrahmanyam 2001), or market microstructure (Smirlock and Starks 1986; Harris 1986), do not immediately apply to holiday-related seasonality. We therefore test four hypotheses for the cross-sectional pre-holiday seasonality below.

Hypothesis I: Relative pre-holiday returns across stocks persist during the pre-holiday periods when investors are expected to have a positive mood.

Hypothesis II: Relative pre-holiday returns across stocks reverse during the post-holiday periods when positive investor moods are expected to recede.

Hypothesis III: The pre-holiday cross-sectional return seasonality is more pronounced among stocks with a retail clientele.

Hypothesis IV: In markets where the aggregate pre-holiday return seasonality is present, the pre-holiday cross-sectional return seasonality is present.

5. Pre-holiday Cross-sectional Seasonality

5.1. Definition of pre-holiday

For the U.S. market, we include thirteen major holidays in the U.S. that have been celebrated for over 100 years as of 2012: New Year's Day, Valentine's Day, Presidents' Day, St. Patrick's Day, Easter, Mother's Day, Memorial Day, Father's Day, Independence Day (Fourth of July), Labor Day, Halloween, Thanksgiving, and Christmas. The dates of these holidays are collected from http://www.timeanddate.com/holidays/us/.

The pre-holiday window is defined as the (–2, 0) trading-day window prior to and/or on each holiday. If the holiday falls on a trading day, the pre-holiday window will include the two trading days prior to the holiday and the holiday itself. If the holiday falls on a non-trading day, the pre-holiday window will include two trading days prior to the holiday.[11] For each pre-holiday window, we calculate the pre-holiday return as the average logarithmic daily return during the (–2, 0) window.[12] Our results are robust if we define the pre-holiday as the (–1, 0) trading-day window.

5.2. Baseline regression

We start the analysis of the pre-holiday seasonality effect through univariate FMB regressions. Unlike our earlier tests that focus on returns in a calendar month or on a weekday, we evaluate returns during the pre-holiday window. Specifically, for each pre-holiday window over our sample period, we run cross-sectional regressions of the current pre-holiday returns across stocks on their historical pre-holiday returns for the same holiday:

$$RET_t^H = \alpha_{k,t} + \gamma_{k,t} RET_{t-k}^H + \varepsilon_t \,, \qquad (1)$$

where $k = 1,\ldots,10$, RET_t^H is the current pre-holiday return, defined as the average logarithmic daily return during a given pre-holiday window in year t, and RET_{t-k}^H is the historical average logarithmic daily return during the same-holiday pre-holiday window in year $t-k$. For example, for the pre-Valentine window in year t, we regress the average daily returns across stocks during this window on their own average daily returns during the pre-Valentine window in year $t-k$. Thus, such regressions help to assess whether certain stocks repeatedly outperform other stocks during the same-holiday pre-holiday window year after year.

[11] A non-trading day may be a holiday, such as Valentine's day, which may fall on a Saturday or Sunday during a given year. Alternatively, a holiday such as Christmas is always a non-trading day.

[12] Our main analyses are based on the logarithmic daily returns to avoid the excessive influence of daily return volatility on the inference based on mean returns. In general, the results are stronger for discrete daily returns, but the inference based on mean discrete returns can significantly deviate from compounded investment returns when volatility is high.

[INSERT TABLE 4 HERE]

In column (1) in Table 4, we report the return responses from the baseline specification in equation (1) for the first 10 annual lags (k=1,…,10). All the average return responses are positive and significant at the 5% level or better for the first nine annual lags and marginally significant for the last lag. A one-standard-deviation (2.06%) increase in the pre-holiday return leads to a 1.7 bps increase (2.06%×0.821%) in daily returns in the same pre-holiday window of the following year. This represents an 8.4% increase relative to the average pre-holiday daily return, or a 19% increase relative to the average daily return in ordinary days outside of pre-holiday windows. The response gradually decreases from 0.82 to 0.44 for the 5th annual lag and, with some spikes at the 7^{th} (0.59) and 8^{th} (0.81) annual lags, eventually reduces to 0.25 for the 10^{th} annual lag. Untabulated tests show that most return responses remain significant for the next 10 annual lags, suggesting the pre-holiday seasonality persists for at least 10-20 years. This evidence suggests that the cross section of pre-holiday stock returns exhibit persistent relative performances year after year.

[INSERT FIGURE 2 HERE]

Figure 2 provides a visual presentation of the pre-holiday cross-sectional seasonality effect by plotting the average return responses at different annual lags. As a placebo test, we show that such persistent relative performances are absent outside of the pre-holiday period. Specifically, we regress daily returns outside of the pre-holiday window across stocks on their own daily returns on the exact same calendar day one to ten years ago. We plot the return responses from the placebo tests for the 10 annual lags in Figure 2A to compare with the return responses for the pre-holiday periods. The return responses from the placebo tests are usually a small fraction in size of the latter, and generally have much weaker statistical significance. Thus, the pre-holiday seasonality is not merely a same-calendar-day seasonal effect.

In addition, the pre-holiday seasonality is not solely driven by a New Year effect. When we exclude the pre-New Year period in the regression, the return responses remain significant with only limited reductions in size. Specifically, Figure 2B plots the average pre-holiday return responses for the first annual lag from the baseline regressions separately for each holiday. As a comparison, we conduct another placebo test, in which we regress individual stocks' non-pre-holiday daily returns on their own same-calendar-day daily returns of the prior year. We report the average return responses separately for each window from the day after the most recent holiday to the day before the current pre-holiday period. For example, the non-pre-holiday bar above "New Year" depicts the average return response by regressing the post-Christmas pre-New Year daily returns across stocks on their own same-calendar-day returns of the prior year. Such regressions yield small and insignificant return responses. Thus, evidence in Figure 2B again suggests that pre-holiday seasonality is not driven by a single holiday or by a same-calendar-day seasonal effect. Instead, it is a unique and robust effect present in the pre-holiday periods across the years.

5.3. Alternative measures of pre-holiday returns

Our hypothesis states that stocks positively influenced by the pre-holiday investor mood will repeatedly outperform during pre-holiday periods. Thus, we can capture a stock's sensitivity to the mood effect on factors using prior returns of the stock during the pre-holiday window. This prediction should hold if we use prior returns for the same or different holiday, and for one or multiple years in the past. Specifically, our main measure, RET_{t-k}^{H}, captures the pre-holiday return for the same holiday in year $t-k$. We construct three other alternative measures of the historical pre-holiday returns: (1) $RET_{t-k-4,t-k}^{H}$, the average daily same-holiday pre-holiday return across the five years ending in year $t-k$; (2) RET_{t-k}^{H13} , the average daily pre-holiday return across the thirteen pre-holiday windows in year $t-k$; and (3) $RET_{t-k}^{H\perp IND}$, the average daily same-holiday pre-holiday return in year $t-k$ minus its industry median across all stocks with the same first two-digit SIC code. The last measure helps to address whether the pre-holiday seasonality is mainly an industry-level seasonality effect.

We then re-estimate equation (1) by replacing RET_{t-k}^{H} with each of the three alternative measures of historical pre-holiday returns and present the estimates in columns (2)-(4) in Table 4. Similar to column (1), we observe positive and mostly highly significant return responses in columns (2)-(4). In particular, we find that RET_{t-k}^{H13} exhibits stronger power: the return response is 2.264 (*t*-statistic = 5.49) for the 1st annual lag and 1.653 (*t*-statistic = 4.74) for the 2nd, which is two to three times of the return response on RET_{t-k}^{H}. One possible reason for the improved estimates is that averaging returns across all pre-holiday windows of the most recent year helps to more accurately capture a stock's recent sensitivity to mood impacts as well as to minimize the noise introduced when measuring returns on a two to three day window.

Taken together, the univariate regression results provide strong support for Hypothesis I that historical pre-holiday returns across stocks are strong positive predictors of their own future pre-holiday returns. This is true no matter whether they are measured over one or all pre-holiday windows of a year, for one or multiple years in the past, and with or without industry adjustment. Thus, stocks tend to periodically outperform or underperform in the cross section during pre-holiday periods in a remarkably persistent way. This finding is consistent with our hypothesis that investor pre-holiday mood induces stock return seasonality in the cross section.

5.4. Pre-holiday seasonality with controls for beta and characteristics

Our results so far suggest that there exists predictable seasonal differences in pre-holiday stock returns. We want to ascertain that this pre-holiday seasonality effect does not simply reflect return seasonality associated with firm characteristics or other known seasonal (e,g, same-calendar-month) effects of stock returns.

Keloharju, Linnainmaa and Nyberg (2015) point out that seasonality in individual stock returns is a necessary consequence of seasonality in factor risk premiums. Thus, when firm factor loadings correlate with firm characteristics, including characteristics in the regressions should significantly diminish the power of historical stock returns in forecasting current stock returns over the same pre-holiday period. Our mood-based hypothesis offers a similar prediction, albeit through a different channel: the pre-holiday mood causes investor misperceptions about common factor signals, resulting in periodic factor mispricing, which may seemingly create seasonality in factor risk premiums. Nevertheless, if observable firm characteristics cannot fully capture the return sensitivity with respect to the mood influence on common factors, historical pre-holiday returns will continue to forecast future pre-holiday returns. Thus, the multivariate regressions can at least reveal whether the historical pre-holiday return is a new predictor of future pre-holiday returns in the cross section, incremental to known firm attributes.

Again, we use the FMB methodology to investigate incremental predictive power of the historical pre-holiday return. For this analysis, we focus on our main proxy for the historical pre-holiday return, RET_{t-k}^{H}, and augment the univariate specification in Table 4 with two sets of controls for different firm attributes, which are defined in Appendix A.

We report in Table 5 the return responses for the first three annual lags of the historical pre-holiday return (RET_{t-k}^{H}) and omit the estimates for other lags for brevity.[13] In the first set of regressions of Table 5, we initially include a set of common controls (market beta, size, book-to-market equity, past short-, intermediate-, and long-run returns) together with the past same-calendar-month return (RET_{t-k}^{M},). For the control variable estimates, market beta, size, and past short-run returns have significant explanatory power, but RET_{t-k}^{M} does not. However, these variables have little

[13] The estimates for annual lags 4 and 5 have similar and slightly lower magnitude and significance.

effect on RET_{t-k}^{H}, which remains highly significant. The results indicate that Heston and Sadka's same-month return persistence effect does not drive our pre-holiday seasonality; in fact, their effect virtually disappears during pre-holiday periods.

[INSERT TABLE 5 HERE]

More importantly, including the control variables has limited impact on the power of RET_{t-k}^{H}. The RET_{t-k}^{H} return response shrinks to 0.73 from 0.82 (Table 2, column (1)) in the first annual lag, a roughly 11% reduction. For the next two annual lags, the reductions are 6% and 13%, respectively, suggesting that the control variables explain a small part of the pre-holiday seasonality effect. The bottom line is that our main explanatory variable stays economically and statistically significant and its power remains long-lasting.

