Mood Beta and Seasonalities in Stock Returns*

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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, weekday, or pre-holiday periods. A model based on the differential sensitivity of stocks to investor mood explains these effects and implies a new set of seasonal patterns. We find that relative performance across stocks during positive mood periods (e.g., January, Friday, the best-return month realized in the year, the best-return day realized in a week, pre-holiday) tends to *persist* in future periods with congruent mood (e.g., January, Friday, pre-holiday), and to *reverse* in periods with non-congruent mood (e.g., October, Monday, post-holiday). Stocks with higher *mood betas* estimated during seasonal windows of strong moods (e.g., January/October, Monday/Friday, or pre-holidays) earn higher expected returns during future positive mood seasons but lower expected returns during future negative mood seasons.

[Key Words] Return seasonality, Investor mood, Mood beta, Market efficiency, Anomalies

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1. Introduction

Extensive research over a period of decades has documented several aggregate market return seasonalities, referring to periodic variation in the mean returns of market index portfolios.[1] A range of evidence that we will discuss suggests that variation in mood may contribute to these seasonalities. More recently, research has uncovered seasonality in the cross section of security returns, meaning the periodic outperformance of certain securities relative to others in the same calendar month (Heston and Sadka 2008, 2010), on the same day of the week (Keloharju, Linnainmaa, and Nyberg 2015), or during the same pre-holiday period (Hirshleifer, Jiang, Meng, and Peterson 2016).

We propose here a theory based on investor mood to offer an integrated explanation for known seasonalities at both the aggregate and cross-sectional levels, and to offer new empirical implications which we also test. In our model, investor positive (negative) mood swings cause periodic optimism (pessimism) in evaluating signals about assets' systematic and idiosyncratic payoff components. This results in seasonal variation in mispricing and return predictability.

Consistent with the model predictions, we uncover a set of new cross-sectional return seasonalities based on the idea that stocks that have been highly sensitive to seasonal mood fluctuations in the past will also be sensitive in the future. In other words, we argue that some stocks have higher sensitivities to mood changes (higher mood betas) than others, which creates a linkage between mood-driven aggregate seasonalities and seasonalities in the cross-section of returns. In particular, we argue that investor mood varies systematically across calendar months, weekdays, and holidays.[2] In consequence, a mood beta estimated using security returns in seasons with mood changes helps to predict future seasonal returns in other periods in which mood is expected to change.

If investor mood swings lead to misperceptions about factor and idiosyncratic payoffs, then there will be both factor and stock-specific mispricing.[3] In periods with positive (negative) mood shifts, stocks with higher loadings on the factor that is becoming overpriced (underpriced), and/or with higher firm-specific sensitivity to the mood shocks, will earn higher (lower) average returns. Thus, aggregate return seasonality will be accompanied by cross-sectional return seasonality.

Furthermore, the history of the sensitivity of a stock's returns to seasonal shifts in aggregate returns can be used to create a proxy for the stock's sensitivity to seasonal mood variation, or mood

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[1] See Keim (1983), Lakonishok and Smidt (1988), and Kamstra, Kramer, and Levi (2003), among others.
[2] See Section 2 for review of the literature on seasonal mood variations.
[3] Such imperfectly rational shifts in misvaluation could also be called shifts in investor sentiment (Baker and Wurgler 2006, 2007), but in our theory these shifts derive from emotional shifts rather than other possible shocks that might also fall under the general rubric of `sentiment.'

beta. Mood beta can in turn be used to predict future returns under mood states that are congruent or non-congruent. Our model of mood and investor beliefs provides new predictions about how mood beta affects returns, as well as predictions consistent with existing patterns of aggregate and cross-sectional return seasonality.

Furthermore, the model delivers several novel predictions regarding cross-sectional seasonal return predictability. Our tests of these predictions indicate that there is predictable return continuation or reversal of returns, looking across different calendar months, weekdays, and holidays over horizons of years or months. These effects are distinct from past findings about seasonalities in cross-sectional return predictability. Specifically, we find that the relative performance across stocks during the seasons that have experienced or on average experience high aggregate returns (e.g., January, Friday, the best-return month realized in the year, the best-return day realized in a week, pre-holiday) tends to *persist* in future seasons when positive mood changes are expected (i.e.., when high aggregate returns are expected, e.g., January, Friday, pre-holiday); and to *reverse* when negative mood changes are expected (i.e., low aggregate returns are expected, e.g., September, October, Monday, post-holiday).

For example, if Stock A outperforms Stock B in January, then it tends to underperform Stock B next September and October (reversal), but tends to outperform Stock B next January (persistence). This pattern continues for years after the conditioning date. Similarly, if A outperforms B on Friday, this relative performance tends to reverse next Monday, but to continue next Friday. This pattern continues for months after the conditioning date. As a third example, Stock A that on average outperforms Stock B immediately before major holidays in the past twelve months, say, up to the current Thanksgiving, will tend to underperform Stock B immediately after Thanksgiving, but outperform Stock B immediately before Christmas that follows. This pattern continues for many subsequent holidays after the conditioning date.

We now discuss each of these effects in turn, starting with month-of-the-year effects. The basic month-of-the-year effect from past literature is the finding that aggregate stock markets tend to do better in certain calendar months (e.g., January) and do worse in other calendar months such as September and October (Lakonishok and Smidt 1988; Bouman and Jacobsen 2002). The strong January performance of stock markets, especially among small firms (Keim 1984), may be related to the investor optimism at the turn of the year, as suggested by findings of Ritter (1988) and Doran, Jiang, and Peterson (2012). The weak September and October performance may derive from the declining number of hours of daytime sunlight and seasonal affective disorder (SAD) effect in early

Autumn (Kamstra, Kramer, and Levi 2003). 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-month cross-sectional persistence effect*.

During our sample period 1963-2015. the average stock excess return (measured by CRSP equal-weighted index return minus the riskfree rate) is highest in January and lowest in October. Thus, we focus on January as a proxy for an investor high-mood state and October for a low-mood state. Using Fama-MacBeth regressions, we verify the finding of Heston and Sadka (2008) for January and October—historical January (October) relative performance tends to persist in future January (October) for the following ten or more years. In our interpretation, stocks that do better than others during one month will tend to do better again in the same month in the future because there is a congruent mood at that time.

Furthermore, we find a new reversal effect that crosses months with *incongruent* moods; historical January (October) returns in the cross section tends to significantly reverse in subsequent Octobers (Januaries). A stock that did better than other stocks last January tends to do worse than other stocks in October for the next five years or so. A one-standard-deviation increase in the historical congruent (incongruent)-calendar-month leads an average 23% increase (17% decrease) in the next ten years, relative to the mean January/October returns.[4]

The model predictions regarding seasonal return persistence and reversal also apply when we identify periods with extreme mood *realizations*. One such example may be months with realized highest or lowest aggregate market returns in a given year. A very high or low market return may directly reflect a swing in investor mood.[5] Thus, the best-market-return month is likely to be associated with a favorable mood state and the worst-market-return month likely indicates an unfavorable mood state. Our theory therefore predicts that cross-sectional performance during the extreme (best or worst) market return month will persist under future congruent mood states and reverse under the future non-congruent mood state.

Empirically, we find exactly that. A one-standard-deviation increase in the historical congruent (incongruent)-mood-month return is associated with an average 30% higher (29% lower) return in each of the next ten January and October months. Again, replacing October with September yields even similar results.

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[4] Replacing October with September, which has the worst value-weighted market excess returns in our sample period, yields qualitatively similar results.

[5] As related evidence, Gulen and Hwang (2012) find that market reactions are uniformly more favorable to corporate announcements made on days with higher market returns, suggesting investor optimism on high market return days.

Our explanation for these effects is not specific to the monthly frequency. A useful way to challenge our theory is therefore to test for comparable cross-sectional seasonalities at other frequencies. Moving to the domain of daily returns, we document a similar set of congruent/incongruent-mood-weekday return persistence and reversal effects.

Previous literature has documented the day-of-the-week effect, the finding that aggregate stock markets tend to do better at the end of the week (Friday) and worse at the beginning of the week (Monday) (French 1980, Lakonishok and Smidt 1988). Section 2 discusses a strand of literature that links Mondays to downbeat moods and Friday to upbeat moods among both the general and the investing population. 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 *congruent-weekday cross-sectional persistence effect*. Our interpretation of this is that stocks that do well on the past good (bad) mood days will continue doing so under future good (bad) mood days.

We confirm this return persistence effect for Monday and Friday returns, and then show, analogous to the monthly results, that a *congruent-mood-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 ten Fridays (Mondays) and beyond, when good (bad) market performance is expected to continue. A one-standard-deviation increase in historical congruent-weekday or congruent-mood-weekday return is associated an average with a 4% or 12% higher return in the subsequent ten Mondays/Fridays.

When market mood is expected to reverse, however, an *incongruent-mood-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 ten Mondays and beyond, and that on Monday or the worst-market-return weekday reverses on subsequent ten Fridays and beyond. At the weekday level, a one-standard-deviation increase in the historical incongruent-weekday or incongruent-mood-weekday return implies an average 19% or 35% return reduction in each of the subsequent ten Mondays and Fridays.

We further show that a similar cross-sectional return persistence and reversal effect is present around holidays. Previous research has found that aggregate stock markets tend to earn substantially higher returns immediately prior to holidays than on other days (Ariel 1990; Lakonishok and Smidt 1988). Anticipation of holidays appears to be associated with rising investor mood (e.g., Frieder and Subrahmanyam 2004; Bergsma and Jiang 2015). At the level of individual stocks, there is pre-holiday cross-sectional seasonality, wherein stocks that historically have earned higher pre-holiday returns on average earn higher pre-holiday returns for the same holiday over the next ten years (Hirshleifer, Jiang, Meng, and Peterson (2016)). Furthermore, pre-holiday relative performance across stocks tends to reverse immediately after the end of holiday breaks.

Our theory explains both the aggregate and cross-sectional pre-holiday effects. Moreover, we extend the finding of Hirshleifer, Jiang, Meng, and Peterson (2016) by showing that the relative pre-holiday returns across stocks persist not only for the subsequent same-, but also different-holidays throughout the year. For example, if a stock has had a higher average return than other stocks right before major holidays over the most recent twelve months, it also tends to have high returns right before major holidays in the following twelve months. When we measure the relative pre-holiday performance using the current holiday, however, the pre-holiday return persistence effect is slightly weaker for the next two to twelve holidays, and reverses for the immediately following holiday.

Similarly, the pre-holiday return reversal effect is present for nearly all of the holidays in the next twelve months when we measure the average pre-holiday performance over the past twelve months. But the reversal effect is significant only for the several immediately following holidays when we condition on the pre-holiday performance over the current holiday. Overall, the pre- and post-holiday findings are largely consistent with our theoretical predictions about cross-sectional return persistence (reversal) in congruent (incongruent) mood seasons.

The cross-sectional return persistence and reversal effects across months, weekdays, and holidays are overall consistent with our theoretical predictions that investors' seasonal mood fluctuations cause seasonal misperceptions about factor and firm-specific payoffs and lead to cross-sectional return seasonalities. These predictions are based on the idea that different stocks have different *mood beta*—a stock's return sensitivity to factor mispricing induced by mood shocks. We argue that the concept of mood beta integrates various seasonality effects. We therefore perform more direct tests of the model prediction that mood betas will help forecast the relative performance of the stocks in seasons with different moods.

We estimate mood beta using a security's return sensitivity to aggregate returns during states of recurring, strong investor mood changes—positive or negative, as in such periods the covement between individual securities and the average security is a manifestation of the impact of large, aggregate mood shocks. For example, we estimate a security's mood beta through a time series regression of the security's monthly returns on the contemporaneous equal-weighted market returns using a rolling 10-year window of only January and October returns (i.e., 20 observations). The slope coefficient is the estimated mood beta, which measures the percentage January (October) return increase (decrease) of the security caused by a one-percent higher (lower) return of an average security in January (October) owing to good (bad) mood shocks. Alternative mood betas are estimated analogously by using Monday/Friday returns, pre-holiday returns, or returns during the month (weekday) based on realized market performance during a year (week).[6] Our theory predicts that stocks with high mood betas estimated using prior seasonal returns with strong mood influences will outperform other stocks when there are positive subsequent mood shocks and underperform upon negative mood shocks. This prediction relies on the premise that mood sensitivity has some stability over time.

In our mood beta tests, we replace the historical seasonal returns in the seasonal regressions with mood betas to forecast future seasonal returns in the cross section in calendar-months, on weekdays and around holidays. We find strong evidence that high mood beta stocks tend to outperform in January, on Fridays, and during pre-holiday periods, and underperform in October, on Mondays. An increase of mood beta by one standard deviation is associated with more than 1.5 percentage points higher (lower) return in the next ten Januaries (Octobers), about 4-5 basis points higher (lower) return on Friday (Monday) in the next several months, and about 3 basis points of return increase on each of the 13 pre-holidays in the next year. There is little evidence that mood beta is related to post-holiday returns. In contrast to mood beta, standard market beta estimated using all calendar months or all weekdays is not expected to capture mood sensitivity. Empirically, it exhibits only weak predictive power for the cross section of stock returns, and in many specifications, carries a negative risk premium (Baker, Bradley, and Wurgler 2011).

Lastly, we show that after accounting for the correlation with mood beta, the historical seasonal returns exhibit significant reduced power in many cases to predict future January/October, Monday/Friday, and pre-/post-holiday returns. In contrast, mood beta exhibits consistent, robust explanatory power to forecast all future seasonal returns but the post-holiday returns. This finding suggests that mood beta plays an important role in explaining the known and the new cross-sectional seasonalities we discover.

2. Literature on Mood Seasonality

[6] We do not use post-holiday returns in estimating mood beta as we find pre-holiday returns in the cross section significantly reverse only immediately after the current holiday but not after the subsequent 12 other holidays over the next 12 months. Thus, the comovement between individual stocks and the average stock is likely to be a noisy measure of mood sensitivity by using post-holiday returns for all holidays.

Our approach is based on the idea that stock return seasonalities associated with calendar months, weekdays, and holidays are caused at least in part by mood fluctuations. Extensive research has documented return seasonalities. Some of these studies provide hints that seasonal mood variations may contribute to such effects.