In the second set of regressions we further control for a set of accounting variables, including the leverage ratio (LEV) (Ferguson and Shockley 2003), asset growth rate (AG) (Cooper, Gulen, and Schill 2008), operation accruals (ACC) (Sloan 1996), investment/asset ratio (IVA) (Lyandres, Sun, and Zhang 2008), external financing (EXFIN) (Bradshaw, Richardson, and Sloan 2006), and net operating assets (NOA) (Hirshleifer, Hou, Teoh, and Zhang 2004). Leverage and asset growth have positive and significant coefficients, and external financing has a negative and significant coefficient. Other variables are insignificant. The RET_{t-k}^{H} variable again remains significant, with little or only mild reductions after controlling for all firm attributes.

Thus, our multivariate regression results show that the historical pre-holiday return conveys novel information to help predict the cross section of future pre-holiday returns relative to a host of known firm attributes. This differs from the same-month return persistence effect, a majority of which is explained by the seasonal effect related to firm characteristics (Keloharju, Linnainmaa and Nyberg 2015). Thus, the pre-holiday cross-sectional seasonality is a novel empirical regularity, regardless of its interpretation.

6. Further evidence related to the mood-based hypothesis

6.1 Post-holiday return reversal

We move to testing Hypothesis II, which predicts a cross-sectional pre-holiday return reversal during the post-holiday period, when pre-holiday uplifted investor moods are expected to recede or reverse. Autore, Bergsma, and Jiang (2015) show that measures of positive investor moods, such as the Happiness Index from the Gallup survey or Facebook, significantly elevate during the two to three days prior to holidays but drop visibly during the two to three days immediately after holidays. In contrast, they show that measures of negative investor moods, such as the CBOE volatility index VIX and the FEARS index (Da, Engelberg, and Gao 2015), exhibit an opposite pattern – they decrease prior to holidays and increase after holidays. When positive moods recede and negative moods dominate subsequent to holidays, our mood-based theory predicts a reversal in the cross-sectional returns.

We run FMB regressions to forecast the cross-sectional post-holiday returns (RET_t^{Post}) using pre-holiday returns, where the post-holiday period is defined as the first two trading days subsequent to a holiday.

$$RET_t^{HPost} = \alpha_{k,t} + \gamma_{k,t} RET_{t-k}^{H} + \varepsilon_t \;, \tag{2}$$

where $k = 0,\ldots,5$. When k is set as 0, the regression tests whether the pre-holiday returns prior to a holiday help to forecast the returns across stocks immediately after this holiday, which occurs after a one-to-three-day break. When k is one or above, the regression forecasts the current post-holiday returns across stocks using historical pre-holiday returns in prior years.

[INSERT TABLE 6 HERE]

We report the estimates in Column (1) in Table 6 to illustrate the main patterns; the estimates when k is greater than 5 are mostly insignificant and thus untabulated. When k is equal to 0, we observe a significant negative return response (–4.13, t-statistic = –11.73). The estimate suggests that a one-standard-deviation increase in RET_{t-k}^{H} leads to a significant 8.88 bps (= 4.13%*2.15%) reduction in the immediate, post-holiday return. The size of the return response is nearly five times the return response (0.821) from regressions of the current on the historical pre-holiday returns with the 1st annual lag (Table 4). Thus, the reversal effect is surprisingly strong, therefore not surprisingly, short-lived: when k is one or above, the return response becomes all insignificant, suggesting the reversal effect concentrates during the current year (when $k = 0$), but not beyond. In other words, the post-holiday reversal that takes place immediately following the holiday appears to be a complete correction of the pre-holiday return.

In the next three columns of Table 6, we replace RET_{t-k}^{H} with three alternative measures of pre-holiday returns as in Table 4: $RET_{t-k-4,t-k}^{H}$, RET_{t-k}^{H13} , and $RET_{t-k}^{H\perp IND}$, all of which are defined as previously except for RET_{t-k}^{H13} for $k = 0$, which is defined as the average daily pre-holiday returns across the most recent thirteen pre-holiday windows as of the current holiday, so that no future information is used when making the forecast. For other lags, however, RET_{t-k}^{H13} continues to be defined as the average daily pre-holiday return across the thirteen pre-holiday windows in year $t - k$.

As shown in Column (2), the return responses on $RET^{H}_{t-k-4,t-k}$ are insignificant for all lags, suggesting no visible reversal is detected during the post-holiday period if we measure the historical pre-holiday return using its same-holiday five-year moving average. This evidence is largely driven by the earlier finding in Column (1) that no reversal is detected beyond k = 0. In Column (3) we find significant or marginally significant return responses on RET^{H13}_{t-k} for lags k = 0 and 2, for which the return response is –1.46 (t-statistic = –1.72) and –1.21 (t-statistic = –2.13), respectively, suggesting only a visible reversal effect occurs during the post-holiday period in the current year and in two years when the historical pre-holiday return is measured by averaging across 13 holidays. In Column (4), $RET^{H\perp IND}_{t-k}$ exhibits similar predictive power to RET^{H}_{t-k}, with a return response of –4.37 (t = –13.33) for the 1st lag and insignificant return responses for other annual lags.

Taken together, the evidence in Table 6 suggests that, while the relative pre-holiday performance across stocks persists for years, it quickly reverses in the immediate post-holiday period. The immediate cross-sectional reversal effect is unlikely to be explained by risk-based stories as risk factor loadings unlikely reverse after a holiday break (one to two days) and factor risk premiums cannot be negative during the post-holiday periods.

6.2 The role of retail trading

Hypothesis III hypothesizes that the pre-holiday seasonality effect is more visible among stocks with a retail clientele. This is because retail investors are more likely to be influenced by mood swings who, in turn, more likely impact prices of securities held or traded by retail investors. These retail-clientele stocks tend to be associated with speculative features (Kumar 2009). Thus, we expect to observe a more pronounced pre-holiday seasonality among such retail-clientele stocks: small stocks, stocks more held by retail investors or stocks with higher idiosyncratic volatility. In contrast, the risk-premium-seasonality-based theory of Keloharju, Linnainmaa and Nyberg (2015) offers no predictions regarding the role of retail trading, as retail trading should not influence how risk premiums are reflected in returns on individual securities.

We split our sample into high and low subsamples based on the median of the three variables (size, institutional ownership, and idiosyncratic volatility). We conduct FMB regressions to investigate whether the historical pre-holiday seasonality return is equally powerful in explaining the cross-section of pre-holiday returns for the two subsamples for each retail clientele variable. Table 7 presents the regression estimates controlling for all firm attributes as in Table 5. For brevity, we only report the estimates when the one-year lag pre-holiday return RET^{H}_{t-k} is the key independent variable.[14]

[INSERT TABLE 7 HERE]

Regressions (1) and (2) show results for the two size subsamples based on whether the firm's size at the end of the previous month is above or below the median breakpoints of all available NYSE firms. RET^{H}_{t-k} is only statistically significant (coefficient = 0.90, *t*-statistic = 3.34) among small firms. Among large firms, pre-holiday seasonality is not observed (coefficient = 0.60, *t*-statistic = 0.97). This is consistent with our hypothesis that retail trading impounds the mood effect into stock prices. Regressions (3) and (4) split the sample based on whether the firm's institutional ownership at the end of the previous month is above or below the median breakpoint of all firms. Consistent with our hypothesis, pre-holiday seasonality is present only within the low institutional ownership subset (coefficient = 0.76, *t*-statistic = 2.80) and absent in the high institutional ownership subset (coefficient = –0.03, *t*-statistic = –0.08). In regressions (5) and (6), the sample is split based on whether the firm's idiosyncratic volatility at the end of the previous month is above or below the median breakpoint, and results show that the return response of RET^{H}_{t-k} is only significant among the higher idiosyncratic volatility subset.

Overall, results in Table 7 provide support for Hypothesis III that the pre-holiday seasonality effect is visible only among stocks with a retail clientele. This evidence suggests that the mood influence channels through retail trading on stocks with speculative features to create the dispersion in firm mispricing prior to holidays. As the proxies for retail clientele also capture limits to arbitrage, our evidence also indicates that the pre-holiday seasonal effect is strong among hard-to-arbitrage stocks.

6.2. Pre-holiday cross-sectional seasonality in foreign equity markets

Lastly, we explore Hypothesis IV, which predicts pre-holiday cross-sectional seasonality exists in markets with pre-holiday aggregate seasonality. Our mood-based theory predicts that the aggregate and cross-sectional pre-holiday seasonality effects originate from a common source: investor pre-holiday mood, and thus should emerge simultaneously. This prediction is shared by the risk-premium-seasonality-based theory as risk premium seasonality can generate both aggregate and

[14] The estimates for annual lags two through five exhibit qualitatively similar patterns between two subsamples.

cross-sectional seasonality. Nevertheless, such exercises help to provide international evidence for the seasonality effect found in the U.S. market.

We examine three countries with large stock markets and a relatively long history: the U.K., Japan and Canada. Kim and Park (1994) show that the aggregate stock markets in these three foreign markets tend to advance prior to their major holidays. We obtain daily stock returns for the period 1980-2012 from DataStream. The sample restricts to common stocks with share price greater than $1. The sample period starts in 1980 to ensure data availability for all three markets. We identify 8 national holidays in Canada, 7 national holidays in U.K. and 14 national holidays in Japan from Wikipedia.[15] For Canada, we select nationwide statutory holidays, and statutory holidays for federal regulated employees (All banks commemorate these holidays, and they are statutory in some provinces and territories). The British holidays we select are celebrated in England, Northern Ireland and Wales. For Japan, all 14 holidays are national, government-recognized holidays.

We use the univariate FMB regressions to test whether the pre-holiday seasonality effect is present in each and all of the three foreign markets combined. We focus on the historical pre-holiday return of the same holiday window (RET_{t-k}^{H}) as the independent variable, where k = 1,…,10.

[INSERT TABLE 8 HERE]

Table 8 reports the estimates for the baseline regressions for the combined sample and each of the three international markets. Column (1) reports the estimates for the 10 annual lags of RET_{t-k}^{H} for the combined sample.[16] The return response of RET_{t-k}^{H} is positive and significant (coefficient = 0.70, *t*-statistic = 2.31) for the 1st annual lag. The return response remains positive for all ten lags but tends to decrease as the lag increases. Seven of the ten return responses are significant at the 5% level, one at the 10% level, and two are insignificant. The evidence generally supports the presence of cross-sectional pre-holiday seasonality when the three markets are studied together.