The January effect refers the outperformance of stocks in general, especially small stocks, do better early in January (Rozeff and Kinney 1976; Keim 1983). U.S. retail investors do not immediately invest the proceeds of stock sales made in December. Instead, they wait until early January to reinvest, suggesting investor optimism at the start of the new year (the parking-the-proceeds hypothesis of Ritter (1988)). Stock markets rise in early January in countries where New Year's Day coincides with January 1st (see discussion by Thaler 1987), and also surrounding cultural New Year's Day in countries where New Year's Day does not coincide with January 1st (Bergsma and Jiang 2015). From the end of December through early January, gaming revenues from interstate lottery sales and the Las Vegas Strip, as well as prices of lottery-like stocks and options increase, again consistent with the notion that both investors and members of the general population become more optimistic at the turn of the year (Doran, Jiang, Peterson 2012).

In contrast to January, September and October (early Fall) are associated with average poor performance of the stock markets. Lakonishok and Smidt (1988) find that the DJIA earned an average September return of –1.47% over the period 1897-1986. In our sample period 1963-2015, the value-weighted CRSP return is the lowest in October (–0.37%) and the equal-weighted CRSP return is the lowest in September (–0.24%). Kamstra, Kramer, and Levi (2003) suggest that Seasonal Affective Disorder (SAD) symptoms tend to occur in late September following the time of the autumn equinox as the length of the day starts to shorten. The shortening daylight hours lead to lower returns in September to October for countries in the Northern Hemisphere, such as the U.S., and in March to April for Southern Hemisphere countries, such as New Zealand. Under this hypothesis, as depression grows during September to October, investors become more pessimistic, resulting in the low market returns observed during this seasonal period. Evidence consistent with the SAD effect is provided through behaviors of financial analysts (Lo and Wu 2010) and mutual fund outflows (Kamstra, Kramer, Levi, and Wermers 2016) in early Fall.

When it comes to weekday, there is also evidence that people tend to be in positive moods on Friday and the weekend and less positive moods on Monday. Several survey studies summarized by Birru (2016) find such weekday mood variations among college students (e.g. Rossi and Rossi 1977; McFarlane, Martin, and Williams 1988) and the general population (Stone, Schneider, Harter 2012;

Helliwell and Wang 2014). Using the weekday variation in the VIX, a measure of investor "fear", Birru (2016) observes higher VIX (lower mood) on Mondays and lower VIX (higher mood) on Fridays and shows that returns to several anomaly strategies exhibit opposite return patterns on Monday versus Friday.

Moving to holidays, 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 and moods tend to dip slightly in the two trading days immediately after the holiday celebration. This evidence suggests that the pre-holiday period is associated with improving investor moods and, therefore, possible optimism biases, and the post-holiday period may be associated with modestly downbeat moods.

Stock market evidence is consistent with such mood shifts. Past research documents that the aggregate stock market tends 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 offers 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).

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 encourages (discourages) risk taking (Bassi, Colacito, and Fulghieri 2013) and positively (negatively) influences stock returns (Saunders 1993; Hirshleifer and Shumway 2003; Goetzmann, Kim, Kumar, and Wang 2015). Furthermore, positive mood indicators predict subsequent return reversals in stock markets (Karabulut 2013).

3. The Model

We present a model to illustrate how investor mood may induce return seasonality at both the aggregate and the cross-section levels. Consider an economy with a group of risk neutral, mood-prone investors.[7] Assuming risk neutral behavioral investors allows the equilibrium price to be set based on

[7] Our setting yields an identical equilibrium if we consider both risk-neutral mood-prone investors and risk-averse rational investors. If, instead, we assume both types of investors are risk averse, the equilibrium price will reflect the weighted average belief of the two investors groups. Either setting yields similar patterns in aggregate and individual

the mistaken perceptions of mood-prone investors in a setting with no risk premiums involved. We also consider the economy with pure rational investors to set our benchmark rational pricing.

3.1 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:

$$\theta_i = \bar{\theta}_i + \beta_{i1} f_1 + \beta_{i2} f_2 + \epsilon_i,$$

where $\bar{\theta}_i$ is the security's mean payoff, β_{ik} ($k = 1, 2$) is the loading of the i^{th} security on the k^{th} factor, f_k is the realization of the k^{th} factor, ϵ_i is the i^{th} firm-specific payoff, $E[f_k] = 0$, $E[f_k^2] = \sigma^2$, $E[f_1 f_2] = 0$, $E[\epsilon_i] = 0$, $E[\epsilon_i^2] = \sigma^2$, $E[\epsilon_j f_k]=0$ for all i, k. The average of β_{ik} is normalized to one for both 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 two factors and the N firm-specific payoffs:

$$s_k^1 = f_k + \varsigma_k^1, \text{ for } k = 1, 2; \text{ and } \nu_i^1 = \epsilon_i + \omega_i^1, \text{ for } i = 1, \ldots, N,$$

where superscript 1 indicates date 1, ς_k^1 is the noise in the factor signal, which is *i.i.d.* as $N(0, \sigma_f^2)$, and ω_i^1 is the noise in the firm-specific signal, which is *i.i.d.* as $N(0, \sigma_\epsilon^2)$.

At date 2, investors are subject to a positive or negative mood shock and receive a second set of signals:

$$s_k^2 = f_k + \varsigma_k^2, \text{ for } k = 1, 2; \text{ and } \nu_i^2 = \epsilon_i + \omega_i^2, \text{ for } i = 1, \ldots, N,$$

where superscript 2 indicates date 2, ς_k^2 is the noise in the factor signal, which is *i.i.d.* as $N(0, \sigma_f^2)$, and ω_i^2 is the noise in the firm-specific signal, which is *i.i.d.* as $N(0, \sigma_\epsilon^2)$. We assume the signal noises are independent across time and firm-specific signals are also independent across stocks. But the distributions of signal noises are the same for both dates, without loss of generality.

Factor 2 represents an easy-to-value factor; its signal is correctly assessed by both groups of investors even under mood influence. In contrast, factor 1 represents a hard-to-value factor. Its signal, as well as all firm-specific signals, are perceived with a bias by investors. We use b to represent the bias induced by a mood shock, and define factor 1's sensitivity to the mood shock as γ_f, and asset i's

stock mispricing. This is a similar approach to that used to tractably model trading behavior and mispricing under overconfidence by Daniel, Hirshleifer, and Subrahmanyam (1998, 2001).

specific sensitivity to the mood shock as γ_i. Thus, the perceived signals on factor 1 (S_1^2) and firm-specific payoffs (V_i^2) are:

$S_1^2 = s_1^2 + \gamma_f b$ and $V_i^2 = v_i^2 + \gamma_i b$,

Under positive investor moods, the optimism bias prevails and $b > 0$, distributed as unif$(0, 2\bar{b})$, while under bad investor moods the pessimism bias dominates and $b < 0$, distributed as unif$(-2\bar{b}, 0)$, where $\bar{b} > 0$. The optimism/pessimism bias associated with good/bad mood states is consistent with the literature in psychology and experimental finance research discussed in Section 2. The parameter $\gamma_f > 0$ and is a constant. The parameter γ_i is fixed for each stock, but in the cross section follows a normal distribution with zero mean ($\bar{\gamma} = 0$). This assumption captures the idea that firm-specific mood sensitivity is randomly distributed across firms and the average firm-specific mood-induced mispricing is cancelled out at the aggregate, leaving the aggregate mood effect purely driven by the sensitivity of perceived factor 1 payoffs to mood shocks.

3.2 Equilibrium pricing

At date 1, investors correctly assess the signals. Thus, conditional on receiving the signals, investors will price the asset as the rational expected payoff,

$$P_i^1 = \bar{\theta}_i + \sum_{k=1}^{K} \beta_{ik} \mathrm{E}\left[\theta_k \middle| s_k^1\right] + \mathrm{E}\left[\epsilon_i \middle| v_i^1\right] = \bar{\theta}_i + \beta_{i1}\delta_f s_1^1 + \beta_{i2}\delta_f s_2^1 + \delta_\epsilon v_i^1, \tag{3.1}$$

where superscript 1 indicates date 1, $\delta_f = \sigma^2/(\sigma^2 + \sigma_f^2)$ and $\delta_\epsilon = \sigma^2/(\sigma^2 + \sigma_\epsilon^2)$, both of which measure the relative precision of the signals. Equation (3.1) shows that the date 1 pricing is determined by the signals as well as the relative precision of the signals and the asset's loadings on the factors.

At date 2, conditional on receiving the signals, investors will price each asset as their subjective expected payoff, inclusive of their bias:

$$P_i^2 = \bar{\theta}_i + \sum_{k=1}^{K} \beta_{i1} \mathrm{E}\left[\theta \middle| s_k^1, S_1^2, s_2^2\right] + \mathrm{E}\left[\epsilon_i \middle| v_i^1, V_i^2\right]$$

$$= \bar{\theta}_i + \beta_{i1}\left[\lambda_f s_1^1 + \lambda_f\left(s_1^2 + \gamma_f b\right)\right] + \beta_{i2}\left[\lambda_f s_2^1 + \lambda_f s_2^2\right] + \left[\lambda_\epsilon v_i^1 + \lambda_\epsilon\left(v_i^2 + \gamma_i b\right)\right], \tag{3.2}$$

where $\lambda_f = \sigma^2\sigma_f^2/(2\sigma^2\sigma_f^2 + \sigma_f^4)$, and $\lambda_\epsilon = \sigma^2\sigma_\epsilon^2/(2\sigma^2\sigma_\epsilon^2 + \sigma_\epsilon^4)$.

When investors are in a good (bad) mood state on date 2, relative to rational pricing ($b = 0$), factor 1 and firm-specific payoffs are inflated (deflated) by γb. Therefore, equation (3.2) implies that, at date 2, assets with a larger β_{i1} (or γ_i) will experience greater mood-induced over- or underpricing than assets with a smaller β_{i1}(or γ_i). The aggregate market is overpriced (underpriced) when factor signals are perceived with a positive (negative) bias as the average β_k is one. In other words, pricing equation (3.2) can explain why the aggregate market outperforms during periods of predictable positive moods (e.g., during January, Friday, pre-holiday trading days), and underperforms during periods of predictable negative moods (e.g., October, Monday), as well as why some stocks consistently outperform the others when mood swings occur.

3.3 Seasonal return predictability

We are interested in the expected asset price change from date 1 to date 2 for a given mood shock. This corresponds to seasonal returns we examine in the empirical tests, such as January/October returns, Monday/Friday returns, and pre/post-holiday returns, when investor moods shift from a neutral to a positive or negative state. In a risk neutral world with zero riskfree rate, ex ante rational expected return should be zero. Thus, average return for date 2 that deviates from zero is mispricing (*M*), or abnormal returns earned due to mood shocks:

$$\mathrm{E}(M_i|b) = \mathrm{E}\big(P_i^2 - P_i^1|b\big) = \beta_{i1}\lambda_f\gamma_f b + \lambda_\epsilon\gamma_i b, \tag{3.3}$$

where the term related to $\gamma_f b$ is inherited factor 1 mispricing and the term related to $\gamma_i b$ is firm-specific mispricing, both induced by the mood shock b.

Furthermore, date 2 mispricing on the equal-weighted aggregate market (*A*) portfolio is

$$\mathrm{E}(M_A|b) = \lambda_f\gamma_f b + \lambda_\epsilon\bar{\gamma} b = \lambda_f\gamma_f b, \tag{3.4}$$

where the second equality applies when the number of securities, *N*, is large, so that firm-specific mood-induced mispricing cancels out in the aggregate ($\bar{\gamma} = 0$).

Equation (3.4) suggests that average stock returns in a predictable mood state can be extreme if mood shock is large. This is consistent with prior empirical findings that aggregate markets tend to earn high January returns, Friday returns, and pre-holiday returns that significantly dwarf returns earned in ordinary months or on ordinary days. In contrast, average aggregate returns in October and Monday are negative, suggesting that the negative mood shocks can even overpower positive risk premia.

Accordingly, shown in equation (3.3.) the cross section of assets is mispriced to the extent of their factor 1 loadings (β_{i1}) and their firm-specific mood sensitivity (γ_i). Thus, relative performance of individual stocks in the cross section is predictable during periods of predictable mood shocks.

Proposition 1: The aggregate market portfolio will experience abnormally high (low) returns during seasonal periods with positive (negative) investor mood swings, and stocks' abnormal returns are positively related to their loadings on the mispriced factor and their firm-specific sensitivity to the mood influence.

3.4 Cross-sectional seasonal return predictability

Unconditionally, stocks with higher β_{i1} or γ_i earn higher (lower) abnormal returns during positive (negative) mood swing seasons. Although neither β_1 nor γ_i is observable, historical seasonal returns can capture their joint influence. For example, during the season with positive mood shocks (b > 0), stocks with higher β_1 and/or higher γ_i will outperform stocks with lower β_1 and/or lower γ_i. Thus, stocks that outperform in the prior mood seasons are expected to continue the outperformance during the next season when the mood shocks are congruent.

To see this formally, consider two mood scenarios for date 2 corresponding to mood shocks *b* and *b'*, respectively. The correlation between seasonal returns is

$$cov[(P_{2i} - P_{1i}), (P_{2i} - P_{1i})'] = [\beta_{i1}^2 \lambda_f^2 \gamma_f^2 + \lambda_\epsilon^2 \gamma_i^2] cov(b, b'). \quad (3.5)$$

Across two congruent mood states, mood shocks are distributed as unif$(0, 2\bar{b})$, thus are positive correlated; $cov(b, b') = \bar{b}^2/3 > 0$. For example, we expect that Friday moods are positively correlated even when Friday fundamental news are independent. As a result, relative performance persists from one Friday to the other. Conversely, when mood states are incongruent (one is drawn from unif$(0, 2\bar{b})$, the other from unif$(-2\bar{b}, 0)$), mood shocks are negatively correlated; $cov(d, d') = -\bar{b}^2/3 < 0$. As a result, relative performance will reverse. One such example is that if the Monday and Friday moods are negatively correlated even when fundamentals are uncorrelated, we expect relative performance across stocks to reverse from Monday to Friday, and from Friday to Monday.

Proposition 2: Historical seasonal returns of a security will be positively related to its future seasonal returns under a congruent mood state, and negatively related to its future seasonal returns under an incongruent mood state.

In prior research (Heston and Sadka 2008; Keloharju, Linnainmaa, and Nyberg 2015), what we describe as a congruent mood state is identified using the same calendar month or weekday. Thus, Proposition 2 helps to explain the prior findings on cross-sectional seasonalities. However, there is a broader implication—that cross-sectional seasonal returns will persist under the congruent mood state and reverse under the incongruent mood state, regardless whether the mood state is identified using seasonal windows or not. In our empirical tests later, we also identify the historical mood state using the realized, extreme aggregate returns in a year or in a week, and surrounding holidays.

3.5 Mood beta

An alternative way to predict seasonal returns across assets is to use the mood beta of each asset, where the mood beta measures a security's sensitivity to mood shocks. There are potentially many ways to identify mood beta. Here we consider periods of strong mood swings, during which security returns mainly reflect mood-induced mispricing and so is the equal-weighted market portfolio—thus, in empirical tests excess returns may be used as a proxy for abnormal returns during such periods. Under our model setting, we can estimate a security's mood beta using a time series regression of the date 2 return of each asset (M_i) on the date 2 return of the aggregate market (M_A):

$$\beta_i^{mood} = \frac{cov(M_i, M_A)}{var(M_A)} = \frac{\beta_{i1}\lambda_f^2\gamma_f^2 + \lambda_\epsilon^2\bar{\gamma}\gamma_i}{\lambda_f^2\gamma_f^2 + \lambda_\epsilon^2\bar{\gamma}^2} = \beta_{i1}\ . \tag{3.6}$$

Again, the last equality reflects the simplification coming from $\bar{\gamma} = 0$ when there are many securities. Equation (3.6) predicts that mood beta will be larger for stocks with a higher loading on the mood-prone factor (β_{i1}). Thus, stocks with a higher mood beta will become more overpriced (underpriced) when factor 1 is becoming overpriced (underpriced) under positive (negative) mood shocks.

Proposition 3: Mood beta is a positive predictor of the cross-section of security returns during positive mood states and a negative predictor during negative mood states.

3.6 Market beta

Market beta is different from mood beta. Market beta measures a stock's return sensitivity to the market portfolio in an economy with pure rational investors (e.g. b = 0). By substituting b with zero in equations (3.1) and (3.2) we obtain the date 2 asset returns in this rational economy. Then regressing date 2 asset *i*'s returns on the market returns in this economy yields

$$\beta_i^A = \frac{cov[(P_{2i} - P_{1i})^R,\ (P_{2A} - P_{1A})^R]}{var(P_{2A} - P_{1A})^R} = \frac{\beta_{i1} + \beta_{i2}}{2} \tag{3.7}$$

That is, market beta is an average loading across all factors, as opposed to the loading on the mood-prone factor. This implies that, if β_{i1} and β_{i2} are not perfectly correlated, when market betas are controlled for, mood beta will continue exhibiting power to forecast future returns under the congruent, or incongruent, mood state.

Proposition 4: Market beta does not subsume the power of mood beta to explain the cross-section of seasonal returns during strong mood states.

Taken together, our model suggests that if investors are subject to the optimism (pessimism) bias under the influence of a positive (negative) mood shock, information signals on factors or firm-specific payoffs will be misperceived with an upward (downward) bias, leading to the dispersed mispricing in the cross section. The historical 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 congruent and incongruent mood state. A mood beta captures the mood sensitivity to mood-prone factors and will positively forecast returns in positive mood states and negatively do so in negative mood states. Therefore, the mood-based theory can explain the seasonal effects at both the aggregate and cross-sectional levels, as well as predicting a set of new seasonal effect (persistence and reversal) in the cross section. We next test these new predictions.

4. Return seasonalities

Our U.S. sample includes common stocks traded on the NYSE, AMEX, and NASDAQ from January 1, 1963 to December 31, 2015. U.S. daily, monthly stock returns and other trading information are from the Center for Research in Security Prices (CRSP). Accounting data are from Compustat. We report the seasonal returns summary statistics in Table 1 with variable definitions presented in Appendix A.

[INSERT TABLE 1 HERE]

4.2. Calendar month seasonal effects

We first replicate the same-calendar-month effect documented by Heston and Sadka (2008) for January and October in our sample period. Then we examine the seasonal return persistence and reversal effects across congruent and incongruent mood seasons at the monthly level.

4.2.1 The same-month return persistence effect

To test the same-calendar-month cross-sectional persistence effect of Heston and Sadka (2008) for January and October, we run the Fama-MacBeth (FMB) regressions of January and October returns across stocks on their historical same-month returns at the 1st to the 10th annual lag:

$$RET_{\mathrm{Jan|Oct},t} = \eta_{k,t} + \gamma_{k,t} RET_{\mathrm{Jan|Oct},t-k} + \varepsilon_t, \tag{4.1}$$

where $k = 1,\ldots,10$, $RET_{\mathrm{Jan|Oct},t}$ is the current January or October return in year t for a given stock , and $RET_{\mathrm{Jan|Oct},t-k}$ is the historical January or October return in year $t-k$ for the same stock. We run cross-sectional regressions as in (4.1) for each January and October and the estimates of $\gamma_{k,t}$ are averaged across the full sample period to yield the estimate for γ_k, 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 significant return responses for all 10 annual lags. The return response represents significant economic impact. For example, for the 1st annual lag the return response is 5.05 (t-statistic = 5.01), suggesting a one-standard-deviation (21.12%) increase in the prior same-month return leads to a 107 bps (21.12%×5.05%) increase in the current same-month return, or a 41% increase relative to the mean January/October monthly returns. The average return response is 2.82, suggesting a one-standard-deviation increase in the historical same-month return elevates the future same-month return by about 23% for the same month in each of the next 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 October stock returns for an extended period of 1963-2015.

4.2.2 The congruent-mood-month return persistence effect

Next, we expand the same-calendar-month return persistence effect to considering historical months with the congruent mood season to January or October. We measure the past positive- (negative-) mood season using the month with the best(worst) aggregate return realized in a year. In line with our model, we measure the aggregate return using the equal-weighted CRSP market index portfolio returns in excess of the risk-free rates.[8] The rationale, as discussed previously, relies on the assumption that extreme realized average returns are more likely to reflect extreme mood swings.

Using FMB regressions, we employ the relative performance across stocks in these historically high-mood (low-mood) seasons to forecast the cross-section of returns in subsequent January (October) months, during which high (low) moods are expected:

$$RET_{\mathrm{Jan|Oct},t} = \eta_{k,t} + \gamma_{k,t} RET_{\mathrm{Best|Worst},t-k} + \varepsilon_t, \tag{4.2}$$

The return responses are reported in Column (2) of Table 2. We obtain positive return responses for 10 annual lags, all significant at the 5% or better. The average return response across all 10 lags is 3.67, implying that a one-standard-deviation (21.47%) increase in the return in the best-market-return (worst-market-return) month of a prior year leads to a 79 bps, or a 30%, higher return returns in each of the subsequent Januarys (Octobers). This evidence supports our conjecture that cross-sectional returns persist across the congruent-mood states, which may occur on different calendar months.

4.2.3 The incongruent-month return reversal effect

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[8] 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, our theory suggests that the mood-induced seasonality is stronger among firms more mood-prone stocks, which are likely smaller firms as individual (mood-prone) investors prefer small stocks.

Next, we test for the cross-sectional reversal effect across incongruent mood states, proxied by January and October. In Column (3) of Table 2, we report estimates of regressions of January and October returns across stocks on their own historical incongruent-calendar-month (October and January, respectively) returns.

$$RET_{\text{Jan|Oct},t} = \eta_{k,t} + \gamma_{k,t} RET_{\text{Oct|Jan},t-k} + \varepsilon_t, \tag{4.3}$$

The estimated return responses are significantly negative for the first four return responses and the 7th lag, and negative but insignificant for the other lags. Specifically, for the 1st annual lag the return response on the historical different-month return in forecasting current-month return is –4.29 (*t*-statistic = –4.02), suggesting a one-standard-deviation increase in last incongruent-month return leads to a 35%, return reduction in the following January/October. This return reversal is substantial and significant despite monthly returns in the prior year typically exhibiting a momentum effect (Jegadeesh and Titman 1993). The evidence thus shows that a cross-sectional reversal effect takes place across the two calendar months with expected, incongruent mood states at least for a few subsequent years.

4.2.4 The incongruent-mood-month return reversal effect

The reversal effect can be also identified using 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 October returns across stocks on their own historical returns in prior years during the incongruent mood months (worst-market-return or best-market-return months), respectively.

$$RET_{\text{Jan|Oct},t} = \eta_{k,t} + \gamma_{k,t} RET_{\text{Worst|Best-Month},t-k} + \varepsilon_t, \tag{4.4}$$

We obtain substantial and significant negative return responses across all 10 annual lags. The return response starts with –5.00 (1st lag, *t*-statistic = –3.72) and gradually recedes to –2.71 (10th lag, *t*-statistic = –2.70), with an average of –3.55, suggesting that a one-standard-deviation increase in the stock return during the past best (worst) market return month leads to an average 29% return reduction in each of the next ten October (January) months, again a remarkably strong reversal effect when investor mood is expected to reverse.

Although in our sample it is October that carries the lowest average stock returns, using the Dow Jones index return from 1897 to 1986 Lakonishok and Smidt (1998) find that September has the lowest average return. Therefore, in our robustness check presented in Appendix B, we use September in place of October to proxy for low-mood states and find qualitatively similar, and in some cases quantitatively slightly weaker, effects. This is consistent with the notion that the SAD effect starts in late September around autumn equinox so that low-mood only influences part of September.

Taken together, our results in Table 2 suggest the existence of strong congruent-mood-month return persistence effects and incongruent-mood-month return reversal effects in the cross section. These effects connect seemingly independent cross-sectional seasonalities across different calendar months with the congruent or incongruent mood seasons.

4.3. Weekday seasonal effect

Moving to higher frequency return seasonalities, we explore whether the cross-sectional persistence and reversal effects are present across weekdays. We first verify the prior findings that stocks as a whole earn higher returns on Fridays and lower returns on Monday during our sample period 1963-2015. We next replicate the same-weekday-return-persistence effect documented by Keloharju, Linnainmaa, and Nyberg (2015), and then generalize it to return persistence and reversal effects across weekdays with congruent and incongruent moods.

4.3.1 The same-weekday return persistence effect

We examine the same-weekday-return-persistence effect using FMB regressions, using only Monday and Friday stock returns:

$$RET_{\mathrm{Mon|Fri},t} = \eta_{k,t} + \gamma_{k,t} RET_{\mathrm{Mon|Fri},t-k} + \varepsilon_t, \tag{4.5}$$

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 an insignificant return response. The return responses of the other 9 lags are all statistically significant at the 1% level, with an average of 0.21. The insignificance at the 1st lag is also observed by Keloharju et al. (2015), owing to the short-term reversal effect of one-month return (Jegadeesh 1990) that appears to be unusually strong during the first week.[9] Across the ten weekly lags, the average return response implies that a one-standard-deviation increase in the daily Monday or Friday return leads to a 12% higher 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

[9] 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.

same-weekday relative performances across individual stocks for a sample with only Monday and Friday returns.

4.3.2 The congruent-mood-weekday return persistence effect

We extend the same-weekday persistence effect to the congruent-mood-weekday persistence effect. Similar to our methods of identifying realized mood states at the monthly frequency, we use the best (worst) market return day realized in a prior week to proxy for positive (negative) mood swing seasons. Then we test whether cross-sectional performance in prior positive (negative) mood seasons persists on subsequent Fridays (Mondays), when the congruent-mood state is predicted.

$$RET_{\text{Mon|Fri},t} = \eta_{k,t} + \gamma_{k,t} RET_{\text{Worst|Best-Weekday},t-k} + \varepsilon_t. \tag{4.6}$$

Column (2) of Table 3 report the estimates. We observe positive and significant or marginally significant return responses for all but the first 3 lags. The return response for the 1st lag is significantly negative, again likely owing to the one-month short-term reversal effect. The economic impact of the average return response is similar to that on historical Monday/Friday returns. In unreported tests, we find a strong cross-sectional return persistence effect across the congruent-mood weekday lasts for weeks and months.

4.3.3 The incongruent-weekday return reversal effect

For the reversal effect across weekdays, we regress Friday or Monday returns across stocks on their different-weekday returns (Monday or Friday, respectively) in prior weeks.

$$RET_{\text{Mon|Fri},t} = \eta_{k,t} + \gamma_{k,t} RET_{\text{Fri|Mon},t-k} + \varepsilon_t. \tag{4.7}$$

As reported in Column (3) of Table 3, we observe negative return responses for the first 10 weekly lags, significant for 8 at the 5% level or better. Again, the average economic impact is more than double that of the first two weekday effects. These estimates suggest that significant different-weekday return reversals exist and are long lasting.

4.3.4 The incongruent-mood-weekday return reversal effect

Analogous to the monthly returns, a stronger reversal effect is also observed across incongruent mood weekdays. We regress Monday (Friday) returns across stocks on their historical returns on the best-market-return (worst-market-return) weekday of the prior week, when the mood state is incongruent.

$$RET_{\text{Mon|Fri},t} = \alpha_{k,t} + \eta_{k,t} RET_{\text{Best|Worst-Weekday},t-k} + \varepsilon_t. \tag{4.8}$$

The return responses reported in Column (4) of Table 3 are negative and significant at the 5% or better for 7 out of 10 weekly lags, suggesting that the reversal effect is long lasting. Again, the economic impact of the reversal effect is similar to the other seasonal effects at the weekday level. Thus, when investor mood switches between non-congruent states in a predictable way, a strong cross-sectional return reversal is in turn predicted.

4.4. Holiday seasonal effect

For the holiday related analyses, 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/. As in other recent studies (Autore, Bergsma, and Jiang 2015; Hirshleifer, Jiang, Meng, and Peterson 2016), we define the pre-holiday window 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.[10] The post-holiday window is defined as (1, 2), the first two trading days immediately after holiday.