For the individual foreign markets, however, the estimates tend to be somewhat smaller and statistically weaker, possibly due to the limited number of pre-holiday windows in each market and

[15] The holidays of the three countries are obtained from Wikipeida by searching "Public holidays in [COUNTRY.]" The Kim and Park (1994) study provides no information as to which holidays are included in their analyses. Holidays in Canada used in our sample include New Year, Easter, Victoria's Day, Canada Day, Labor Day, Canadian Thanksgiving, Veterans Day, and Christmas. Holidays in UK used in our sample include New Year, St. Patrick's Day, Easter, Spring Bank Holiday, Summer Bank Holiday, Halloween, and Christmas. Holidays in Japan used in our sample include New Year, Coming of Age day, National Foundation Day, Spring Equinox, Showa Day, Constitution Memorial Day, Children's Day, Sea Day, Respect for the Aged Day, Autumnal Equinox, Sports Day, Culture Day, Labor Thanksgiving Day, and the Emperor's Birthday.

[16] If two or more countries share the same holiday (e.g., New Year's day), it is treated as one pre-holiday window with country fixed effects included in the cross-sectional regressions for that pre-holiday.

the considerably shorter sample period relative to the U.S. sample. Nevertheless, 28 out of 30 RET_{t-k}^{H} return responses are positive, and nearly half are significant or marginally significant. Although the results from individual foreign markets are weaker than those from our U.S. baseline regression in Table 4, the evidence in Table 8 largely suggests the existence and long-lasting effect of pre-holiday seasonality in the three foreign countries when examined jointly.

7. Conclusion

Stock markets as a whole are long known to exhibit strong seasonality in aggregate returns, but there is limited knowledge about return seasonality in the cross section, and even more limited is our understanding of the causes of these seasonal effects. We posit that investor mood fluctuations are in part responsible for both the aggregate and cross-sectional return seasonalities. In our model, investor optimism or pessimism is influenced by positive or negative moods. Such optimism or pessimism bias causes misperception of signals regarding common return factors, and thereby factor mispricing. In consequence, individual stocks become mispriced according to their loadings on the mispriced factors, and this leads to a linkage between the aggregate and cross-sectional mispricing.

Consistent with the mood-based theory, we uncover a large set of cross-sectional seasonality across calendar months or weekdays. Stocks that outperform in the past when investors are in upbeat moods (e.g., January, Friday, best-market-return month realized in a year, best-market-return day realized in a week) are predicted to outperform when an upbeat mood is expected (e.g. January, Friday). Similarly, stocks that do well under investor downbeat mood states (e.g., September, Monday, worst-market-return month realized in a year, worst-market-return day realized in a week) continue to do well when a downbeat mood state is expected (e.g., September, Monday). However, a reversal of relative performances across stocks is predicted when investors are expected to switch between upbeat and downbeat moods. In other words, the cross section of stock returns in a given calendar month or on a weekday can be predicted by not only their historical same-calendar-month or same-weekday returns, but also by their historical different-calendar-month or different-weekday returns with the same, or different, mood states.

Furthermore, we uncover novel cross-sectional pre-holiday seasonality in individual stock returns, where pre-holiday seasons induce periodic, recurring positive investor moods. We show that average daily returns prior to or on major holidays across stocks can be predicted by their own average daily pre-holiday returns for the same, or different, holidays observed one to ten years ago. This effect is significant, long-lasting, present in foreign equity markets, and robust to controls for beta and a host of firm attributes. The pre-holiday relative performance across stocks tends to reverse during the immediate post-holiday period. Moreover, the pre-holiday seasonality effect is more pronounced among stocks that are likely to be held or traded by mood-prone, retail investors.

Taken together, we uncover a set of novel cross-sectional seasonalities in individual stock returns that connects calendar months, weekdays, and holidays, which can be explained by a coherent theory based on investor mood swings. Our evidence thus suggests that investor moods are an important source of stock market seasonality both at the aggregate and in the cross section.

References

Ariel, R. A. 1990. High stock returns before holidays: Existence and evidence on possible causes. *Journal of Finance, 45*, 1611-1626.

Autore, D., Bergsma, K., and Jiang, D. 2015. The pre-holiday corporate announcement effect, *Working Paper*, http://papers.ssrn.com/abstract_id=2520489.

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

Baker, M., and Wurgler, J. 2007. Investor sentiment in the stock market. *Journal of Economic Perspectives*, *21*, 129-152.

Bergsma, K., and Jiang, D. 2015. Cultural New Year holidays and stock returns around the world. *Financial Management,* forthcoming. DOI: 10.1111/fima.12094

Bialkowski, J., Etebari, A., and Wisniewski, T. P. 2012. Fast profits: Investor sentiment and stock returns during Ramadan. *Journal of Banking and Finance, 36*, 835-845.

Bouman, S., and Jacobsen, B. 2002. The Halloween indicator, "sell in May and go away": Another puzzle. *American Economic Review*, *92*, 1618-1635.

Bradshaw, M. T., Richardson, S. A., and Sloan, R. G. 2006. The relation between corporate financing activities, analysts' forecasts and stock returns. *Journal of Accounting and Economics, 42,* 53-85.

Chang, T., Hartzmark, S. M., Solomon, D. H., and Soltes, E. F. 2015. Being surprised by the unsurprising: Earnings seasonality and stock returns. *Working paper*, http://papers.ssrn.com/abstract_id=2460166.

Chordia, T., Roll, R., and Subrahmanyam, A. 2001. Market liquidity and trading activity. *Journal of Finance, 56,* 501-530.

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

Da, Z., Engelberg, J., and Gao, P. 2015. The sum of all FEARS investor sentiment and asset prices. *Review of Financial Studies, 28,* 1-32.

Damodaran, A. 1989. The weekend effect in information releases: A study of earnings and dividend announcement. *Review of Financial Studies, 2,* 607-623.

Daniel, K. D., Hirshleifer, D., and Subrahmanyam, A. 1998. Investor psychology and security market under and overreactions. *Journal of Finance, 53*, 1839-1886.

Daniel, K. D., Hirshleifer, D., and Subrahmanyam, A. 2001. Overconfidence, arbitrage, and equilibrium asset pricing. *Journal of Finance*, *56*, 921-965.

De Bondt, W. F. M. and Thaler, R., 1985. Does the stock market overreact? *Journal of Finance*, 40, 793-805.

Doran, J. S., Jiang, D., and Peterson, D. R. 2012. Gambling preference and the New Year effect of assets with lottery features. *Review of Finance, 16*, 685-731.

Fabozzi, F. J., Ma, C. K., and Briley, J. E. 1994. Holiday trading in futures markets. *Journal of Finance, 49*, 307-324.

Fama, E. F., and French, K. R. 1992. The cross-section of expected stock returns. *Journal of Finance, 47,* 427-465.

Fama, E. F., and French, K. R. 1993. Common risk factors in the returns on stocks and bonds. *Journal of financial economics, 33*, 3-56.

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

Ferguson, M. F., and Shockley, R. L. 2003. Equilibrium "anomalies". *Journal of Finance, 58,* 2549-2580.

Fields, M. J. 1934. Security prices and stock exchange holidays in relation to short selling. *Journal of Business, 7,* 328-338.

Forgas, J. P. 1995. Mood and judgment: the affect infusion model (AIM). *Psychological Bulletin*, *117*, 39-66.

Frazzini, Andrea and Owen Lamont, 2007. The earnings announcement premium and trading volume. NBER Working Paper Series no. 13090.

French, K. 1980. Stock returns and the weekend effect. *Journal of Financial Economics, 8,* 55-69.

Frieder, L., and Subrahmanyam, A. 2004. Nonsecular regularities in returns and volume. *Financial Analysts Journal, 60*, 29-34.

Gibbons, M. R., and Hess, P. 1981. Day of the week effects and asset returns. *Journal of Business, 54*, 579-596.

Goetzmann, W. N., Kim, D., Kumar, A., and Wang, Q. 2015. Weather-induced mood, institutional investors, and stock returns. *Review of Financial Studies*, *28*, 73-111.

Grinblatt, M., and Keloharju, M. 2001. What makes investors trade? *Journal of Finance*, *56*, 589-616.

Harris, L. 1986. A transaction data study of weekly and intradaily patterns in stock returns. *Journal of Financial Economics,* 16, 99-117

Hartzmark, S. M., and Solomon, D. H. 2013. The dividend month premium. *Journal of Financial Economics, 109*, 640-660.

Heston, S. L., and Sadka, R. 2008. Seasonality in the cross-section of stock returns. *Journal of Financial Economics, 87*, 418-445.

Heston, S. L., and Sadka, R. 2010. Seasonality in the cross-section of stock returns: The international evidence. *Journal of Financial and Quantitative Analysis, 45*, 1133-1160.

Hirshleifer, D., Hou, K., Teoh, S. H., and Zhang, Y. 2004. Do investors overvalue firms with bloated balance sheets? *Journal of Accounting and Economics, 38,* 297-331.

Hirshleifer, D., and Jiang, D. 2010. A financing-based misvaluation factor and the cross-section of expected returns. *Review of Financial Studies*, *23*, 3401-3436.

Hirshleifer, D., and Shumway, T. 2003. Good day sunshine: Stock returns and the weather. *Journal of Finance, 58*, 1009-1032.

Jegadeesh, N. 1990. Evidence of predictable behavior of security returns. *Journal of Finance, 45,* 881-898.

Kamstra, M. J., Kramer, L. A., and Levi, M. D. 2003. Winter blues: A SAD stock market cycle. *American Economic Review*, *93*, 324-343.

Kaplanski, G., Levy, H., Veld, C., and Veld-Merkoulova, Y. 2015. Do happy people make optimistic investors? *Journal of Financial and Quantitative Analysis*, *50*, 145-168.

Karabulut, Y. 2013. Can Facebook predict stock market activity? *Working paper*, http://papers.ssrn.com/abstract_id=1919008

Keim, D. B. 1983. Size-related anomalies and stock return seasonality: Further empirical evidence. *Journal of Financial Economics, 12*, 13-32.

Keloharju, M., Linnainmaa, J. T., and Nyberg, P. 2015. Return seasonalities. *Journal of Finance*, forthcoming. http://papers.ssrn.com/abstract_id=2224246.

Kim, C. W., and Park, J. 1994. Holiday effects and stock returns: Further evidence. *Journal of Financial and Quantitative Analysis, 29*, 145-157.

Kumar, A. 2009. Who gambles in the stock market?. *Journal of Finance, 64*, 1889-1933.

Lakonishok, J., and Smidt, S. 1988. Are seasonal anomalies real? A ninety-year perspective. *Review of Financial Studies*, *1*, 403-425.

Lyandres, E., Sun, L., and Zhang, L. 2008. The new issues puzzle: Testing the investment-based explanation. *Review of Financial Studies, 21,* 2825-2855.