We verify the pre-holiday effect (Fields 1934; Aril 1990) using our sample from 1963-2015. In this period the average daily pre-holiday return is roughly 4 times that earned in other trading days. Hirshleifer, Jiang, Meng, and Peterson (2016) find that the relative pre-holiday performance across stocks tends to repeat year after year on the same holiday and to reverse immediately after the same holiday. We extend their analysis to examining the pre-holiday return persistence and post-holiday reversal effects across different holidays, assuming anticipation of holidays is associated with uplifting moods and returning from holidays are accompanied by modestly downbeat moods.

4.4.1 Pre-holiday return persistence effect

We test for the pre-holiday seasonality effect through FMB regressions. Unlike Hirshleifer, Jiang, Meng, and Peterson (2016), we use the daily pre-holiday stock return (not average daily return) as the dependent variable to be consistent with our weekday FMB regressions. Moreover, our return

[10] 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.

predictor is the pre-holiday return of the stock for the k^{th} lagged holiday to test the link across different holidays. In contrast, Hirshleifer et al. (2016) use the pre-holiday return of a stock for the same holiday during the k^{th} lagged year. Specifically, we run cross-sectional regressions of the current daily pre-holiday returns across stocks on their historical pre-holiday returns for a lagged holiday:

$$RET_{\text{Preholiday},t} = \alpha_{k,t} + \gamma_{k,t} RET_{\text{Preholiday},t-k} + \varepsilon_t, \tag{4.9}$$

where $k = 1,\ldots,13$, $RET_{\text{Preholiday},t}$ is the current logarithmic daily pre-holiday return for holiday t, and $RET_{\text{Preholiday},t-k}$ is the historical average logarithmic pre-holiday daily return for holiday $t - k$. As there are 13 holidays in a year, the reported lags cover all holidays in a year including the same holiday exactly one year ago. Therefore, the return response here captures the persistence of the relative pre-holiday returns over one year horizon across the 13 major holidays.

[INSERT TABLE 4 HERE]

In Column (1) in Table 4, we report the return responses for the 13 holiday lags ($k = 1,\ldots,13$), with 11 positive, 8 among which are significant at the 10% level or better. A one-standard-deviation (4.50%) increase in the pre-holiday return is associated with a 76 bps higher daily pre-holiday returns in the next 13 pre-holiday periods. This represents a 300% higher average return during pre-holiday periods.

As a less-noisy way to assess the long-lasting persistence effect of pre-holiday returns, we replace $RET_{\text{Preholiday},t-k}$ with the average logarithmic daily return across 13 most recent holidays as of holiday $t - k$, denoted as $\overline{RET}_{\text{Preholiday},t-k}$. As reported under Column (2) of Table 4, both the statistic and economic significance of the return responses visibly improves, with 10 out of 13 lags significantly positive at 5% level or better. A possible reason for the stronger result is that the mean pre-holiday return over an extensive historical period helps better capture the seasonal, expected return (Keloharju, Linnainmaa, and Nyberg 2015) under the congruent mood state—in this context, the pre-holiday periods.

This evidence suggests that the cross section of pre-holiday stock returns exhibit persistent relative performances across different holidays in the following twelve months. The finding extends that of Hirshleifer, Meng, Jiang, and Peterson (2016) based on the same-holiday seasonal effect and shows that stock returns across different holidays are connected by common uplifted moods.

4.4.2 Post-holiday return reversal effect

We next test for the pre-holiday return *reversal* effect in the post-holiday periods. We run cross-sectional regressions of the current daily post-holiday returns across stocks on their historical pre-holiday returns in the current or prior holidays:

$$RET_{\text{Postholiday},t} = \eta_{k,t} + \gamma_{k,t} RET_{\text{Preholiday},t-k} + \varepsilon_t, \tag{4.10}$$

where $k = 0,\ldots,13$, $RET_{\text{Postholiday},t}$ is the current logarithmic daily post-holiday return for holiday t, and $RET_{\text{Preholiday},t-k}$ is the historical average logarithmic daily return during the pre-holiday window for $t-k$. When $k = 0$, the regression tests whether pre-holiday return reverses immediately after the holiday break. When $k = 13$, the regression tests whether pre-holiday return reverses following the same holiday exactly one year ago.

We report the estimates in Column (3) in Table 4. When $k = 0$, we observe a large negative return response (–10.6, *t*-statistic = –15.5). This finding confirms that of Hirshleifer, Jiang, Meng, and Peterson (2016). This return response suggests that a one-standard-deviation increase in pre-holiday return leads to a significant 48 bps lower daily return in the immediate, post-holiday period, during which the unconditional mean daily return is only 8 bps. However, the reversal effect is short-lived and significant at the 10% level or better only for four of the first five lags. The shorter life of the reversal effect is compatible with the finding of Autore, Bergsma, and Jiang (2015) that pre-holiday returns measured over one holiday tend to reverse in the subsequent 2 to 3 weeks after the holiday. In Column (4), when we replace $RET_{\text{Preholiday},t-k}$ with $\overline{RET}_{\text{Preholiday},t-k}$, the results are stronger; 12 out of 14 return responses are negative and significant at the 10% or level, suggesting a more visible and more long-lasting reversal effect when we use the less noisy, average pre-holiday return over many recent holidays.

Taken together, the evidence in Table 4 suggests that, the relative pre-holiday performance across stocks tends to persist during the pre-holiday periods and reverse during the post-holiday periods across different holidays in a year. 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.

5. Mood Beta and Return Seasonality

The evidence in Tables 2 to 4 is consistent with our model predictions that relative stock performance tends to persist between congruent mood seasons and to reverse between incongruent mood seasons across the cycle of calendar months, days of the week, and surrounding holidays. We now move to using mood beta to integrate the various seasonality effects.

5.1 Mood beta and calendar month seasonal effect

5.1.1 January/October mood beta

To forecast calendar month seasonal returns, we estimate mood beta for each stock from regressions of a stock's January and October excess returns ($XRET_{i,\text{Jan|Oct}}$) on the contemporaneous equal-weighted aggregate market excess returns ($XRET_{A,\text{Jan|Sept}}$), using a 10-year rolling window.

$$XRET_{i,\text{Jan|Oct}} = \alpha_i + \beta_{i,\text{Jan/Oct}}^{\text{Mood}} XRET_{A,\text{Jan|Oct}} + \varepsilon_i. \tag{4.11}$$

The estimated mood beta measures the average stock return change in response to the aggregate return change in January and October, during which mood swings presumably dictate the systematic return fluctuations. In unreported tests, we use an alternative mood beta measure, defined as the ratio, $(XRET_{i,\text{Jan}} - XRET_{i,\text{Oct}})/(XRET_{A,\text{Jan}} - XRET_{A,\text{Oct}})$, and obtain similar, and sometimes slightly stronger results, than using the regression-based mood beta. The ratio-based mood beta also captures the average stock return change from October to January when the aggregate return changes from October to January. A higher mood beta under both measures indicates that a stock tends to earn higher January return and lower October returns while the market on average earns a positive January and negative October return.

In the second stage, we run Fama-MacBeth regressions of future stocks' January/October returns in the cross section on their own mood beta, estimated using prior return information ending in year $t-k$, where $k = 1,\ldots,10$. Our theory predicts that higher mood beta stocks will do better in January and worse in October. Thus, our cross-sectional regressions flip the sign of the mood beta (equivalent to flipping the sign of estimated slope coefficient) when forecasting October returns so that the estimated coefficient on mood beta is expected to be positive:

$$RET_{\text{Jan},t} = \eta_{k,t} + \lambda_{k,t}\beta_{\text{Jan/Oct},t-k}^{\text{Mood}} + \varepsilon_t, \text{ and } RET_{\text{Sept},t} = \eta_{k,t} - \lambda_{k,t}\beta_{\text{Jan/Oct},t-k}^{\text{Mood}} + \varepsilon_t. \tag{4.12}$$

We call the average slope coefficient λ_k the mood premium, which captures the absolute return spread between the high and low mood beta securities in positive or negative mood seasons. As reported in Column (1) of Table 5, Panel A, the estimated mood beta premiums are indeed all positive and significant at the 1% level for 10 annual lags. The 1st annual lag return response is 1.80 (*t*-statistic = 4.63), suggesting a change of mood beta by one standard deviation (0.88) leads to an average 141 bps return increase (decrease) in the next January (October). The mood beta premium remains relatively stable over annual lags, reducing to 1.27 (*t*-statistic = 4.08) at the 10th lag, suggesting a stable pricing effect of mood beta during these strong mood states.

The positive mood beta premium supports our theory that return seasonality is related to stocks' mood sensitivity. To explore the extent to which the calendar-month seasonal effects are explained by mood beta, we orthogonalize the historical January/October returns on mood beta. The orthogonalized historical seasonal return, denoted as $RET^{\perp}_{\text{Jan}|\text{Oct},t-k}$, may proxy for firm-specific mood sensitivity or a component that is totally unrelated to mood. Regardless, we add both mood beta and the orthogonalized historical same-month returns to the Fama-MacBeth regression as below:

$$RET_{\text{Jan},t} = \eta_{k,t} + \lambda_{k,t}\beta^{\text{Mood}}_{i,\text{Jan/Oct},t-k} + \gamma_{k,t}RET^{\perp}_{\text{Jan}|\text{Oct},t-k} + \varepsilon_t \quad , \quad \text{and}$$

$$RET_{\text{Oct},t} = \eta_{k,t} - \lambda_{k,t}\beta^{\text{Mood}}_{i,\text{Jan/Oct},t-k} + \gamma_{k,t}RET^{\perp}_{\text{Jan}|\text{Oct},t-k} + \varepsilon_t. \tag{4.13}$$

Shown in specification (2) of Table 5, after accounting the correlation with mood beta, the orthogonalized historical same-month remains positive but significant for only half of the 10 lags. The visible reduction in the predictive power of the historical seasonal return relative to that of the baseline seasonal return predictive regression (Column (1) of Table 2) suggests that mood beta captures a major and stable component of the historical seasonal returns.

To test whether mood beta explains the incongruent-month return reversal effect, we add both mood beta and the orthogonalized historical incongruent-month returns to the Fama-MacBeth regression as below:

$$RET_{\text{Jan},t} = \eta_{k,t} + \lambda_{k,t}\beta^{\text{Mood}}_{i,\text{Jan/Oct},t-k} + \gamma_{k,t}RET^{\perp}_{\text{Oct}|\text{Jan},t-k} + \varepsilon_t \quad , \quad \text{and}$$

$$RET_{\text{Oct},t} = \eta_{k,t} - \lambda_{k,t}\beta^{\text{Mood}}_{i,\text{Jan/Oct},t-k} + \gamma_{k,t}RET^{\perp}_{\text{Oct}|\text{Jan},t-k} + \varepsilon_t. \tag{4.14}$$

Shown in specification (3) of Table 5, the orthogonalized historical incongruent-month return exhibits considerably diminishing predictive power; it is significant only for the first 3 lags. The results thus suggest that a large fraction of the incongruent-month return reversal effect is explained by mood beta.

5.1.2 Best/worst-month mood beta

To explain the congruent (incongruent)-mood-month seasonal effect, we estimate mood beta for each security from regressions of returns during the best- and worst-market-return months in each year, again using a 10-year window.

$$XRET_{i,\text{Best}|\text{Worst-Month}} = \alpha_i + \beta^{\text{Mood}}_{i,\text{Best/Worst-Month}}XRET_{A,\text{Best}|\text{Worst-Month}} + \varepsilon_i. \tag{4.15}$$

Again, we obtain similar results if we define mood beta as a ratio, $(XRET_{i,\text{Best}} - XRET_{i,\text{Worst}})/(XRET_{A,\text{Best}} - XRET_{A,\text{Worst}})$.

In the second stage, we run Fama-MacBeth regressions of future stocks' January/October returns in the cross section on their own mood beta with and without the orthogonalized historical best-/worst-month in a year with lags from 1 to 10. As in regressions (4.12), we add a negative sign in front of the slope coefficient of mood beta for October regressions so that the slope coefficient (mood beta premium) measures the absolute return spread between high and low mood beta stocks.

Shown in Columns (1) and (2) of Table 5, Panel B, the mood premium is positive and significant for all 10 lags, ranging from 1.94% to 2.62%, considerably bigger than that estimated using the January/October mood beta, suggesting a stronger mood beta effect. More importantly, the orthogonalized historical same-month return loses its predictive power for a majority of lags. The findings suggest that most of the same-mood-month return persistence effect is explained by mood beta.

The estimates in Specification (3) of Panel B show that the orthogonalized historical incongruent-mood-month return becomes insignificant for all but the first three lags, suggesting the long-lived incongruent-mood-month reversal effect is mainly attributed to a security's mood beta. Overall, the results show that mood beta accounts for a majority, if not all, of the month level persistence and reversal return seasonalities.

5.2 Mood beta and weekday seasonal effect

5.2.1 Monday/Friday mood beta

Moving to weekday seasonality, we estimate mood beta for each security from regressions of a stock's Monday and Friday excess returns on the corresponding equal-weighted market excess returns using a 6-month rolling window, for which we have verified earlier that the same-weekday persistence effect is present.

$$XRET_{i,\mathrm{Mon|Fri}} = \alpha_i + \beta_{i,\mathrm{Mon/Fri}}^{\mathrm{Mood}} XRET_{A,\mathrm{Mon|Fri}} + \varepsilon_i. \tag{4.16}$$

We obtain somewhat stronger results if we define mood beta as a ratio, $(XRET_{i,\mathrm{Fri}} - XRET_{i,\mathrm{Mon}})/(XRET_{A,\mathrm{Fri}} - XRET_{A,\mathrm{Mon}})$.

We next use the Monday/Friday mood beta to forecast future Monday/Friday returns with and without the historical orthogonalized same-weekday returns. As reported in Columns (1) and (2) of Table 6, Panel A, the estimated mood beta premium is positive and significant at the 1% for all 10 lags, with the size of the premium remains mostly unchanged at 4 bps per day. The estimated return response on the historical orthogonalized same-weekday return is positive and significant for all but the 1st lag.

Similar patterns are observed under Column (3), where we test whether the incongruent-weekday reversal effect is accounted by mood beta. Here we observe that the mood beta is significantly positive for all lags and the historical orthogonalized incongruent-weekday return is negative and significant for 7 out of 10 lags. The results suggest that mood beta can only partially explain the congruent-weekday return persistence and incongruent-weekday return reversal effects.

5.2.2 Best/worst weekday mood beta

At the daily frequency, we also estimate each stock's mood beta from time-series regressions of the best-/worst-weekday returns using a 6-month rolling window.

$$XRET_{i,\mathrm{Best|Worst-Weekday}} = \alpha_i + \beta^{Mood}_{i,\mathrm{Best/Worst-Weekday}} XRET_{\mathrm{mkt,Best|Worst-Weekday}} + \varepsilon_i. \quad (4.16)$$

Again, we conduct Fama-MacBeth regressions using the mood beta to forecast future Monday and Friday returns. Shown in Table 6, Panel B, the mood beta premium is significantly positive, at 5 bps per day, for all 10 lags, both with and without the orthogonalized historical seasonal returns. In contrast, the orthogonalized historical seasonal returns on the best-/worst-market return weekday carries mostly insignificant coefficient in explaining the congruent-(incongruent-)mood-weekday persistence (reversal) effect. The evidence suggests that mood beta is largely responsible for the congruent-mood-state return persistence and incongruent -mood-state return reversal effects.

5.3 Mood beta and the holiday seasonality effect

To explain the holiday seasonality effect, we estimate each stock's mood beta from time-series regressions of the pre-holiday returns using a 12-month rolling window.

$$XRET_{i,\mathrm{preholiday}} = \alpha_i + \beta^{\mathrm{Mood}}_{i,\mathrm{Preholiday}} XRET_{m,\mathrm{Preholiday}} + \varepsilon_i. \quad (4.17)$$

We use only pre-holiday returns to estimate mood beta as our results in Table 4 suggest that the reversal effect in the post-holiday periods is present only for a few immediately subsequent holidays. Thus, using post-holiday returns across all holidays likely reduce the accuracy of mood beta estimates. In unreported tests, we find that the ratio-based mood beta measure, defined as $(XRET_{i,\mathrm{Preholiday}} - XRET_{i,\mathrm{Postholiday}})/(XRET_{A,\mathrm{Preholiday}} - XRET_{A,\mathrm{Postholiday}})$, exhibit weaker power to predict both the pre- and post-holiday cross-sectional returns. This may also due to the fact that post-holiday periods do not represent strong negative mood states.

Then we use the pre-holiday mood beta estimated in equation (4.17) to forecast the pre- and post-holiday returns in the cross section. Again, as we flip the sign of the mood beta coefficient when forecasting the post-holiday returns, the estimate mood beta premium is the absolute return spread between the high-minus-low (low-minus-high) mood beta stocks during the pre-(post-)holiday period. We also use the mood beta to explain the pre-holiday return persistence and post-holiday return reversal effect.

Shown in Table 7, we find a positive mood beta premium significant at the 5% or better for all 13 holiday lags when mood beta is the pre-holiday return predictor, with and without adding the orthogonalized historical pre-holiday return (specifications (1) and (2)). The mood beta premium becomes insignificant during the post-holiday period (specification (3)), suggesting that mood beta does not capture the post-holiday return reversal as good as the historical pre-holiday returns, as presented in Table 4.

The orthogonalized historical pre-holiday return is significantly positive for 7 out of 13 lags when forecasting the pre-holiday return, and significantly negative for k = 0, 1, 2, and 4, similar to the pattern observed for the original historical pre-holiday return reported in Columns (1) and (3) of Table 4. This evidence suggests that the both the pre-holiday return persistence and post-holiday return reversal effect based on historical pre-holiday returns are relatively robust with the inclusion of mood beta. However, mood beta only accounts for the pre-holiday return persistence, not the post-holiday return reversal, effect. Again, this is likely due to the short-lived post-holiday reversal effect for pre-holiday returns measured over holiday by holiday.

6. Robustness

6.1 Controls for firm characteristics and factor risks

Our results so far suggest that there exists predictable seasonal return persistence and reversal effects across mood seasons identified using months, weekdays, and holidays. And these seasonal effects can be at least partially, and sometimes fully, accounted for by a security's mood beta. In this section we want to ascertain that these results do not simply reflect return seasonality associated with firm characteristics or factor risk premium.

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 seasonal stock returns.

Our mood-based hypothesis offers a similar prediction, albeit through a different channel: mood shocks cause investor misperceptions about common factor signals, resulting in periodic factor mispricing, which may create seemingly seasonal patterns in factor risk premiums, or in the characteristics-return relationship when characteristics correlate with mood sensitivity. Nevertheless, if observable firm characteristics do not fully capture the return sensitivity with respect to the mood influence on common factors, historical seasonal returns or mood beta will continue to forecast future pre-holiday returns. Thus, the multivariate regressions can at least reveal whether historical seasonal returns or mood beta is a new predictor of future seasonal returns in the cross section, incremental to known firm attributes.

We control the effect of firm characteristics by replacing both of the dependent and independent variables in the forecasting regressions in Tables 2-4 with the characteristics-adjusted, as opposed to raw, returns. Specifically, for each month or day, we run a first-pass cross-sectional regression of stock returns on logarithmic firm size (logME), logarithmic book-to-market equity (logB/M), short-, intermediate-, and long-horizon past returns (RET(–1), RET(–12, –2), RET(–36, –13)), leverage (LEV), asset growth (AG), accruals (ACC), the investment-to-asset ratio (IVA), external financing (EXFIN), and net operating assets (NOA), all defined in the Appendix A. We retain the residuals from each cross-sectional regressions as the characteristics-adjusted returns.

Then we run second-pass Fama-MacBeth regressions of the characteristics-adjusted seasonal returns (e.g., January/October, Monday/Friday, pre-/post-holiday) on historical characteristics-adjusted seasonal returns as in Tables 2, 3, and 4. For brevity, we report the estimates with the year, week, and holiday lag 1, lags 2-5, and lags 6-10. The estimates for the multiple lags are obtained by regressing the dependent variable on the average independent variables across the designated lags (e.g., Heston and Sadka 2008).

As shown in Table 8, the seasonality effects largely survive when we examine the characteristics-adjusted returns. Historical returns remain positive (negative) and mostly significant when forecasting future congruent (incongruent) seasonal returns. The significance across different lags for various seasonal effects is similar to that obtained using raw returns. Thus, return seasonality associated with firm characteristics do not fully account for the documented return persistence and reversal effects.

As a second test, we control for the effect of risk premium by replacing raw seasonal returns in the Fama-MacBeth regressions with risk-adjusted returns. The risk-adjusted monthly or daily return is the excess return of a stock minus the predicted return based on the Fama-French-Carhart four-factor model. Factor loadings are estimated using a rolling 12-month window of daily stock returns regressed on the four factor returns up to the most recent month. The loadings are updated monthly. As presented in Table 9, our main results related to the seasonal return persistence and reversal effects largely survives by using the risk-adjusted stock returns. Thus, risk premiums are not sufficient to explain our findings.

6.1 Controls for market beta and sentiment beta

Another possible concern is whether our mood beta simply proxy for market beta. If individual stocks comove with the market in any day or month, a randomly selected set of days or months will reproduce the market beta. On the surface, this concern is not warranted as rational pricing models predict no negative market premium in a pre-designated month (e.g., October) or day (e.g., Monday). Nevertheless, we reassure the concern by controlling for market beta in our regressions with mood beta, where market beta is estimated by regressing the daily returns of a stock on the value-weighted CRSP index over the most recent 12 months.

Another possible concern is that the mood beta may be another proxy for sentiment beta. Investor sentiment usually refers to collective variation in mistaken beliefs or imperfectly rational preferences (Baker and Wurgler 2016, 2017). Mood is a more specific hypothesis, since it focuses on variations due to investor affective states. Also, mood can vary at a high frequency (daily or even hourly), whereas sentiment is usually viewed as relating to attitudes that shift more slowly (see, e.g., Cronqvist and Jiang 2016). To show the incremental explanatory power of mood beta, we include sentiment beta in the regression, where sentiment beta is estimated using the most recent 60 (at least 36) monthly return regressed on the CRSP value-weighted index return and the Baker and Wurgler (2006) sentiment index.

Thus, our regressions use mood beta, market beta, and sentiment beta to forecast future January/October, Monday/Friday, Pre-/Post-holiday returns in the cross section. Our estimates reported in Table 10 (Panels A, B, and C) indicate that, across all specifications and lags, the mood beta premium remains significant, except for forecasting the post-holiday returns, in the presence of market beta and sentiment beta. In contrast, market beta tends to carry no or significantly negative premium, in contrast to theory prediction. Sentiment beta tends to exhibit insignificant forecast power. Thus, neither market beta nor sentiment beta subsumes the power of mood beta.

7. Conclusion

It has long been known that stock markets exhibit strong aggregate seasonality. There is much less knowledge about return seasonality in the cross section, and even less about the causes of such seasonal effects. We hypothesize that investor mood seasonal variations are in part responsible for both aggregate and cross-sectional return seasonalities. In our model, investor optimism or pessimism is induced by predictable positive or negative mood seasonal swings. Such optimism or pessimism causes factor-wide and firm-specific mispricing. Individual stocks inherit this mispricing according to their sensitivities to the mood shocks (mood betas). This links aggregate and cross-sectional mispricing, and links the cross-sectional performances of stocks during congruent and incongruent mood seasons.

Consistent with the mood-based theory, we document a variety of strong, novel cross-sectional return seasonalities across calendar months, weekdays, and holidays. Stocks that outperform in the past seasons when investors are in upbeat moods tend to outperform in future seasons when an upbeat mood is expected, and to underperform in future seasons when an downbeat mood is expected. Furthermore, mood beta, which measures a security's mood sensitivity to factor-wide mispricing as estimated during strong mood seasons, helps to account for a substantial part of seasonal return persistence and reversal effects.

These cross-sectional return persistence and reversal effects are hard to reconcile with a risk-based story. In such a story, 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. This does not seem very plausible, especially at the daily frequency or in relation to holidays. So theories based upon seasonal variation in factor risk premiums (as in Keloharju, Linnainmaa, and Nyberg (2015)) seem unlikely to fully explain our findings. Overall, our evidence suggests that investor mood is an important contributor to stock return seasonalities.

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Appendix A: Variable Definition

Variables	**Definitions**
$RET_{Best\text{-}month}$	A stock's return in the highest market return month of a year, where the highest market return month is identified using CRSP equal-weighted total market index.
$RET_{Worst\text{-}month}$	A stock's return in the lowest market return month of a year, where the highest market return month is identified using CRSP equal-weighted total market index.
$RET_{Best\text{-}weekday}$	A stock's return in the highest market return day of a week, where the highest market return week is identified using CRSP equal-weighted total market index.
$RET_{Worst\text{-}weekday}$	A stock's return in the lowest market return day of a week, where the highest market return week is identified using CRSP equal-weighted total market index.
$RET_{Preholiday}$	Pre-holiday return for a holiday, defined as the average daily logarithmic return of a stock during a given pre-holiday window in a given year. 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.
$\overline{RET}_{Preholiday}$	Pre-holiday return over 13 holidays, defined as the average daily logarithmic return of a stock across a rolling window of 13 most recent pre-holiday window. 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.
$RET_{Postholiday}$	Post-holiday return, defined as the daily logarithmic return of a given stock during the post-holiday window for a given holiday. The post-holiday window refers to the (0, 2) trading day window, where day 0 is the holiday.
$\beta^{Mood}_{Jan/Oct}$	Mood beta that is estimated using January and October monthly returns over a 10-year rolling window from a market model, updated annually.
$\beta^{Mood}_{Best/Worst\text{-}month}$	Mood beta that is estimated using a stock's returns in the best- and worst-market-return months of a year over a 10-year rolling window from a market model, updated annually.
$\beta^{Mood}_{Mon/Fri}$	Mood beta that is estimated using Monday and Friday returns over a 6-month rolling window from a market model, updated monthly.

$\beta^{Mood}{}_{Best/Worst\text{-}weekday}$	Mood beta that is estimated using a stock's returns in the best- and worst-market-return days of a week over a 6-month rolling window from a market model, updated monthly.
$\beta^{Mood}{}_{Preholiday}$	Mood beta that is estimated using pre-holiday daily returns over a 12-month (13-holiday) rolling window from a market model, updated monthly.
$\beta^{MKT}{}_{Month}$	Market beta that is estimated using monthly returns over a 10-year rolling window from a market model, updated annually.
$\beta^{MKT}{}_{Day}$	Market beta that is estimated using daily returns over a 6-month rolling window from a market model, updated monthly.
β^{SENT}	Sentiment beta that is estimated from regressions of monthly returns over a 60-month rolling window on the Baker and Wugler (2007) orthogonalized sentiment index and the CRSP value-weighted returns, updated monthly.
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.
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.

Table 1: Summary Statistics

This table reports the summary statistics of the main variables. The analysis includes common stocks traded on the NYSE, AMEX, or NASDAQ. All returns are in percentages. The sample period is from January 1, 1963 to December 31, 2015.