Peterson, D. R. 1990. Stock return seasonalities and earnings information. *Journal of Financial and Quantitative Analysis, 25,* 187-201.

Pettengill, G. N. 1989. Holiday closings and security returns. *Journal of Financial Research, 12,* 57-67.

Polk, C., and Sapienza, P. 2009. The stock market and corporate investment: A test of catering theory. *Review of Financial Studies, 22,* 198-217.

Rozeff, M. S., and Kinney, W. R. 1976. Capital market seasonality: The case of stock returns. *Journal of Financial Economics, 3,* 379-402.

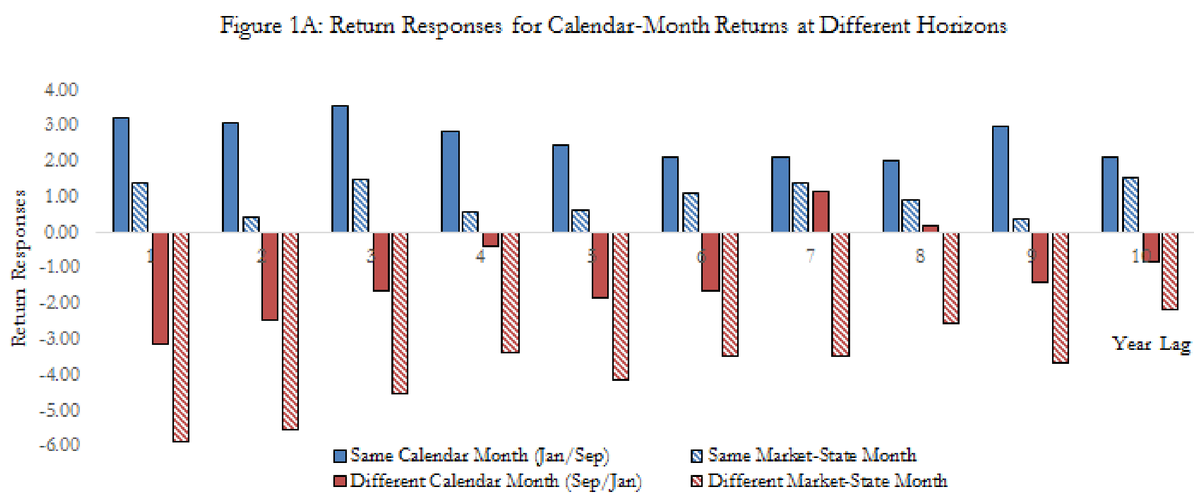
Saunders, E. M. 1993. Stock prices and Wall Street weather. *American Economic Review*, *83*, 1337-1345.

Sloan, R. 1996. Do stock prices fully reflect information in accruals and cash flows about future earnings?. *Accounting Review, 71,* 289-315.

Smirlock, M., and Starks, L. 1986. Day-of-the-week and intraday effects in stock returns. *Journal of Financial Economics, 17,* 197-210.

Figure 1: Return Responses for Calendar-Month or Weekday Returns

This figure plots the coefficients of Fama-MacBeth regressions (i.e. return responses) testing same-season return persistence and cross-season return reversal effects. In Figure 1A, return responses of regressing January (September) returns across stocks on their own historical same-month (January or September) returns are plotted in the solid blue bars, return responses on their own historical same-mood (best-market-return or worst-market-return) month return are plotted in the shaded blue bars, return responses on their own historical different-month (September or January) returns are plotted in the solid orange bars, and return responses on their own historical different-mood (worst-market-return or worst-market-return) month returns are plotted in the shaded orange bars. Return response are plotted for the 1st to the 10th annual lag. In Figure 1B, , return responses of regressing Monday (Friday) returns across stocks on their own historical same-weekday (Monday or Friday) returns are plotted in the solid blue bars, return responses on their own historical same-mood (worst-market-return or best-market-return) weekday return are plotted in the shaded blue bars, return responses on their own historical different-weekday (Friday or Monday) returns are plotted in the solid orange bars, and return responses on their own historical different-mood (best-market-return or worst-market-return) weekday returns are plotted in the shaded orange bars. Return response are plotted for the 1st to the 10th weekly lag.



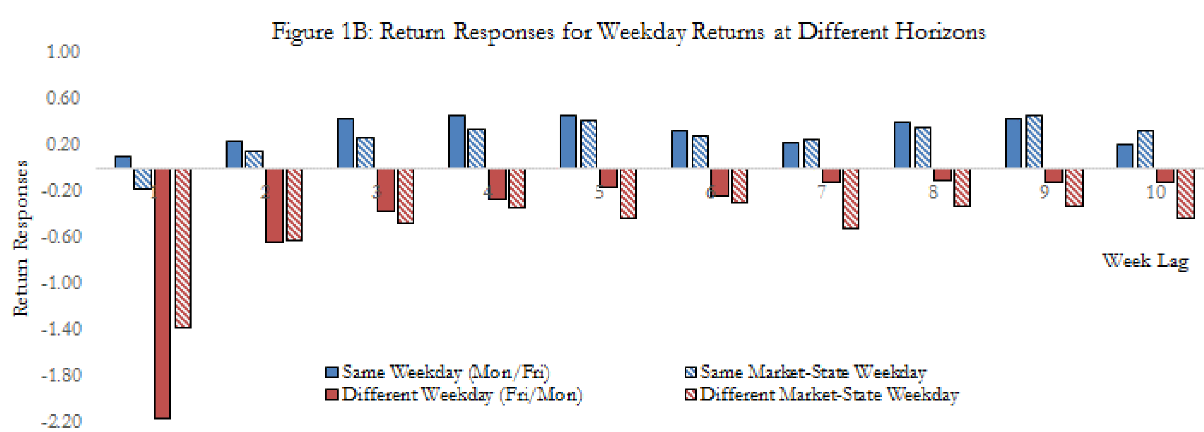


Figure 2: Return Responses for Pre-holiday Returns

This figure plots the coefficients of Fama-MacBeth regressions (i.e. return responses) testing pre-holiday cross-sectional seasonality compared with the coefficients during non-pre-holiday trading days. In Figure 2A, left bars represent the return responses, the coefficients of RET_{t-k}^{H} , in our baseline regressions, plotted for ten annual lags. Right bars represent the return responses from a placebo test, in which we regress non-pre-holiday daily returns across stocks on their own daily returns on the same calendar day one to ten years ago. In Figure 2B, the return responses at the first annual lag are plotted for each pre-holiday window and shown in left bars. Right bars represent the return responses from a placebo test, in which we regress non-pre-holiday daily returns across stocks on their own daily returns on the same calendar day of the prior year, separately for the windows between the day after the most recent holiday and the day before the current pre-holiday window. For example, the non-pre-holiday bar above *New Year* refers to the return response by regressing post-Christmas and pre-New Year daily returns across stocks on their own same-calendar-day returns of the prior year.

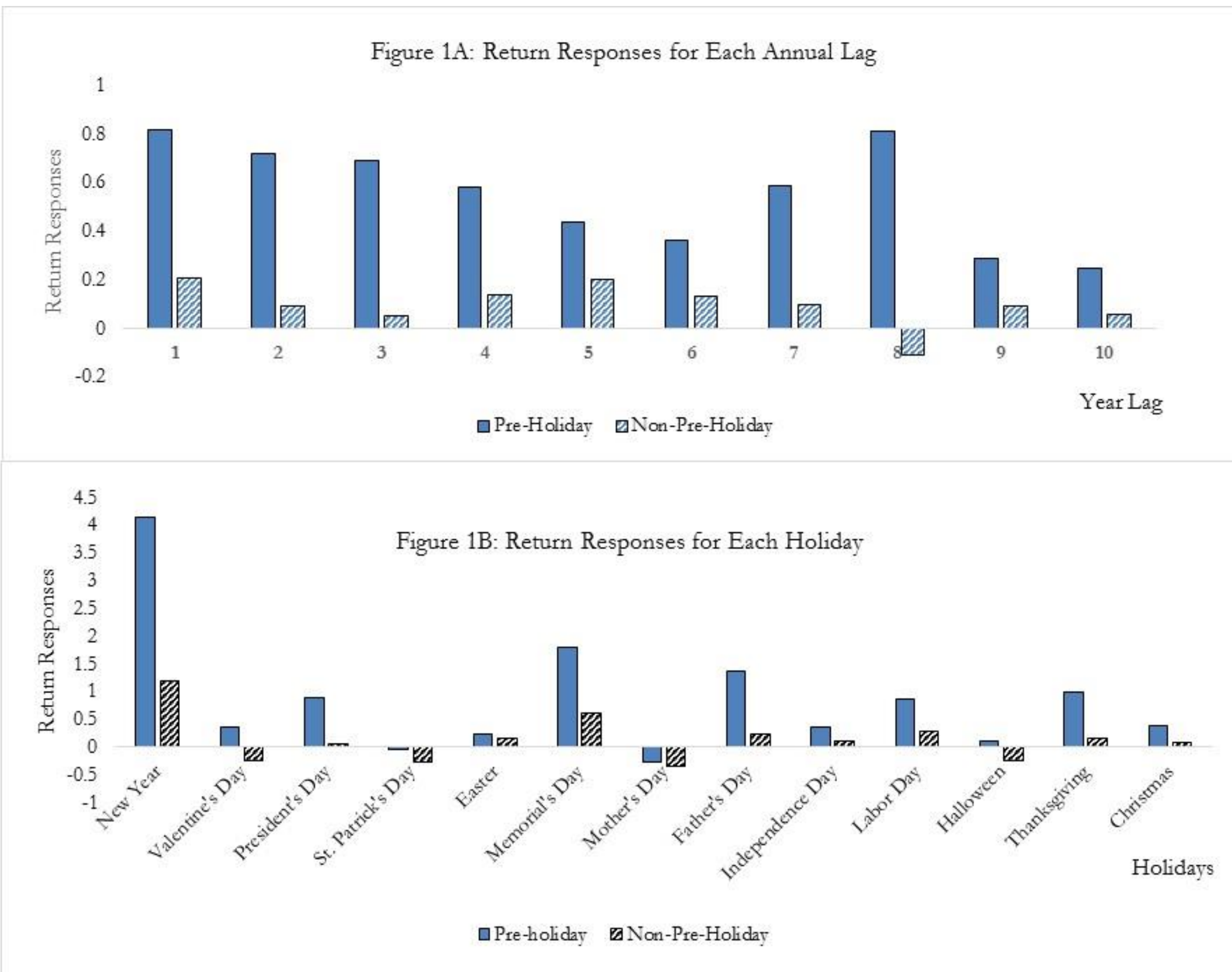


Table 1: Summary Statistics of Key Variables

This table reports the summary statistics of the dependent variables, independent variables, control variables and sorting variables. The analysis includes common stocks traded on the NYSE, AMEX, or NASDAQ. All variables are defined in Appendix A. All returns and idiosyncratic volatility are in percentages. The sample period is from January 1, 1963 to December 31, 2012.