Variables	Mean	Median	Standard Deviation	10% Percentile	25% Percentile	75% Percentile	90% Percentile
RET_{Jan}	5.84	2.25	23.14	–12.39	–4.65	11.75	26.09
RET_{Oct}	–0.61	–0.29	18.31	–19.98	–8.80	6.70	16.84
$RET_{Best–month}$	5.84	2.25	23.14	–12.39	–4.65	11.75	26.09
$RET_{Worst–month}$	–0.61	–0.29	18.31	–19.98	–8.80	6.70	16.84
RET_{Mon}	–0.09	0.00	4.58	–3.79	–1.44	1.04	3.39
RET_{Fri}	0.22	0.00	4.46	–3.19	–1.10	1.23	3.66
$RET_{Best–weekday}$	–0.09	0.00	4.58	–3.79	–1.44	1.04	3.39
$RET_{Worst–weekday}$	0.22	0.00	4.46	–3.19	–1.10	1.23	3.66
$RET_{Preholiday}$	0.24	0.00	4.50	–3.17	–1.06	1.25	3.70
$RET_{Postholiday}$	0.08	0.00	4.66	–3.50	–1.27	1.17	3.57
$\beta^{Mood}{}_{Jan/Oct}$	1.00	0.88	1.08	0.07	0.45	1.37	2.00
$\beta^{Mood}{}_{Best/Worst–month}$	1.02	0.92	0.75	0.29	0.56	1.34	1.83
$\beta^{Mood}{}_{Mon/Fri}$	1.05	0.95	1.29	–0.10	0.36	1.63	2.42
$\beta^{Mood}{}_{Best/Worst–weekday}$	1.05	0.96	1.12	–0.01	0.39	1.60	2.31
$\beta^{Mood}{}_{Preholiday}$	1.05	0.91	2.02	–0.49	0.20	1.75	2.83
$\beta^{MKT}{}_{Month}$	1.09	1.03	0.65	0.34	0.65	1.44	1.88
$\beta^{MKT}{}_{Day}$	0.74	0.66	0.78	–0.04	0.24	1.17	1.69
β^{SENT}	0.00	0.00	0.06	–0.06	–0.02	0.02	0.05
Log(ME)	4.46	4.27	2.15	1.83	2.89	5.88	7.36
Log(B/M)	–0.42	–0.32	0.95	–1.62	–0.94	0.21	0.67
LEV	1.32	0.07	3.71	0.01	0.01	0.89	3.09
AG	–0.09	–0.18	0.66	–0.50	–0.50	0.10	0.33
ACC	–0.33	–0.53	0.31	–0.53	–0.53	–0.07	0.03
NOA	0.24	–0.16	0.51	–0.16	–0.16	0.68	0.88
IVA	–0.14	–0.39	0.30	–0.39	–0.39	0.06	0.19
EXFIN	–0.13	–0.27	0.25	–0.27	–0.27	–0.01	0.08
RET(–1)	0.01	0.00	0.18	–0.15	–0.06	0.07	0.17
RET(–12, –2)	0.14	0.06	0.70	–0.45	–0.20	0.33	0.71
RET(–36, –13)	0.35	0.15	1.21	–0.54	–0.22	0.61	1.28

Table 2: Monthly Cross-Sectional Return Persistence and Reversal Effects

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 a 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 worst-market-return (best-market-return) month of a 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-MacBeth t-statistics are corrected for heteroscedasticity and autocorrelation using Newey and West (1987). 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, 2015.

	Congruent Month Return Persistence		Incongruent Month Return Reversal	
Dependent Variable	$RET_{Jan/Oct,\ t}$		$RET_{Jan/Oct,\ t}$	
Independent Variable	$RET_{Jan/Oct\ t-k}$	$RET_{Best/Worst\text{-}month,\ t-k}$	$RET_{Jan/Oct\ t-k}$	$RET_{Best/Worst\text{-}month,\ t-k}$
Year Lag (k)	(1)	(2)	(3)	(4)
1	5.05***	4.06***	–4.29***	–5.00***
	(5.01)	(3.56)	(–4.02)	(–3.72)
2	3.48***	4.28***	–4.74***	–5.92***
	(4.79)	(4.20)	(–4.33)	(–5.07)
3	3.20***	3.01***	–3.32***	–5.23***
	(3.64)	(2.72)	(–2.83)	(–4.20)
4	4.04***	3.91***	–2.57***	–3.90***
	(4.27)	(3.34)	(–2.65)	(–3.12)
5	2.50***	3.99***	–1.66	–4.72***
	(2.82)	(2.97)	(–1.41)	(–3.79)
6	2.26**	4.57***	–1.41	–3.41***
	(2.43)	(4.08)	(–1.52)	(–3.13)
7	2.67**	5.29***	–1.87**	–2.43**
	(2.02)	(5.18)	(–2.23)	(–2.05)
8	2.32**	4.63***	–0.19	–3.32***
	(2.22)	(3.59)	(–0.17)	(–2.88)
9	2.87***	4.12***	–1.46	–2.40*
	(2.68)	(3.68)	(–1.20)	(–1.94)
10	2.68***	2.52**	–1.09	–2.71***
	(3.00)	(2.32)	(–0.94)	(–2.70)

Table 3: Weekday Cross-Sectional Return Persistence and Reversal Effects

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 worst-market-return (best-market-return) day of a 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-MacBeth t-statistics are corrected for heteroscedasticity and autocorrelation using Newey and West (1987). 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, 2015.

	Congruent Weekday Return Persistence		Incongruent Weekday Return Reversal	
Dependent Variable	$\mathrm{RET}_{\mathrm{Mon/Fri},\,t}$		$\mathrm{RET}_{\mathrm{Mon/Fri},\,t}$	
Independent Variable	$\mathrm{RET}_{\mathrm{Mon/Fri},\,t-k}$	$\mathrm{RET}_{\mathrm{Worst/Best\text{-}weekday},\,t-k}$	$\mathrm{RET}_{\mathrm{Fri/Mon},\,t-k}$	$\mathrm{RET}_{\mathrm{Best/Worst\text{-}weekday},\,t-k}$
Week Lag (k)	(1)	(2)	(3)	(4)
1	–0.02	–0.69***	–5.11***	–1.96***
	(–0.27)	(–7.42)	(–31.0)	(–17.0)
2	0.22***	0.10	–0.64***	–0.43***
	(3.10)	(1.34)	(–9.14)	(–5.81)
3	0.36***	0.07	–0.35***	–0.25***
	(4.89)	(0.94)	(–5.03)	(–3.45)
4	0.34***	0.26***	–0.24***	–0.21***
	(4.96)	(3.69)	(–3.41)	(–3.03)
5	0.20***	0.18***	–0.15**	–0.19***
	(3.16)	(2.58)	(–2.40)	(–2.92)
6	0.21***	0.21***	–0.13**	–0.12*
	(3.30)	(3.12)	(–2.05)	(–1.80)
7	0.17***	0.13**	–0.16**	–0.26***
	(2.63)	(1.97)	(–2.44)	(–3.79)
8	0.35***	0.26***	–0.11*	–0.08
	(5.29)	(3.90)	(–1.73)	(–1.25)
9	0.28***	0.16**	–0.07	–0.12*
	(4.33)	(2.38)	(–1.04)	(–1.78)
10	0.23***	0.17***	–0.22***	–0.17***
	(3.63)	(2.66)	(–3.54)	(–2.64)

Table 4: Holiday 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 pre-holiday return persistence and reversal effects in the cross section. For the return persistence effect, we regress daily pre-holiday returns across stocks on their own past average daily pre-holiday return in the pre-holiday period for holiday $t-k$, denoted as $\mathrm{RET}_{\mathrm{Preholiday},\, t-k}$, or across the most recent 13 holidays as of holiday $t-k$, denoted as $\overline{\mathrm{RET}}_{\mathrm{Preholiday},\, t-k}$, and report the time series average of the return responses in column (1). For the return reversal effect, we regress daily post-holiday returns across stocks on their own past average daily pre-holiday return in the current or prior pre-holiday periods and report the time series average of the return responses in column (2). The reported Fama-MacBeth t-statistics are corrected for heteroscedasticity and autocorrelation using Newey and West (1987). 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, 2015.

Dependent Variable	$\mathrm{RET}_{\mathrm{Preholiday},\, t}$		$\mathrm{RET}_{\mathrm{Postholiday}}$	
Independent Variable	$\mathrm{RET}_{\mathrm{Preholiday},\, t-k}$	$\overline{\mathrm{RET}}_{\mathrm{Preholiday},\, t-k}$	$\mathrm{RET}_{\mathrm{Preholiday},\, t-k}$	$\overline{\mathrm{RET}}_{\mathrm{Preholiday},\, t-k}$
Holiday Lag (k)	(1)	(1)	(2)	(2)
0			–10.6***	–13.3***
			(–15.5)	(–13.1)
1	–0.86***	2.16***	–0.76***	–2.45***
	(–4.64)	(3.60)	(–3.48)	(–3.18)
2	0.26*	3.14***	–0.40*	–1.55**
	(1.74)	(5.23)	(–1.96)	(–2.18)
3	0.34**	2.95***	–0.24	–1.15*
	(2.19)	(5.16)	(–1.13)	(–1.66)
4	0.47***	2.69***	–0.60***	–1.21
	(3.07)	(4.93)	(–3.04)	(–1.64)
5	0.39***	2.37***	0.12	–0.79
	(2.95)	(4.42)	(0.63)	(–1.12)
6	0.13	1.94***	–0.01	–1.21*
	(0.95)	(3.66)	(–0.05)	(–1.78)
7	0.43***	1.70***	–0.25	–1.53**
	(3.64)	(3.45)	(–1.36)	(–2.29)
8	0.28*	1.37***	0.08	–1.28*
	(1.94)	(2.73)	(0.48)	(–1.92)
9	0.24*	1.09**	–0.04	–1.48**
	(1.74)	(2.19)	(–0.21)	(–2.28)
10	–0.01	0.91*	–0.33*	–1.67**
	(–0.08)	(1.88)	(–1.65)	(–2.56)
11	0.05	1.03**	–0.03	–1.73***
	(0.39)	(1.99)	(–0.19)	(–2.75)
12	0.05	0.69	0.22	–1.82***
	(0.32)	(1.39)	(1.18)	(–2.87)
13	0.43***	0.80*	–0.15	–2.60***
	(2.71)	(1.66)	(–0.86)	(–4.23)

Table 5: Monthly Mood Beta as a Predictor in the Cross Section of Monthly Returns

This table examines the predictive power of monthly mood beta to forecast future seasonal monthly returns in Fama-MacBeth regressions. The monthly mood beta ($\beta^{Mood}{}_{Jan/Sept,\, t-k}$) is the coefficient estimate by regressing a stock's January and October excess return on the contemporaneous equal-weighted market excess return from a 10-year rolling window as of year $t-k$, updated year by year. $\beta^{Mood}{}_{Best/Worst\text{-}Month,\, t-k}$ uses a stock's best/worst month returns to estimate instead. In Panel A, we test for the congruent-month persistence effect and incongruent month reversal effect using $\beta^{Mood}{}_{Jan/Sept,\, t-k}$. Under column (1), when forecasting future January returns, the independent variable is the stock's historical mood beta ($\beta^{Mood}{}_{Jan/Sept,\, t-k}$), and when forecasting future October returns, it is $-\beta^{Mood}{}_{Jan/Sept,\, t-k}$. Column (2) adds to column (1) another independent variable, the residual historical congruent-month return ($RET^{\perp}{}_{Jan/Sept,\, t-k}$), which is orthogolized to the mood beta used in the same regression. Column (3) replaces the independent variables for the January regressions with those for the October regressions and vice versa. Panel B replaces $\beta^{Mood}{}_{Jan/Sept,\, t-k}$ with $\beta^{Mood}{}_{Best/Worst\text{-}Month,\, t-k}$ to test for the congruent-mood persistence effect and incongruent-mood persistence effect. The reported Fama-MacBeth t-statistics are corrected for heteroscedasticity and autocorrelation using Newey and West (1987). 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, 2015.

Panel A	Month Beta	Congruent Month Return Persistence		Incongruent Month Return Reversal	
Dependent Variable	$RET_{Jan/Oct,\, t}$				
Independent Variable	$\pm\beta^{Mood}{}_{Jan/Oct,\, t-k}$	$\pm\beta^{Mood}{}_{Jan/Oct,\, t-k}$	$RET^{\perp}{}_{Jan/Oct,\, t-k}$	$\pm\beta^{Mood}{}_{Jan/Oct,\, t-k}$	$RET^{\perp}{}_{Oct/\, Jan,\, t-k}$
Year Lag	(1)	(2)		(3)	
1	1.80***	1.97***	3.59***	1.92***	–3.03***
	(4.63)	(4.80)	(4.60)	(4.80)	(–3.81)
2	1.68***	1.82***	2.11***	1.80***	–3.58***
	(4.67)	(4.35)	(3.44)	(4.38)	(–4.39)
3	1.64***	1.79***	2.20***	1.81***	–2.14***
	(4.37)	(4.51)	(3.27)	(4.49)	(–2.68)
4	1.64***	1.68***	3.47***	1.64***	–1.38*
	(4.39)	(4.57)	(4.53)	(4.58)	(–1.80)
5	1.61***	1.60***	1.17	1.71***	–0.54
	(4.59)	(4.21)	(1.32)	(4.24)	(–0.59)
6	1.54***	1.59***	1.68**	1.53***	–0.64
	(4.73)	(4.21)	(2.46)	(4.07)	(–0.84)
7	1.45***	1.57***	1.81*	1.44***	–0.59
	(4.66)	(3.72)	(1.77)	(3.51)	(–0.78)
8	1.45***	1.68***	0.92	1.60***	0.21
	(4.51)	(3.73)	(1.18)	(3.61)	(0.26)
9	1.40***	1.67***	1.55*	1.67***	–0.66
	(4.51)	(3.56)	(1.74)	(3.61)	(–0.76)
10	1.27***	1.49***	1.23	1.47***	–0.93
	(4.08)	(3.01)	(1.66)	(2.98)	(–0.92)

Panel B	Mood Beta	Congruent Mood Month Return Persistence		Incongruent Mood Month Return Reversal	
Dependent Variable	$RET_{Jan/Oct,\,t}$				
Independent Variable	$\pm\beta^{Mood}{}_{Best/Worst\text{-}Month,\ t-k}$	$\pm\beta^{Mood}{}_{Best/Worst\text{-}month,\ t-k}$	$RET^{\perp}{}_{Best/Worst\text{-}month,\ t-k}$	$\pm^{Mood}{}_{Best/Worst\text{-}month,\ t-k}$	$RET^{\perp}{}_{Worst/Best\text{-}month,\ t-k}$
Year Lag	(1)	(2)		(3)	
1	2.58***	2.59***	0.87	2.69***	–2.05**
	(4.80)	(4.80)	(1.27)	(4.66)	(–2.47)
2	2.58***	2.58***	0.71	2.64***	–2.51***
	(4.88)	(4.86)	(1.16)	(4.64)	(–4.30)
3	2.61***	2.62***	-0.23	2.54***	–2.05***
	(5.06)	(5.05)	(-0.31)	(4.76)	(–2.82)
4	2.56***	2.56***	0.83	2.45***	–1.04
	(5.09)	(5.12)	(1.05)	(4.53)	(–1.11)
5	2.53***	2.53***	0.83	2.56***	–1.14
	(5.21)	(5.18)	(1.03)	(4.97)	(–1.60)
6	2.53***	2.53***	1.40**	2.38***	–0.40
	(5.54)	(5.53)	(2.31)	(5.17)	(–0.59)
7	2.31***	2.30***	2.58***	2.14***	0.42
	(4.67)	(4.66)	(3.86)	(4.56)	(0.43)
8	2.28***	2.27***	1.58*	2.07***	–1.07
	(4.85)	(4.81)	(1.98)	(4.55)	(–1.07)
9	2.13***	2.13***	1.14*	2.15***	0.13
	(4.90)	(4.87)	(1.73)	(4.70)	(0.15)
10	1.97***	1.94***	-0.44	1.96***	0.45
	(4.79)	(4.71)	(-0.44)	(4.60)	(0.44)

Table 6: Weekly Mood Beta as a Predictor in the Cross Section of Weekday Returns

This table examines the predictive power of weekly mood beta to forecast future seasonal weekday returns. The weekly mood beta ($\beta^{Mood}{}_{Mon/Fri,\, t-k}$) is the coefficient estimate by regressing a stock's Monday and Friday excess return regress on the contemporaneous market excess return from a 6-month rolling window, updated month by month. $\beta^{Mood}{}_{Best/Worst\text{-}Weekday,\, t-k}$ uses a stock's best/worst weekday returns to estimate instead. In Panel A, we test for the congruent weekday persistence effect and incongruent weekday reversal effect using $\beta^{Mood}{}_{Mon/Fri,\, t-k}$. Under column (1), when forecasting future Friday returns, the independent variable is the stock's historical mood beta ($\beta^{Mood}{}_{Mon/Fri,\, t-k}$), and when forecasting future Monday returns, it is $-\beta^{Mood}{}_{Mon/Fri,\, t-k}$. Column (2) adds to column (1) another independent variable, the residual historical congruent-weekday return ($RET^{\perp}{}_{Mon/Fri,\, t-k}$), which is orthogolized to the mood beta used in the same regression. Column (3) replaces the independent variables for the Monday regressions with those for the Friday regressions and vice versa. Panel B replaces $\beta^{Mood}{}_{Mon/Fri,\, t-k}$ with $\beta^{Mood}{}_{Best/Worst\text{-}Weekday,\, t-k}$ to test for the congruent-mood-weekday persistence effect and incongruent-mood-weekday persistence effect. The reported Fama-MacBeth *t*-statistics are corrected for heteroscedasticity and autocorrelation using Newey and West (1987). 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, 2015.

Panel A	Mood Beta	Congruent Weekday Return Persistence		Incongruent Weekday Return Reversal	
Dependent Variable	$RET_{Mon/Fri,\, t}$				
Independent Variable	$\mp\beta^{Mood}{}_{Mon/Fri,\, t-k}$	$\mp\beta^{Mood}{}_{Mon/Fri,\, t-k}$	$RET^{\perp}{}_{Mon/Fri,\, t-k}$	$\mp\beta^{Mood}{}_{Mon/Fri,\, t-k}$	$RET^{\perp}{}_{Fri/Mon,\, t-k}$
Week Lag	(1)	(2)		(3)	
1	0.05***	0.05***	–0.07	0.05***	–5.17***
	(6.75)	(6.76)	(–1.03)	(6.80)	(–32.0)
2	0.04***	0.04***	0.18***	0.04***	–0.58***
	(6.08)	(6.06)	(2.77)	(6.75)	(–8.90)
3	0.04***	0.04***	0.34***	0.04***	–0.32***
	(5.88)	(5.87)	(4.93)	(6.14)	(–5.23)
4	0.04***	0.04***	0.27***	0.04***	–0.19***
	(6.03)	(6.02)	(4.56)	(6.40)	(–2.97)
5	0.04***	0.04***	0.15**	0.04***	–0.10*
	(6.75)	(6.74)	(2.57)	(6.28)	(–1.79)
6	0.04***	0.04***	0.17***	0.05***	–0.09
	(6.96)	(6.94)	(2.94)	(7.58)	(–1.47)
7	0.04***	0.04***	0.15***	0.04***	–0.14**
	(6.19)	(6.17)	(2.69)	(6.81)	(–2.35)
8	0.04***	0.04***	0.31***	0.04***	–0.09*
	(5.91)	(5.91)	(5.10)	(6.66)	(–1.65)

9	0.04***	0.04***	0.22***	0.04***	–0.06
	(6.70)	(6.68)	(3.78)	(6.46)	(–0.92)
10	0.04***	0.04***	0.19***	0.04***	–0.19***
	(6.50)	(6.49)	(3.31)	(6.99)	(–3.45)
Panel B	Mood Beta	Congruent Mood Weekday Return Persistence		Incongruent Mood Weekday Return Reversal	
Dependent Variable	$RET_{Mon/Fri,\ t}$				
Independent Variable	$\mp\beta^{Mood}_{Best/Worst\text{-}weekday,\ t-k}$	$\mp\beta^{Mood}_{Best/Worst\text{-}weekday,\ t-k}$	$RET^{\perp}_{Worst/Best\text{-}weekday,\ t-k}$	$\mp\beta^{Mood}_{Best/Worst\text{-}weekday,\ t-k}$	$RET^{\perp}_{Best/Worst\text{-}weekday,\ t-k}$
Week Lag	(1)	(2)		(3)	
1	0.05***	0.05***	–0.89***	0.05***	–1.88***
	(5.93)	(5.96)	(–10.8)	(6.59)	(–17.4)
2	0.05***	0.05***	–0.04	0.05***	–0.33***
	(6.08)	(6.06)	(–0.58)	(6.05)	(–5.37)
3	0.05***	0.05***	–0.03	0.05***	–0.13**
	(6.17)	(6.15)	(–0.56)	(6.23)	(–2.15)
4	0.05***	0.05***	0.09	0.05***	–0.09*
	(6.13)	(6.11)	(1.57)	(6.10)	(–1.65)
5	0.05***	0.05***	0.05	0.05***	–0.07
	(6.21)	(6.19)	(0.89)	(6.17)	(–1.30)
6	0.05***	0.05***	0.10*	0.05***	–0.01
	(6.41)	(6.40)	(1.74)	(6.38)	(–0.26)
7	0.05***	0.05***	0.03	0.05***	–0.12**
	(6.53)	(6.51)	(0.61)	(6.54)	(–2.17)
8	0.05***	0.05***	0.12**	0.05***	0.02
	(6.51)	(6.52)	(2.11)	(6.52)	(0.38)
9	0.05***	0.05***	0.01	0.05***	0.00
	(6.54)	(6.54)	(0.14)	(6.63)	(0.08)
10	0.05***	0.05***	0.06	0.05***	–0.06
	(6.57)	(6.58)	(1.04)	(6.61)	(–1.07)

Table 7: Pre-holiday Mood Beta as a Predictor in the Cross Section of Pre-/Post-holiday Returns

This table examines the predictive power of pre-holiday mood beta to forecast future pre-holiday and post-holiday returns in the cross section. Columns (1) and (2) are estimates of forecasting pre-holiday returns and Column (3) and (4) are estimates of forecasting post-holiday returns. The pre-holiday mood beta ($\beta^{Mood}_{Preholiday,\ t-k}$) is the coefficient estimate by regressing a stock's daily pre-holiday excess return on the contemporaneous market excess return from a 12-month rolling window as of holiday $t-k$, updated month by month. Column (1) uses $\beta^{Mood}_{Preholiday,\ t-k}$ as the only independent variable and column (2) adds the orthogonalized historical pre-holiday return for holiday $t-k$ ($RET^{\perp}_{Preholiday,\ t-k}$). Columns (3) uses $-\beta^{Mood}_{Preholiday,\ t-k}$ as the only independent variable and column (4) adds $RET^{\perp}_{Preholiday,\ t-k}$. The reported Fama-MacBeth t-statistics are corrected for heteroscedasticity and autocorrelation using Newey and West (1987). 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, 2015.

Panel A						
Dependent Variable	$RET_{Preholiday,\ t}$	$RET_{Preholiday,\ t}$		$RET_{Postholiday,\ t}$	$RET_{Postholiday,\ t}$	
Independent Variable	$+\beta^{Mood}_{Preholiday,\ t-k}$	$+\beta^{Mood}_{Preholiday,\ t-k}$	$RET^{\perp}_{Preholiday,\ t-k}$	$-\beta^{Mood}_{Preholiday,\ t-k}$	$-\beta^{Mood}_{Preholiday,\ t-k}$	$RET^{\perp}_{Preholiday,\ t-k}$
Holiday Lag	(1)	(2)		(3)	(4)	
				0.00	0.00	–10.7***
				(0.52)	(0.54)	(–15.7)
1	0.02**	0.02**	–0.83***	0.01	0.01	–0.81***
	(2.17)	(2.17)	(–4.72)	(1.07)	(1.07)	(–3.96)
2	0.02**	0.01**	0.23	0.01	0.01	–0.38**
	(2.26)	(2.23)	(1.59)	(0.96)	(0.96)	(–1.99)
3	0.01**	0.01**	0.31**	0.01	0.01	–0.27
	(2.15)	(2.14)	(2.15)	(1.04)	(1.04)	(–1.39)
4	0.02**	0.02**	0.46***	0.01	0.01	–0.60***
	(2.22)	(2.21)	(3.19)	(1.11)	(1.10)	(–3.34)
5	0.02**	0.02**	0.41***	0.01	0.01	0.08
	(2.36)	(2.35)	(3.29)	(1.11)	(1.09)	(0.44)
6	0.01**	0.01**	0.11	0.01	0.01	–0.03
	(2.21)	(2.22)	(0.79)	(1.12)	(1.11)	(–0.19)
7	0.01**	0.01**	0.43***	0.01	0.01	–0.24
	(2.30)	(2.31)	(3.85)	(1.00)	(1.00)	(–1.43)
8	0.02**	0.02**	0.26*	0.01	0.01	0.05
	(2.46)	(2.48)	(1.92)	(1.58)	(1.57)	(0.32)
9	0.01**	0.01**	0.26*	0.01	0.01	–0.03
	(2.39)	(2.41)	(1.94)	(0.94)	(0.91)	(–0.19)
10	0.02**	0.02**	–0.01	0.01	0.01	–0.31
	(2.55)	(2.55)	(–0.05)	(1.06)	(1.05)	(–1.61)
11	0.02***	0.02***	0.02	0.01	0.01	–0.01
	(2.66)	(2.64)	(0.15)	(1.41)	(1.40)	(–0.09)
12	0.02***	0.02***	0.06	0.01	0.01	0.20

	(2.71)	(2.71)	(0.43)	(0.85)	(0.86)	(1.17)
13	0.02***	0.02***	0.43***	0.00	0.00	–0.15
	(2.78)	(2.78)	(2.82)	(0.39)	(0.40)	(–0.88)

Table 8: Seasonalities Based on Characteristics-Adjusted Return

This table uses characteristics-adjusted return, instead of raw return, to test the month, weekday, and holiday-related seasonalities. For each month or day, we run a cross-sectional regression of stock returns on market beta (β^{MKT}), logarithmic firm size (log(ME)), logarithmic book-to-market equity (log(BM)), short-, intermediate-, and long-horizon past returns (RET(-1), RET(-12,-2), RET(-36,-13)), leverage (LEV), asset growth (AG), accruals (ACC), the investment-to-asset ratio (IVA), external financing (EXFIN), and net operating assets (NOA), all defined in the Appendix A. The characteristics-adjusted return is the residual from the cross-sectional regression. Then we run Fama-MacBeth regressions by replacing raw returns (both dependent and independent variables) in Tables 2, 3, and 4 with the characteristics-adjusted returns. Panel A reports the results for the calendar-month seasonal effect. Panel B reports the results for the weekday seasonal effect. Panel C reports the results for the holiday seasonal effect. For brevity, we report lag 1, lag 2-5, and lag 6-10, where the lag 2-5 (6-10) estimates are from regressions of the current returns on the average lagged returns from year $t-2$ to $t-5$ ($t-6$ to $t-10$). The reported Fama-MacBeth t-statistics are corrected for heteroscedasticity and autocorrelation using Newey and West (1987). 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, 2015.

Panel A: Calendar Month Seasonality

	Congruent Month Return Persistence		Incongruent Month Return Reversal	
Dependent Variable	$RET_{Jany/Oct,\ t}$		$RET_{Jany/Oct,\ t}$	
Independent Variable	$RET_{Jan/Oct,\ t-k}$	$RET_{Best/Worst\text{-}month,\ t-k}$	$RET_{Oct\ /Jan,\ t-k}$	$RET_{Worst/Best\text{-}month,\ t-k}$
Year Lag (k)	(1)	(2)	(3)	(4)
1	2.01***	1.46**	–2.30***	–1.17
	(4.44)	(2.38)	(–3.76)	(–1.46)
2~5	2.94***	3.06***	–2.11**	–1.96**
	(3.00)	(3.32)	(–2.22)	(–2.33)
6~10	4.98***	4.17***	–1.14	–1.38**
	(5.31)	(3.41)	(–1.40)	(–2.04)

Panel B: Weekday Seasonality

	Congruent Weekday Return Persistence		Incongruent Weekday Return Reversal	
Dependent Variable	$RET_{Mon/Fri,\ t}$		$RET_{Mon/Fri,\ t}$	
Independent Variable	$RET_{Mon/Fri,\ t-k}$	$RET_{Worst/Best\text{-}weekday,\ t-k}$	$RET_{Fri/Mon,\ t-k}$	$RET_{Best/Worst\text{-}weekday,\ t-k}$
Week Lag (k)	(1)	(2)	(3)	(4)
1	–0.19	–0.87***	–5.41***	–1.99***
	(–1.44)	(–5.48)	(–30.3)	(–10.4)
2~5	1.08***	0.53***	–0.98***	–0.55***
	(4.85)	(2.62)	(–5.32)	(–3.15)
6~10	0.77***	0.42*	–0.54***	–0.27
	(4.51)	(1.89)	(–2.87)	(–1.12)

Panel C: Holiday Seasonality

Dependent Variable	$RET_{Preholiday,\ t}$	$RET_{Postholiday,\ t}$
Independent Variable	$RET_{Preholiday,\ t\text{-}k}$	$RET_{Preholiday,\ t\text{-}k}$
Holiday Lag (k)	(1)	(2)
0		–10.7***
		(–21.6)
1	–0.67***	–0.62**
	(–2.81)	(–2.45)
2~7	1.96***	–0.20
	(4.12)	(–0.46)
8~13	1.70***	0.29
	(4.03)	(0.61)

Table 9: Seasonalities Based on Factor-Adjusted Return

This table uses factor-adjusted return, instead of raw return, to test the month, weekday, and holiday-related seasonalities. For each month or day, we calculate the factor-adjusted return of each stock as the realized excess return minus the predicted return based on the Fama-French-Cohart four-factor model. The factor loadings are estimated by using a 12-month rolling window of daily stock returns regressed on the four factors up to the prior month. Then we run Fama-MacBeth regressions by replacing raw returns (both dependent and independent variables) in Tables 2, 3, and 4 with the characteristics-adjusted returns. Panel A reports the results for the calendar-month seasonal effect. Panel B reports the results for the weekday seasonal effect. Panel C reports the results for the holiday seasonal effect. For brevity, we report lag 1, lag 2-5, and lag 6-10, where the lag 2-5 (6-10) estimates are from regressions of the current returns on the average lagged returns from year $t-2$ to $t-5$ ($t-6$ to $t-10$). The reported Fama-MacBeth t-statistics are corrected for heteroscedasticity and autocorrelation using Newey and West (1987). 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, 2015.