	Mean	Median	Stdev.	10% Pctl.	25% Pctl.	75% Pctl.	90% Pctl.
Key dependent and independent variables:							
RET_t^{Jan}	5.58	2.33	21.90	–11.56	–4.04	10.87	24.46
RET_t^{Sept}	–0.07	0.00	15.74	–15.63	–6.98	5.71	14.47
$RET_t^{Jan/Sept}$	2.75	0.74	19.26	–13.66	–5.56	8.17	19.51
$RET_t^{Best\ month}$	10.08	5.88	24.34	–7.38	0.00	15.63	30.33
$RET_t^{Worst\ month}$	–8.22	–6.60	15.33	–26.25	–15.38	0.00	5.36
$RET_t^{Best/Worst\ month}$	0.89	0.00	22.28	–19.77	–9.03	8.00	20.51
RET_t^{Fri}	–0.04	0.00	3.20	–3.03	–1.31	1.07	2.90
RET_t^{Mon}	0.19	0.00	3.04	–2.59	–1.04	1.20	3.07
$RET_t^{Fri/Mon}$	0.08	0.00	3.06	–2.74	–1.14	1.11	2.91
$RET_t^{Best\ weekday}$	0.87	0.27	3.27	–1.92	–0.42	1.94	4.11
$RET_t^{Worst\ weekday}$	–0.69	–0.37	3.10	–3.80	–1.92	0.36	2.02
$RET_t^{Best/Worst\ weekday}$	0.09	0.00	3.28	–3.00	–1.25	1.23	3.21
RET_t^{H}	0.20	0.00	2.15	–1.71	–0.67	0.90	2.22
RET_{t-k}^{H}	0.20	0.01	2.06	–1.69	–0.66	0.88	2.24
$RET_{t-k-4,t-k}^{H}$	0.22	0.09	1.57	–0.12	–0.38	0.69	1.54
RET_{t-k}^{H13}	0.26	0.13	1.36	–0.52	–0.15	0.49	1.02
$RET_{t-k}^{H\perp IND}$	0.16	0.00	2.06	–1.64	–0.67	0.82	2.06
RET_t^{HPost}	0.07	0.00	2.20	–1.98	–0.83	0.86	2.15
Control variables and sorting variables:							
RET_{t-k}^{M}	1.15	0.00	15.31	–14.48	–6.06	6.67	16.28
ACC	0.25	–0.03	1.24	–0.11	–0.07	0.06	0.74
AG (%)	1.81	0.08	4.37	–0.72	0.08	1.96	2.43
β	0.69	0.64	1.88	0.09	0.31	1.00	1.37
B/M	0.86	0.68	0.93	0.21	0.38	1.09	1.62
EXFIN	0.01	0.00	0.18	–0.05	–0.01	0.04	0.11
IVA	0.66	0.05	2.54	–0.03	0.01	0.73	2.62
LEV	2.65	0.76	8.17	0.10	0.26	2.17	6.83
ME	548.24	51.05	970.4	5.64	14.34	216.77	824.05
NOA	0.56	0.70	1.25	0.12	0.48	0.85	1.02
R(–1)	0.88	1.41	4.77	–3.54	–0.05	2.62	4.30
R(–12, –2)	6.92	1.50	32.28	–27.50	–2.45	20.55	32.49
R(– 36, –13)	19.54	26.46	59.07	–46.09	0.24	46.58	71.95
Institutional ownership	0.35	0.30	0.28	0.02	0.10	0.58	0.78
Idiosyncratic volatility	3.50	3.03	2.04	1.47	2.05	4.44	6.11

Table 2: Calendar-Month Return Persistence and Reversal Effects in the Cross Section

This table reports the estimates of Fama-MacBeth regressions at the individual stock level to test for return persistence and reversal effects across calendar months in the cross section. For the return persistence effect, we regress January (September) returns across stocks on their own past January (September) returns and report the time series average of the return responses in column (1). We also regress January (September) returns across stocks on their own returns during the best-market-return (worst-market-return) month of the prior year and report the time series average of the return responses in column (2). For the return reversal effect, we regress January (September) return across stocks on their own past September (January) returns and report the time series average of the return responses in column (3). We also regress January (September) returns across stocks on their own returns during the best-market-return (worst-market-return) month of the prior year and report the time series average of the return responses in column (4). Past best- and worst-market-return months are identified using equal-weighted CRSP market excess return. Regression estimates are reported in percentage and for annual lag 1-10. The reported Fama and MacBeth (1973) *t*-statistics in parentheses are corrected for heteroscedasticity and autocorrelation following Newey and West (1987) (correction for 4 lags). The symbols *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. The sample period is from January 1, 1963 to December 31, 2012.

	Return Persistence		Return Reversal	
Dependent Variable Independent Variable Year Lag	January/September Historical January/September (1)	January/September Historical Best/Worst month (2)	January/September Historical September/January (3)	January/September Historical Worst/Best month (4)
1	3.24***	1.39**	–3.13***	–5.84***
	(3.75)	(2.16)	(–3.34)	(–4.43)
2	3.09***	0.43	–2.43***	–5.52***
	(5.01)	(0.74)	(–3.65)	(–5.41)
3	3.56***	1.50**	–1.63**	–4.52***
	(5.84)	(2.40)	(–2.42)	(–4.27)
4	2.87***	0.59	–0.38	–3.37***
	(3.92)	(1.02)	(–0.55)	(–3.80)
5	2.47***	0.66	–1.82**	–4.14***
	(3.79)	(0.88)	(–2.04)	(–3.22)
6	2.14***	1.12**	–1.61**	–3.44***
	(4.26)	(2.03)	(–2.43)	(–3.27)
7	2.13***	1.39***	1.16*	–3.47***
	(3.71)	(3.18)	(1.73)	(–3.52)
8	2.02***	0.92***	0.22	–2.52***
	(2.66)	(2.76)	(0.39)	(–3.36)
9	3.01***	0.39	–1.37**	–3.63***
	(4.03)	(0.73)	(–2.01)	(–3.51)
10	2.11***	1.54***	–0.82	–2.16***
	(3.93)	(3.48)	(–0.93)	(–2.76)

Table 3: Weekday Return Persistence and Reversal Effects in the Cross Section

This table reports the estimates of Fama-MacBeth regressions at the individual stock level to test for return persistence and return reversal effects in weekday stock returns in the cross section. For the return persistence effect, we regress Monday (Friday) returns across stocks on their own past Monday (Friday) returns and report the time series average of the return responses in column (1). We regress Monday (Friday) returns across stocks on their own returns during the best-market-return (worst-market-return) day of the prior week and report the time series average of the return responses in column (2). For the return reversal effect, we regress Monday (Friday) returns across stocks on their own past Friday (Monday) returns and report the time series average of the return responses in column (3). We regress Monday (Friday) returns across stocks on their own returns during the best-market-return (worst-market-return) day of the prior week and report the time series average of the return responses in column (4). Past best- and worst-market-return weekdays are identified using equal-weighted CRSP market excess return. Regression estimates are reported in percentage and for weekly lag 1-10. The reported Fama and MacBeth (1973) *t*-statistics in parentheses are corrected for heteroscedasticity and autocorrelation following Newey and West (1987) (correction for 5 lags). The symbols *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. The sample period is from January 1, 1963 to December 31, 2012.

	Return Persistence		Return Reversal	
Dependent Variable	Monday/Friday	Monday/Friday	Monday/Friday	Monday/Friday
Independent Variable	Historical Monday/Friday	Historical Worst/Best weekday	Historical Friday/Monday	Historical Best/Worst weekday
Week Lag	(1)	(2)	(3)	(4)
1	0.11	–0.18*	–2.16***	–1.38***
	(1.16)	(–1.67)	(–14.13)	(–12.31)
2	0.24***	0.15*	–0.64***	–0.62***
	(2.83)	(1.68)	(–7.80)	(–6.70)
3	0.44***	0.26***	–0.36***	–0.48***
	(5.28)	(2.89)	(–4.55)	(–5.66)
4	0.47***	0.34***	–0.27***	–0.33***
	(5.44)	(3.84)	(–3.43)	(–3.89)
5	0.47***	0.42***	–0.17**	–0.42***
	(6.04)	(4.98)	(–2.20)	(–5.06)
6	0.33***	0.29***	–0.23***	–0.29***
	(4.26)	(3.53)	(–3.03)	(–3.50)
7	0.22***	0.26***	–0.12	–0.52***
	(2.72)	(3.10)	(–1.60)	(–6.43)
8	0.41***	0.36***	–0.10	–0.33***
	(5.35)	(4.40)	(–1.32)	(–4.10)
9	0.43***	0.46***	–0.11	–0.33***
	(5.63)	(5.79)	(–1.48)	(–4.08)
10	0.20***	0.33***	–0.11	–0.42***
	(2.70)	(4.19)	(–1.48)	(–5.26)

Table 4: Pre-holiday Seasonal Effect in the Cross Section

This table reports the estimates of Fama-MacBeth regressions at the individual stock level to test for the pre-holiday seasonality effect using four historical pre-holiday return measures. For each pre-holiday window we run cross-sectional regression:

$$RET_t^H = \alpha_{k,t} + \gamma_{k,t} RET_{t-k}^H + \varepsilon_t$$

where *k* = 1, 2, ..., 10. We report the time–series average of $\gamma_{k,t}$ and its corresponding *t*–statistic in Column (1). In Columns (2) – (4), we replace the independent variable with one of the three alternative historical pre-holiday return measures: $RET_{t-k-4,t-k}^H$, RET_{t-k}^{H13}, and $RET_{t-k}^{H\perp IND}$. All variables are defined in Appendix A. Regression estimates are reported in percentage. The reported Fama and MacBeth (1973) *t*-statistics in parentheses are corrected for heteroskedasticity and autocorrelation following Newey and West (1987) (correction for 12 lags). The symbols *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. The sample period is from January 1, 1963 to December 31, 2012.

Dependent Variable	RET_t^H			
Independent Variables	(1)	(2)	(3)	(4)
Year Lag (*k*)	RET_{t-k}^H	$RET_{t-k-4,t-k}^H$	RET_{t-k}^{H13}	$RET_{t-k}^{H\perp IND}$
1	0.821***	0.888***	2.264***	0.809***
	(4.43)	(5.05)	(5.49)	(4.83)
2	0.719***	0.959***	1.653***	0.713***
	(4.16)	(5.23)	(4.74)	(4.43)
3	0.691***	0.673***	1.007***	0.607***
	(3.75)	(3.64)	(2.76)	(3.61)
4	0.582**	0.790***	1.397***	0.308*
	(2.06)	(4.28)	(4.07)	(1.88)
5	0.443**	0.859***	1.558***	0.413**
	(2.49)	(4.49)	(3.98)	(2.48)
6	0.356**	0.906***	1.545***	0.293*
	(2.05)	(4.54)	(4.08)	(1.79)
7	0.592***	0.774***	1.188***	0.548***
	(3.25)	(3.91)	(3.07)	(3.19)
8	0.814***	0.418**	1.567***	0.790***
	(4.23)	(1.99)	(3.63)	(4.34)
9	0.291**	0.378*	1.889***	0.309*
	(1.98)	(1.76)	(4.44)	(1.84)
10	0.252*	0.613***	1.033**	0.258
	(1.73)	(2.76)	(2.35)	(1.51)

Table 5: Pre-holiday Seasonal Effect in the Cross Section with Controls for Firm Attributes

This table reports the estimates of the multivariate Fama-MacBeth regressions that test for the pre-holiday seasonality effect, controlling for a host of firm attributes. The dependent variable is the pre-holiday average daily return, RET_t^H. The key independent variable is the past same-holiday pre-holiday return, RET_{t-k}^H. We report estimates for three annual lags (*k* = 1, 2, 3). Regressions in the left panel control for basic firm characteristics, while regressions in the right panel further control for more firm accounting ratios. All variables are defined in Appendix A. For each pre-holiday window, we run a cross-sectional regression. We report the time series average of the return responses and the corresponding *t*-statistics. Regression estimates are multiplied by 10,000 for log(B/M), *R*(–12, –2), *R*(–36, –13), LEV, ACC, and IVA, and by 100 for the others. The reported Fama and MacBeth (1973) *t*-statistics in parentheses are corrected for heteroskedasticity and autocorrelation following Newey and West (1987) (correction for 12 lags). The symbols *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. The sample period is from January 1, 1963 to December 31, 2012.

Dependent Variable:	RET_t^H					
	Years Lagged (*k*)			Years Lagged (*k*)		
	k =1	*k* =2	*k* =3	*k* =1	*k* =2	*k* =3
RET_{t-k}^H	0.73***	0.68***	0.60**	0.66***	0.74***	0.49*
	(2.93)	(2.85)	(2.49)	(2.59)	(2.84)	(1.95)
RET_{t-k}^M	–0.01	–0.02	0.08*	0.01	–0.01	0.08**
	(–0.06)	(–0.01)	(1.91)	(0.17)	(–0.10)	(1.99)
β	0.10***	0.10***	0.10***	0.10***	0.09***	0.09***
	(4.05)	(4.07)	(4.00)	(3.74)	(3.67)	(3.55)
Log(ME)	–0.02***	–0.02***	–0.02***	–0.02***	–0.02***	–0.02***
	(–3.85)	(–4.01)	(–4.30)	(–3.82)	(–3.82)	(–4.11)
Log(B/M)	–0.12	–0.35	–0.37	–0.11	–0.27	–0.51
	(–0.22)	(–0.64)	(–0.66)	(–0.17)	(–0.44)	(–0.78)
R(–1)	–0.23***	–0.23***	–0.23***	–0.23***	–0.24***	–0.25***
	(–4.57)	(–4.50)	(–4.57)	(–4.34)	(–4.36)	(–4.60)
R(–12, –2)	–0.83	–0.52	1.23	–2.81	–2.51	–1.38
	(–0.43)	(–0.27)	(0.64)	(–1.41)	(–1.26)	(–0.69)
R(–36, –13)	0.14	–1.09	–2.13**	0.10	–1.32	–2.96***
	(0.19)	(–1.27)	(–2.16)	(–0.13)	(–1.43)	(–2.86)
LEV				0.40**	0.44**	0.47**
				(2.34)	(2.29)	(2.43)
AG				0.09***	0.10***	0.12***
				(3.71)	(3.56)	(4.50)
ACC				0.47	–0.85	1.08
				(0.12)	(–0.20)	(0.24)
IVA				–1.12	0.72	1.02
				(–0.33)	(0.20)	(0.27)
EXFIN				–0.13***	–0.16***	–0.17***
				(–2.63)	(–3.24)	(–3.35)
NOA				–0.02	–0.02	–0.03
				(–1.19)	(–1.12)	(–1.53)

Table 6: Pre-holiday Return Reversal in the Post-holiday Period

This table reports the estimates of Fama-MacBeth regressions at the individual stock level to test for pre-holiday return reversal effects in the post-holiday periods using four historical pre-holiday return measures. For each post-holiday window, we run cross-sectional regression of the post-holiday returns on pre-holiday returns:

$$RET_t^{HPost} = \alpha_{k,t} + \gamma_{k,t} RET_{t-k}^{H} + \varepsilon_t$$

where *k* = 0, 2, ..., 10. We report the time–series average of $\gamma_{k,t}$ and its corresponding *t*–statistic. In regression (2) – (4), we replace the independent variable with one of three alternative pre-holiday return measures: $RET_{t-k-4,t-k}^{H}$, RET_{t-k}^{H13}, and $RET_{t-k}^{H\perp IND}$. All variables are defined in Appendix A. When *k* is set to zero, RET_{t-k}^{H13} is defined as defined as the average daily pre-holiday returns across the most recent thirteen pre-holiday windows as of the current holiday so no future information is used when making the forecast. Regression estimates are reported in percentage. The reported Fama and MacBeth (1973) *t*-statistics in parentheses are corrected for heteroscedasticity and autocorrelation following Newey and West (1987) (correction for 13 lags). The symbols *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. The sample period is from January 1, 1963 to December 31, 2012.

Dependent Variable	RET_t^{HPost}			
Independent Variable	(1)	(2)	(3)	(4)
Year Lag	RET_{t-k}^{H}	$RET_{t-k-4,t-k}^{H}$	RET_{t-k}^{H13}	$RET_{t-k}^{H\perp IND}$
0 (Current year)	–4.13***	–0.31	–1.46*	–4.37***
	(–11.73)	(–1.57)	(–1.72)	(–13.33)
1 (Last year)	–0.11	–0.18	–0.43	–0.08
	(–0.52)	(–0.88)	(–0.80)	(–0.44)
2	–0.26	0.27	–1.21**	–0.21
	(–1.23)	(1.21)	(–2.13)	(–1.12)
3	0.14	0.23	–0.02	0.11
	(0.68)	(1.01)	(–0.05)	(0.59)
4	–0.02	0.17	0.08	0.01
	(–0.11)	(0.80)	(0.21)	(0.05)
5	0.03	0.15	0.04	0.03
	(0.14)	(0.68)	(0.08)	(0.16)

Table 7: Pre-holiday Seasonal Effect: Subsample Analysis

This table reports the estimates of multivariate Fama–MacBeth regressions for different subsamples that test for pre-holiday seasonality, controlling for various past returns and firm characteristics. The dependent variable is the pre-holiday daily return, RET_t^H. The key independent variable is the past pre-holiday daily return, RET_{t-k}^H. We report estimates for a one-year lag (*k* = 1). In regressions (1) and (2) the sample is split into two subsamples based on whether the firm's size at the end of the previous month is above or below the median breakpoints of all available NYSE firms for that month. In regressions (3) and (4) the sample is split into two subsamples based on whether the most recent quarter-end institutional ownership is above or below the median. In regressions (5) and (6) the sample is split into two subsamples based on whether the idiosyncratic volatility measured during the previous month is above or below the median. Regression estimates are multiplied by 10,000 for log(B/M), *R*(–12, –2), *R*(–36, –13), LEV, ACC, and IVA, and by 100 for the others. The reported Fama and MacBeth (1973) *t*-statistics in parentheses are corrected for heteroskedasticity and autocorrelation following Newey and West (1987) (correction for 12 lags). The symbols *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. The sample period is from January 1, 1963 to December 31, 2012.

	Firm Size		Institutional Ownership		Idiosyncratic Volatility	
	(1) Small	(2) Large	(3) Low	(4) High	(5) Low	(6) High
RET_{t-k}^H	0.90***	0.60	0.76**	–0.03	0.05	0.19**
	(3.34)	(0.97)	(2.80)	(–0.08)	(0.17)	(2.38)
RET_{t-k}^M	0.01	–0.10	0.03	–0.02	0.06	0.01
	(0.31)	(–0.93)	(0.50)	(–0.46)	(1.22)	(0.07)
β	0.10***	0.09***	0.08***	0.10***	0.10***	0.07**
	(3.80)	(2.75)	(2.87)	(3.78)	(3.83)	(2.15)
Log(ME)	–0.02***	–0.05***	–0.02***	–0.02***	–0.01**	–0.02*
	(–4.00)	(–7.44)	(–3.03)	(–3.81)	(–2.34)	(–1.93)
Log(B/M)	0.37	0.25	–1.12	0.08	0.39	0.14
	(–0.53)	(0.21)	(–1.11)	(0.12)	(0.61)	(0.09)
R(–1)	–0.24***	–0.25**	–0.16**	–0.27**	–0.33***	–0.26***
	(–4.46)	(–2.47)	(–2.18)	(–4.55)	(–5.44)	(–3.77)
R(–12, –2)	–0.04**	0.04	–0.06**	–0.01	0.01	–0.09***
	(–2.18)	(1.15)	(–2.36)	(–0.61)	(0.34)	(–3.44)
R(–36, –13)	0.10	–1.47	0.83	–1.20	0.78	–0.76
	(–0.12)	(–0.73)	(0.68)	(–1.28)	(0.86)	(–0.51)
LEV	0.48***	–0.50	0.43	0.43*	0.16	1.24**
	(2.70)	(–0.59)	(1.48)	(1.91)	(0.67)	(1.96)
AG	0.08***	0.17**	0.08**	0.09**	0.11***	0.08
	(3.00)	(2.39)	(2.07)	(3.14)	(3.39)	(1.46)
ACC	–0.18	–4.55	–2.62	2.73	3.99	–2.26
	(–0.04)	(–0.47)	(–0.41)	(0.59)	(0.91)	(–0.28)
IVA	–0.90	–3.23	–0.73	–0.47	–0.95	2.82
	(–0.25)	(–0.39)	(–0.13)	(–0.12)	(–0.24)	(0.36)
EXFIN	–0.11**	–0.34***	–0.04	–0.17***	–0.21**	–0.10
	(–2.18)	(–2.66)	(–0.43)	(–2.94)	(–3.59)	(–0.89)
NOA	–0.02	0.00	–0.08***	0.01	–0.01	–0.06
	(–1.08)	(0.08)	(–2.67)	(0.53)	(–0.28)	(–1.56)

Table 8: Pre-holiday Seasonal Effect in International Markets

This table reports the estimates of Fama-MacBeth regressions at individual stock level to test for the pre-holiday seasonality effect using international data. We report the results for each of the three countries: Canada, UK, and Japan, and the combined sample by controlling for country fixed effects. For each pre-holiday trading window, we run the cross-sectional regression:

$$RET_t^H = \alpha_{k,t} + \gamma_{k,t} RET_{t-k}^H + \varepsilon_t$$

where k = 1, 2, ..., 10. We report the time-series average of $\gamma_{k,t}$ and its corresponding t-statistic. The reported Fama and MacBeth (1973) t-statistics in parentheses are corrected for heteroskedasticity and autocorrelation following Newey and West (1987) (correction for 12 lags). The symbols *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. The sample period is from January 1, 1980 to December 31, 2012.