Panel A: Calendar Month Seasonality

	Congruent Month Return Persistence		Incongruent Month Return Reversal	
Dependent Variable	$RET_{Jany/Oct,\ t}$		$RET_{Jany/Oct,\ t}$	
Independent Variable	$RET_{Jan/Oct,\ t-k}$	$RET_{Best/Worst\text{-}month,\ t-k}$	$RET_{Oct/Jan,\ t-k}$	$RET_{Worst/Best\text{-}month,\ t-k}$
Year Lag (k)	(1)	(2)	(3)	(4)
1	1.60***	0.44	–2.04***	–2.97***
	(3.03)	(0.90)	(–3.20)	(–3.22)
2~5	4.69***	1.87**	–3.32***	–5.35***
	(8.18)	(2.28)	(–5.23)	(–7.58)
6~10	4.72***	3.51***	–2.19***	–2.33***
	(5.21)	(4.21)	(–3.54)	(–3.86)

Panel B: Weekday Seasonality

	Congruent Weekday Return Persistence		Incongruent Weekday Return Reversal	
Dependent Variable	$RET_{Mon/Fri,\ t}$		$RET_{Mon/Fri,\ t}$	
Independent Variable	$RET_{Mon/Fri,\ t-k}$	$RET_{Worst/Best\text{-}weekday,\ t-k}$	$RET_{Fri/Mon,\ t-k}$	$RET_{Best/Worst\text{-}weekday,\ t-k}$
Week Lag (k)	(1)	(2)	(3)	(4)
1	0.04	–0.75***	–4.92***	–1.77***
	(0.57)	(–8.76)	(–32.2)	(–16.5)
2~5	0.83***	0.10	–0.94***	–0.41***
	(6.35)	(0.77)	(–8.00)	(–3.39)
6~10	0.79***	0.17	–0.32***	0.31**
	(6.86)	(1.35)	(–2.67)	(2.42)

Panel C: Holiday Seasonality

Dependent Variable	$RET_{Preholiday,\ t}$	$RET_{Postholiday,\ t}$
Independent Variable	$RET_{Preholiday,\ t\text{-}k}$	$RET_{Preholiday,\ t\text{-}k}$
Holiday Lag (k)	(1)	(2)
0		–9.98***
		(–22.0)
1	–0.56***	–0.73***
	(–3.42)	(–3.51)
2~7	1.50***	–0.50
	(4.72)	(–1.43)
8~13	0.26	–0.00
	(0.89)	(–0.01)

Table 10: Mood Beta and Market Beta as Predictors in the Cross Section of Returns

This table examines the predictive power of mood beta to forecast future seasonal returns in Fama-MacBeth regressions, after controlling for market beta. Panel A column (1) uses monthly (estimated with January/October returns) mood beta and market beta to predict January/October return, column (2) uses best/worst month mood beta and market beta to predict January/October return. Panel B column (1) uses weekday (estimated with Monday/Friday returns) mood beta and market beta to predict Monday/Friday return, column (2) uses best/worst weekday mood beta and market beta to predict Monday/Friday return. Panel C column (1) uses pre-holiday mood beta and market beta to predict pre-holiday return and column (2) uses the same variables to predict post-holiday return. When forecasting future January/Friday/Preholiday returns, the independent variable is the stock's historical mood beta (β^{Mood}_{t-k}), and when forecasting future October/Monday/Postholiday returns, it is $-\beta^{Mood}_{t-k}$. The reported Fama-MacBeth *t*-statistics are corrected for heteroscedasticity and autocorrelation using Newey and West (1987). 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, 2015.

Panel A:	Congruent/Incongruent Month			Congruent/Incongruent Mood Month		
Dependent Variable	$RET_{Jan/Oct,\ t}$			$RET_{Jan/Oct,\ t}$		
Independent Variable	$\pm\beta^{Mood}_{Jan/Oct,\ t-k}$	β^{MKT}_{Month}	β^{SENT}	$\pm\beta^{Mood}_{Best/Worst\text{-}month,\ t-k}$	β^{MKT}_{Month}	β^{SENT}
Year Lag		(1)			(2)	
1	1.79***	–0.36	0.74	3.24***	–1.04**	1.84
	(4.79)	(–0.88)	(0.05)	(5.26)	(–2.30)	(0.15)
2	1.56***	–0.13	–2.47	3.22***	–0.78*	0.88
	(5.07)	(–0.33)	(–0.22)	(5.46)	(–1.93)	(0.08)
3	1.44***	–0.16	–10.0	3.06***	–0.99***	–6.87
	(4.36)	(–0.47)	(–1.15)	(5.50)	(–2.66)	(–0.85)
4	1.42***	–0.04	–10.3	2.88***	–0.98***	–12.4
	(4.58)	(–0.11)	(–1.36)	(5.47)	(–2.63)	(–1.40)
5	1.33***	0.05	–8.94***	3.09***	–0.61	–17.3**
	(4.70)	(0.14)	(–2.76)	(6.08)	(–1.31)	(–2.16)
6	1.29***	–0.15	–11.8**	3.02***	–1.00***	–11.8**
	(4.46)	(–0.49)	(–2.24)	(6.02)	(–2.71)	(–2.47)
7	1.19***	–0.20	–17.0**	2.58***	–0.92***	–12.2*
	(3.74)	(–0.67)	(–2.29)	(4.68)	(–2.87)	(–1.67)
8	1.31***	–0.28	–6.55	2.59***	–0.92***	2.56
	(3.92)	(–0.96)	(–1.07)	(4.97)	(–2.71)	(0.27)
9	1.26***	–0.21	–2.32	2.46***	–0.49	9.29
	(3.44)	(–0.70)	(–0.54)	(4.27)	(–1.48)	(1.16)
10	1.18***	–0.19	–6.29	2.23***	–0.45	–5.83
	(2.81)	(–0.63)	(–0.87)	(4.03)	(–1.27)	(–0.86)

Panel B:	Congruent/Incongruent Weekday			Congruent/Incongruent Mood Weekday		
Dependent Variable	$RET_{Mon/Fri,\, t}$ t			$RET_{Mon/Fri,\, t}$		
Independent Variable Year Lag	$\mp\beta^{Mood}{}_{Mon/Fri,\, t-k}$	$\beta^{MKT}{}_{Day}$ (1)	β^{SENT}	$\mp\beta^{Mood}{}_{Best/Worst\ weekday,\, t-k}$	$\beta^{MKT}{}_{Day}$ (2)	β^{SENT}
1	0.03***	–0.07***	–0.08	0.04***	–0.08***	–0.06
	(5.08)	(–5.21)	(–0.72)	(4.56)	(–4.69)	(–0.51)
2	0.02***	–0.07***	–0.06	0.03***	–0.08***	–0.03
	(4.61)	(–5.18)	(–0.63)	(3.97)	(–5.39)	(–0.30)
3	0.02***	–0.07***	–0.08	0.03***	–0.08***	–0.07
	(4.89)	(–5.46)	(–0.85)	(4.02)	(–5.54)	(–0.73)
4	0.03***	–0.07***	–0.09	0.03***	–0.08***	–0.09
	(5.27)	(–5.52)	(–0.88)	(4.03)	(–5.38)	(–0.93)
5	0.03***	–0.07***	–0.09	0.03***	–0.08***	–0.09
	(5.23)	(–5.80)	(–0.90)	(4.21)	(–5.37)	(–0.91)
6	0.02***	–0.07***	–0.11	0.04***	–0.08***	–0.09
	(4.81)	(–5.94)	(–1.12)	(4.56)	(–5.33)	(–0.98)
7	0.02***	–0.08***	–0.11	0.04***	–0.08***	–0.09
	(4.59)	(–6.12)	(–1.11)	(4.89)	(–5.74)	(–0.95)
8	0.02***	–0.08***	–0.10	0.04***	–0.08***	–0.09
	(4.43)	(–6.08)	(–1.00)	(4.87)	(–6.00)	(–1.02)
9	0.02***	–0.08***	–0.10	0.03***	–0.08***	–0.09
	(4.42)	(–6.29)	(–1.02)	(4.44)	(–5.96)	(–0.99)
10	0.02***	–0.08***	–0.11	0.04***	–0.08***	–0.08
	(5.09)	(–6.29)	(–1.13)	(4.58)	(–6.09)	(–0.90)

Panel C:	Preholiday to Preholiday			Preholiday to Postholiday		
Dependent Variable	$RET_{Preholiday,\ t}$			$RET_{Postholiday,\ t}$		
Independent Variable Year Lag	$+\beta^{Mood}{}_{Preholiday,\ t-k}$	$\beta^{MKT}{}_{Day}$ (1)	β^{SENT}	$-\beta^{Mood}{}_{Preholiday,\ t-k}$	$\beta^{MKT}{}_{Day}$ (2)	β^{SENT}
1				–0.00	–0.01	0.36**
				(–0.77)	(–0.39)	(1.98)
2	0.01**	0.04*	–0.05	–0.00	–0.02	0.36**
	(2.48)	(1.96)	(–0.32)	(–0.04)	(–0.65)	(2.10)
3	0.01***	0.03*	–0.09	–0.00	–0.01	0.26
	(2.68)	(1.82)	(–0.63)	(–0.31)	(–0.60)	(1.47)
4	0.01**	0.04**	–0.14	–0.00	–0.02	0.12
	(2.15)	(2.09)	(–1.03)	(–0.36)	(–0.93)	(0.68)
5	0.01**	0.03*	–0.11	–0.00	–0.02	0.12
	(2.17)	(1.88)	(–0.85)	(–0.03)	(–0.79)	(0.70)
6	0.01**	0.03*	–0.10	0.00	–0.01	0.04
	(2.33)	(1.89)	(–0.73)	(0.44)	(–0.41)	(0.22)
7	0.01*	0.03*	–0.04	–0.00	–0.01	0.11
	(1.75)	(1.88)	(–0.33)	(–0.18)	(–0.27)	(0.66)
8	0.01	0.03*	–0.05	–0.00	–0.01	0.11
	(1.53)	(1.70)	(–0.36)	(–0.27)	(–0.24)	(0.61)
9	0.01	0.03**	–0.04	0.00	–0.02	0.13
	(1.46)	(1.96)	(–0.29)	(0.34)	(–0.74)	(0.84)
10	0.00	0.03*	0.04	–0.00	0.00	0.23
	(1.15)	(1.86)	(0.28)	(–0.08)	(0.14)	(1.48)
11	0.00	0.03*	–0.02	–0.00	–0.02	0.13
	(1.01)	(1.92)	(–0.12)	(–0.68)	(–0.64)	(0.79)
12	0.01*	0.03*	–0.03	–0.00	–0.02	0.26
	(1.91)	(1.96)	(–0.19)	(–0.30)	(–0.87)	(1.58)
13	0.01**	0.03*	0.01	–0.01	–0.02	0.19
	(2.33)	(1.74)	(0.09)	(–1.10)	(–1.07)	(1.15)
14	0.01**	0.03*	–0.00	–0.01	–0.01	0.23
	(2.40)	(1.71)	(–0.00)	(–1.07)	(–0.70)	(1.59)

Appendix B: January/September 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, using September as a negative mood month as a robustness. 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 a 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 worst-market-return (best-market-return) month of a 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-MacBeth t-statistics are corrected for heteroscedasticity and autocorrelation using Newey and West (1987). 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, 2015.

	Congruent Month Return Persistence		Incongruent Month Return Reversal	
Dependent Variable	$RET_{Jany/Sept,\ t}$		$RET_{Jan/Sept,\ t}$	
Independent Variable	$RET_{Jan/Sept,\ t-k}$	$RET_{Best/Worst\text{-}month,\ t-k}$	$RET_{Sept/Jan,\ t-k}$	$RET_{Worst/Best\text{-}month,\ t-k}$
Year Lag (k)	(1)	(2)	(3)	(4)
1	3.35***	3.88***	–3.26***	–5.96***
	(3.43)	(4.02)	(–3.18)	(–4.56)
2	3.67***	3.35***	–1.97**	–5.77***
	(5.20)	(3.36)	(–2.18)	(–5.26)
3	3.51***	3.41***	–1.63**	–4.83***
	(4.65)	(3.14)	(–2.14)	(–4.25)
4	3.16***	3.28***	–0.55	–4.17***
	(3.10)	(3.10)	(–0.74)	(–3.94)
5	2.66***	2.53**	–1.69***	–4.35***
	(2.92)	(2.43)	(–2.64)	(–3.84)
6	2.12**	3.88***	–0.03	–4.22***
	(2.52)	(4.24)	(–0.04)	(–2.99)
7	2.80***	4.39***	0.91	–2.50**
	(2.93)	(4.44)	(1.25)	(–2.32)
8	2.14**	2.88***	–0.01	–2.96***
	(2.54)	(2.75)	(–0.02)	(–3.08)
9	1.76**	2.22***	–1.23	–2.42**
	(2.19)	(2.83)	(–1.42)	(–2.29)
10	1.95**	2.39***	–0.48	–1.43*
	(2.05)	(2.96)	(–0.58)	(–1.74)