	(1) All	(2) Canada	(3) UK	(4) Japan
Year Lag (k)	RET_{t-k}^H	RET_{t-k}^H	RET_{t-k}^H	RET_{t-k}^H
1	0.70**	0.45**	0.35	0.33*
	(2.31)	(2.44)	(1.22)	(1.75)
2	0.64**	0.46**	0.41*	0.24*
	(2.27)	(2.06)	(1.85)	(1.66)
3	0.47**	0.48**	0.32*	0.11
	(2.20)	(2.09)	(1.86)	(1.36)
4	0.41*	0.31	0.20	0.40***
	(1.79)	(0.71)	(0.77)	(2.87)
5	0.46**	0.32	0.27*	0.31*
	(2.11)	(1.36)	(1.65)	(1.86)
6	0.54**	0.16	0.29	–0.17
	(2.18)	(0.69)	(1.46)	(–0.22)
7	0.40	0.49**	0.15*	0.21
	(1.62)	(2.54)	(1.71)	(0.92)
8	0.61**	0.33*	0.28	0.05
	(2.23)	(1.79)	(0.20)	(0.95)
9	0.44**	0.26	0.35	–0.30
	(2.35)	(1.55)	(0.28)	(–0.64)
10	0.19	0.20	0.17	0.26**
	(1.44)	(0.84)	(1.51)	(1.99)
Number of Firms	5,840	3,370	1,550	920
Number of Holidays	29	8	7	14

Appendix A: Variable Definition

Variables	**Definitions**
RET_t^H	Current pre-holiday return, defined as the average daily logarithmic return of a stock during a given pre-holiday window in year *t*. The pre-holiday window refers to the (–2, 0) trading day window, where day 0 is the holiday. If a holiday is a trading day, the holiday itself is included.
RET_{t-k}^H	Historical same-holiday pre-holiday return, defined as the average daily logarithmic return of a given stock during the pre-holiday window for the exact same holiday in year *t* – *k*, where *k* = 1, 2,…,10. This is the main independent variable designed to capture the pre-holiday seasonality effect.
$RET_{t-k-4,t-k}^H$	The 5-year moving average of the historical same-holiday pre-holiday returns, defined as the average of the historical same-holiday pre-holiday returns of a given stock from year *t* – *k* – 4 to year *t* – *k*. This is an alternative measure to capture the pre-holiday seasonality effect.
RET_{t-k}^{H13}	Historical all-holiday pre-holiday return, defined as the average of RET_{t-k}^H across all 13 pre-holiday windows for a given stock during year *t* – *k*, where *k* = 1, 2,…,10. This is an alternative measure to capture the pre-holiday seasonality effect.
$RET_{t-k}^{H\perp IND}$	Historical industry-adjusted same-holiday pre-holiday return, defined as the average of RET_{t-k}^H of a given stock minus the industry median of RET_{t-k}^H across all stocks in the same industry during year *t* – *k*, where *k* = 1, 2,…10. This variable is an alternative measure to capture the pre-holiday seasonality effect.
RET_t^{HPost}	Current post-holiday return, defined as the average daily logarithmic return of a stock during a given post-holiday window in year *t*. The post-holiday window refers to the (1, 2) trading day window, where day 1 is the first trading day after a holiday.
RET_{t-k}^M	Past same-calendar-month return for a given stock in year *t* – *k*, where *k* = 1, 2,… ,10. This variable is designed to capture the same-month cross-sectional return persistence effect documented by Heston and Sadka (2008).
Operating accruals (ACC)	Following Hirshleifer, Hou, Teoh, and Zhang (2004), we define operating accruals as changes in current assets (ACT) minus changes in cash (CH), minus changes in current liabilities (LCT), plus changes in short–term debt (DLC), plus changes in taxes payable (TXP), and minus depreciation and amortization expense (DP), deflated by the lagged total assets (AT). This variable is winsorized at 1% and 99% levels.
Asset growth (AG)	Following Cooper, Gulen, and Schill (2008), asset growth is calculated as the annual change in total assets ($AT – AT_{t-1}$) divided by AT_{t-1}. This variable is winsorized at 1% and 99% levels.

β	Monthly market beta for individual stocks that is estimated using daily returns over a 12-month rolling window from a market model.
Book–to–market equity (B/M)	Following Polk and Sapienza (2009), we define BE as stockholders' equity, plus balance sheet deferred taxes (TXDB) and investment tax credit (ITCB), plus postretirement benefit liabilities (PRBA), minus the book value of preference stocks. Set TXDB, ITCB, or PRBA to zero if unavailable. Depending on availability, in order of preference, we use redemption (PSTKRV), liquidation (PSTKL), carrying value (PSTK), or zero if none is available. Stockholders' equity is measured as the book value of shareholder equity (SEQ). If SEQ is missing, we use the book value of common equity (CEQ), plus the book value of preferred stock. If CEQ is not available, we use the book value of assets (AT) minus total liabilities (LT). To compute BM, we match BE for all fiscal year-ends in calendar year $t-1$ with the firm's market equity at the end of December of year $t-1$. B/M measured as of the end of year $t-1$ is used to forecast returns from July of year t to June of year $t+1$. This variable is winsorized at 1% and 99% levels.
External financing (EXFIN)	Following Hirshleifer and Jiang (2010), external financing is defined as the net amount of cash flow received from external financing activities, including net equity and debt financing, scaled by total assets (AT). Net equity financing is defined as the sale of common and preferred stock (SSTK) minus the purchase of common and preferred stock (PRSTKC), and minus cash dividends paid (DV). Net debt financing is defined as the issuance of long-term debt (DLTIS) minus the reduction in long-term debt (DLTR). This variable is winsorized at 1% and 99% levels.
Investment/asset ratio (IVA)	Following Lyandres, Sun, and Zhang (2008), we measure investment-to-assets as the annual change in gross property, plant, and equipment (PPEGT) plus the annual change in inventories (INVT) divided by the lagged book value of assets (AT). This variable is winsorized at 1% and 99% levels.
Leverage (LEV)	Following Ferguson and Shockley (2003), we measure leverage as the book value of total liabilities (LT) over the market value of equity. We match LT for all fiscal year–ends in calendar year $t-1$ with the firm's market equity at the end of December of year $t-1$. This variable is winsorized at 1% and 99% levels.
Market equity (ME)	Following Fama and French (1992), we use Firm's market equity (stock price multiplied by shares outstanding) at the end of the most recent June. Reported in $ millions.
Net Operating Assets (NOA)	Following Hirshleifer, Hou, Teoh, and Zhang (2004), net operating assets are defined as the difference of operating assets and operating liabilities, scaled by lagged total assets. Operating assets are total assets (AT) minus cash and short–term investment (CHE). Operating liabilities are total assets (AT) minus the sum of short–term debt (DLC), long–term debt (DLTT), minority interest (MIB), preferred stock (PSTK), and common equity (CEQ), deflated by the lagged total assets (AT). This variable is winsorized at 1% and 99% levels.

$R(-1)$	Stock return in month $t-1$. Reported in percentages.
$R(-12, -2)$	Cumulative stock return from month $t-12$ through $t-2$. Reported in percentages.
$R(-36, -13)$	Cumulative stock return from month $t-36$ through $t-13$. Reported in percentages.
Institutional ownership	The most recent quarter-end ownership, defined as the total shares held by institution investors scaled by the company's outstanding shares. We collect firm's institutional ownership data from Thomson Reuter's 13F institutional holdings database.
Idiosyncratic volatility	Monthly idiosyncratic volatility is computed as the standard deviation of the residuals from a time-series regression of 17 or more daily returns within the previous month on the Fama and French (1993) three factors. Reported in percentages.

Appendix B: Calendar-Month Seasonal Effects Using October in Place of September

This table reports the estimates of Fama-MacBeth regressions at the individual stock level to test for return persistence and reversal effects across calendar months in the cross section. For the return persistence effect, we regress January (October) returns across stocks on their own past January (October) returns and report the time series average of the return responses in column (1). We also regress January (October) returns across stocks on their own returns during the best-market-return (worst-market-return) month of the prior year and report the time series average of the return responses in column (2). For the return reversal effect, we regress January (October) return across stocks on their own past October (January) returns and report the time series average of the return responses in column (3). We also regress January (October) returns across stocks on their own returns during the best-market-return (worst-market-return) month of the prior year and report the time series average of the return responses in column (4). Past best- and worst-market-return months are identified using equal-weighted market excess return. Regression estimates are reported in percentage and for annual lag 1-10. The reported Fama and MacBeth (1973) *t*-statistics in parentheses are corrected for heteroscedasticity and autocorrelation following Newey and West (1987) (correction for 4 lags). The symbols *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. The sample period is from January 1, 1963 to December 31, 2012.

	Return Persistence		Return Reversal	
Dependent Variable	January/October	January/October	January/October	January/October
Independent Variable	Historical January/October	Historical Best/Worst month	Historical October/January	Historical Worst/Best month
Year Lag	(1)	(2)	(3)	(4)
1	4.16***	1.18	-3.12***	-5.70***
	(5.63)	(1.32)	(-3.43)	(-4.34)
2	2.84***	1.38**	-3.26***	-5.61***
	(5.10)	(1.99)	(-4.76)	(-5.44)
3	2.76***	1.43**	-2.86***	-4.77***
	(4.43)	(1.96)	(-3.23)	(-4.61)
4	4.59***	0.72	-3.29***	-3.44***
	(5.24)	(1.11)	(-4.40)	(-3.70)
5	2.85***	1.86**	-3.10***	-4.11***
	(3.98)	(2.16)	(-2.91)	(-3.07)
6	2.44***	1.50*	-2.41***	-3.26***
	(3.83)	(1.85)	(-2.94)	(-3.11)
7	2.76***	2.19***	-1.18*	-3.39***
	(4.25)	(3.43)	(-1.81)	(-3.27)
8	3.79***	1.53*	-1.31**	-2.67***
	(4.79)	(1.81)	(-1.96)	(-3.50)
9	3.50***	1.46*	-3.07***	-3.92***
	(4.02)	(1.78)	(-3.74)	(-3.51)
10	2.63***	1.99**	-2.12**	-2.11***
	(3.79)	(2.27)	(-2.28)	(-2.81)

Appendix C: The Model

We present a model to illustrate how investor mood may induce return seasonality at the aggregate level and in the cross section. Consider an economy with two groups of investors. One group is subject to the influence of mood, referred to as *mood-prone investors* (M), and the other group is not, referred to as *rational investors* (R). For tractability, we assume that M investors are risk neutral and R investors are risk averse. This is a similar setting to the overconfidence-based model by Daniel, Hirshleifer, and Subrahmanyam (1998): Assuming risk neutral behavioral investors allows the equilibrium price to be set by behavioral investors in a setting with no risk premiums involved.[17]

C.1 Basic setup

There are four dates, 0, 1, 2, and 3. At date 0, investors are endowed with asset holdings. It is common knowledge that there are N risky assets, $i = 1,\ldots N$, whose payoffs, θ_i, are generated from a factor model:

$$\theta_i = \sum_{k=1}^{K} \beta_{ik} f_k + \epsilon_i,$$

where β_{ik} is the loading of the i^{th} security on the k^{th} factor, f_k is the realization of the kth factor, ϵ_i is the i^{th} firm-specific payoff, $E[f_k] = \mu_k$, $E[f_k^2] = \sigma_k^2$, $E[f_j f_k] = 0$ for all $j \neq k$, $E[\epsilon_i] = 0$, $E[\epsilon_j f_k]=0$ for all i, k. The average of β_{ik} is normalized to one for all factors. The values of β_{ik} are common knowledge at date 0, but the realizations of f_k and ϵ_i are not revealed until the last date (date 3).

At date 1, which represents an ordinary day with no mood influence, investors receive a set of signals for the common factors:

$$s_{1k} = f_k + \varepsilon_k, \text{ for } k = 1,\ldots,K,$$

where ε_k is the noise in the signal, which is *i.i.d.* as $N(0, \sigma_\varepsilon^2)$. We do not model investors receiving firm-specific signals regarding ϵ_i because the same degree of optimism bias on firm-specific signals cannot produce persistent relative performances unless the signals repeat themselves year after year, which is unlikely given ϵ_i is a random variable. An alternative approach is to assume that optimism bias is persistently and different across stocks but such an assumption will be ad hoc.

[17] Even with risk-averse M investors, the mood effect on pricing will remain in equilibrium, similar to the inference by Daniel, Hirshleifer, and Subrahmanyam (2001) for investor overconfidence. However, considering risk neutral M investors makes the model more tractable.

At date 1, as no investors are under the influence of mood, both *M* and *R* investors correctly assess the signals. Thus, conditional on receiving the signals, *M* investors will price the asset as the asset rational expected payoff,

$$P_{1i} = \sum_{k=1}^{K} \beta_{ik} \mathrm{E}[\theta | s_{1k}] = \sum_{k=1}^{K} \beta_{ik} \delta_{1k} s_{1k}, \tag{C1}$$

where $\delta_{1k} = \frac{\sigma_k^2}{\sigma_k^2 + \sigma_\varepsilon^2}$ for $k = 1, \ldots, K$, which measures the relative precision of the signal s_{1k}. Equation (C1) shows that the date 1 pricing of asset *i* is a function of the factor signals, the relative precision of the signals, and the loadings of asset *i* on the factors whose signals are received.

We model date 2 to represent the day when investors are under the positive mood influence (such as the pre-holiday period). We discuss the effect of a negative mood later. At date 2, investors receive a second set of signals for factors:

$$s_{2k} = f_k + \eta_k, \text{ for } k = 1, \ldots, K,$$

where η_k is the noise in the signal, which is *i.i.d.* as $N(0, \sigma_\eta^2)$. The signals are correctly assessed by *R* investors but, under the influence of pre-holiday mood, are misperceived with a positive bias (d_k) by *M* investors:

$$m_{2k} = s_{2k} + d_k, \text{ where } d_k > 0.$$

The optimism bias under positive moods is consistent with the literature in psychology and experimental finance research discussed in Section 2. Conditional on receiving the signals at date 2, *M* investors will price each asset as their expected payoff of the asset conditional on the signals received at both date 1 and date 2,

$$P_{2i} = \beta_{ik} \mathrm{E}[\theta | s_{1k}, m_{2k}] = \sum_{k=1}^{K} \beta_{ik} \left[\frac{\sigma_k^2 \sigma_\eta^2}{D_k} s_{1k} + \frac{\sigma_k^2 \sigma_\varepsilon^2}{D_k} (s_{2k} + d_k)\right], \tag{C2}$$

where $D_k = \sigma_k^2(\sigma_\eta^2 + \sigma_\varepsilon^2) + \sigma_\varepsilon^2 \sigma_\eta^2$.

When investors are in a good mood state on date 2, relative to rational pricing, for each factor the second signal s_{2k} is inflated by d_k. Therefore, equation (C2) implies that, at date 2, assets with a larger β_k will inherit greater overpricing from factor *k* overpricing than assets with a smaller β_k. The aggregate market is overpriced since factor signals are perceived with a positive bias and the average β_k is one. In other words, pricing equation (C2) can explain why the aggregate market outperforms when investors have predictable positive moods (e.g., during pre-holiday trading days), as well as why some stocks outperform the others when mood swings occur.

To make a more direct connection to our empirical tests later, we are interested in the unconditional expected asset price changes from date 1 to date 2, which correspond to our expected pre-holiday returns in the empirical tests:

$$\mathrm{E}(P_{2i} - P_{1i}) = \sum_{k=1}^{K} \beta_{ik} \left[\frac{\sigma_k^2 \sigma_\varepsilon^4}{D_k(\sigma_k^2 + \sigma_\varepsilon^2)} \mu_k + \frac{\sigma_k^2 \sigma_\varepsilon^2}{D_k} d_k \right]. \tag{C3}$$

In equation (C3), the terms related to μ_k are the price adjustments towards the mean factor payoffs after the revelation of the second set of factor signals, and the terms related to d_k (positive) are induced by factor overpricing due to optimism biases. For short-term (pre-holiday) price changes, the terms related to μ_k represent the riskfree returns on the factor portfolios and, therefore, should be fairly small. In contrast, the terms related to d_k (mispricing) can be large, depending on intensity of the positive pre-holiday mood of investors. Thus, the mispricing term can dominate the date 2 price change. This is consistent with the prior finding that the aggregate markets tend to earn pre-holiday returns significantly dwarfing returns on ordinary days.

More formally, if date 2 is an ordinary day (no mood influence), the rational price adjustment from date 1 to date 2 should be

$$\mathrm{E}(P_{2i} - P_{1i})^* = \sum_{k=1}^{K} \beta_{ik} \frac{\sigma_k^2 \sigma_\varepsilon^4}{D_k(\sigma_k^2 + \sigma_\varepsilon^2)} \mu_k. \tag{C4}$$

Thus, relative to expected returns on an ordinary day, the pre-holiday expected return is inflated by

$$\mathrm{E}(M_i) = \mathrm{E}(P_{2i} - P_{1i}) - \mathrm{E}(P_{2i} - P_{1i})^* = \sum_{k=1}^{K} \beta_{ik} \frac{\sigma_k^2 \sigma_\varepsilon^2}{D_k} d_k. \tag{C5}$$

Equation (C5) is the ex ante expected date 2 mispricing before factor signals are received. It suggests the aggregate market (β_k=1 for k = 1, …, K) will experience abnormally high returns due to pre-holiday overpricing. The cross section of assets is mispriced according to their factor loadings to the misperceived factors (β_{ik}), the factor volatility (σ_k^2), and the noisiness of the date 1 factor signals relative to that of date 2 signals (σ_ε^2/D_k). Thus, the relative expected pre-holiday performance of individual stocks in the cross section is predictable and persistent.

Unconditionally, stocks with higher average weighted factor loadings earn greater pre-holiday abnormal returns. Conditional on factor signals, however, equation (C3) implies that the degree of an individual stock's mispricing is mostly influenced by the optimism bias (d_k) of the misperceived factors to which the stock has more extreme exposures. Thus, the dispersion of pre-holiday stock mispricing may across holidays or positive-mood seasons as different factor signals arrive.

In our setting, factor loadings will also help predict the expected pre-holiday mispricing. However, empirically factor loadings are not directly observable. Furthermore, factor loadings may not fully capture the extent of stock mispricing induced by investor mood if *M* investors only trade a subset of assets—so the extent to which investor mood impacts assets also depends on the trading propensity of *M* investors on a given asset. This implies that, when market betas or firm characteristics correlated with factor loadings are controlled for, historical positive-mood (e.g., pre-holiday) returns may continue exhibiting incremental power to forecast future returns under the same mood state.

Taken together, our model suggests that if investors are subject to the optimism bias under the influence of a positive mood, information signals on factors will be misperceived with an upward bias, leading to the dispersed mispricing in the cross section. The historical positive-mood seasonal return will therefore proxy for the degree of individual stock mispricing induced by mood and help to forecast future returns of the stock under the same, positive mood state. The mood-based theory can explain the seasonal effects at both the aggregate and cross-sectional levels.

C.2 The negative mood effect on return seasonality

Lastly, we explore a unique prediction of the mood-based theory, which connects the effect of a positive investor mood to that of a negative investor mood. Specifically, the mood-based model predicts that the relative performances of individual stocks when investors are in good moods will reverse when investors switch to relatively bad moods. To see this, consider a modified equation (C6), whereby investors are under the influence of a negative mood so that the factor signal is perceived with a downward bias, $-d_k$ ($d_k > 0$). In this case, the expected mispricing of asset *i* is:

$$\mathrm{E}(M_i) = -\sum_{i=1}^{K} \beta_{ik} \frac{\sigma_k^2 \sigma_\varepsilon^2}{D_k} d_k. \qquad \text{(C6)}$$

Comparing equation (C6) with equation (C5), we conclude that stocks with higher β_{ik} are predicted to experience higher returns when investors undergo positive mood swings (equation (C5)) but experience lower returns when investors undergo negative mood swings (equation (C6)). The reverse holds for stocks with lower β_{ik}. As a result, relative performances of stocks in upbeat mood states will negatively predict their relative performances in downbeat mood state, and vice versa when investors switch from negative to positive mood states.

This prediction is unique to the mood-based theory, in which seasonal effects across different times of year are induced and connected through predictable investor mood fluctuations. In contrast, the risk-premium-seasonality-based theory makes no prediction about the connection between stocks' relative performances across different seasons of the year, as this theory is silent about the source of seasonality in risk premiums – as a result, seasonal effects in risk premiums can arise from different factors at different times of the year.