NBER WORKING PAPER SERIES

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Working Paper 24676
http://www.nber.org/papers/w24676

NATIONAL BUREAU OF ECONOMIC RESEARCH
1050 Massachusetts Avenue
Cambridge, MA 02138
June 2018

We thank Alexander Barinov, Ling Cen, Kent Daniel, Iftekhar Hasan, Juhani Linnainmaa, Antti Llmanen, Lin Peng, Sang Byung Seo, Alain Wouassom, Chengxi Yin, and Bohui Zhang, and seminar participants at Stony Brook University, Auburn University, CUNY-Baruch, Fordham University, the 2017 ASSA-AFE, the 2017 CICF, and the 2018 MFA. The Online Appendix can be found at https://sites.google.com/site/danlingjiang/. The views expressed herein are those of the authors and do not necessarily reflect the views of the National Bureau of Economic Research.

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NBER Working Paper No. 24676
June 2018
JEL No. D53,D91,G12,G14,G4,G41

ABSTRACT

Existing research has documented cross-sectional seasonality of stock returns—the periodic outperformance of certain stocks during the same calendar months or weekdays. A model in which assets differ in their sensitivities to investor mood explains these effects and implies other seasonal patterns. We find that relative performance across individual stocks or stock portfolios during past high or low mood months and weekdays tends to recur/reverse in periods with congruent/noncongruent mood. Furthermore, assets with higher sensitivities to aggregate mood—higher mood betas—subsequently earn higher/lower returns during high/low mood periods, including those induced by Daylight Saving Time changes, weather conditions and anticipation of major holidays.

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1. Introduction

Extensive research has documented several aggregate market return seasonalities—periodic variation in the mean returns of market index portfolios.[1] Recent studies have also identified seasonality in the cross section of security returns—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 2016), during certain weekdays (Birru 2018), or during the pre-holiday period (Hirshleifer, Jiang, Meng, and Peterson 2016).[2]

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 at both the monthly and daily returns; and to offer extensive new empirical implications that we test. Mood here refers to emotion-induced variation in investor preferences or beliefs. It differs from purely cognitive errors such as overconfidence and extrapolative expectation, or cognitive constraints such as attention. Mood is a special case of investor sentiment (e.g., Baker and Wurgler 2006, 2007), which is a general term that includes shifts deriving from both affective, such as emotions and feelings, and non-affective sources, such as shifts in attention or in the adoption of heuristic ideas about the prospects of the market or particular stocks.

Mood affects economic decision making through a variety of pathways (Lerner et al. 2015). Here our focus is on the effects of emotional valence (whether the mood is good or bad). In our model, seasonal investor mood swings cause periodic optimism or pessimism in evaluating signals about assets' systematic and idiosyncratic payoff components. This results in seasonal variations in factor and stock-specific mispricing and, accordingly, seasonal return predictability.[3] A stock's sensitivity to seasonal mood shifts can be captured by its historical seasonal mean returns, or its historical seasonal return sensitivity to aggregate returns, which we call "mood beta." We show in the model and in the data that both measures of mood sensitivity help to predict future seasonal returns in other periods in which mood is expected to persist or change.

In our model, during periods with positive mood shifts, stocks that have higher sensitivities to ascending mood earn higher average returns, and the reverse holds for negative mood shifts. High

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

[2] See Hartzmark and Solomon (2018) for a review of a general line of literature on market impounding of the information in recurring firm events.

[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 changing moods rather than other possible shocks that might also fall under the general rubric of sentiment.

mood sensitivity of a stock can result from high loadings on a factor that is subject to mispricing. The different mood sensitivity of different assets implies that aggregate return seasonality induces cross-sectional return seasonality. In addition, the model predicts that cross-sectional return differentials will recur during congruent-mood periods and reverse during noncongruent-mood periods.

The key premise of the model predictions is that investor mood varies systematically across calendar months and weekdays. As we review later, various experimental, survey, and empirical studies have provided such evidence. These previous studies motivate us to identify mood states by the calendar months or weekdays with high or low historical average or realized stock market performances.

Specifically, we use January, March and Friday to proxy for the high mood state; all three are associated with high average full-sample historical returns. Furthermore, early January is associated with the uplifted mood of the New Year period (Thaler 1987; Bergsma and Jiang 2016), March is associated with the highest recovery from seasonal affective disorder (SAD) (Kamstra et al. 2017), and Friday induces an upbeat mood in anticipation of the weekend break (Helliwell and Wang 2014, Birru 2018).[4]

These studies also suggest identifying the low mood state by using September, October, and Monday; all three are linked to low average full-sample historical returns. Moreover, the two months in early Fall are associated with the highest onset of the SAD effect (Kamstra et al. 2017), and Monday induces downbeat mood at the start of the week (e.g., Rossi and Rossi 1977; McFarlane, Martin, and Williams 1988; Stone, Schneider, Harter 2012; Helliwell and Wang 2014, Birru 2018).[5]

Realized investor mood swings, on the other hand, are identified as the months or weekdays with the highest or lowest equal-weighted market excess return realized in a given year or week. The motivation here is that higher realized returns of the broad market tend to reflect more optimistic mood swings, and vice versa. In robustness checks, we also identify high or low mood periods by using the extreme historical average returns up to the preceding year or month, or the extreme full-sample average returns in either odd or even years.

[4] DellaVigna and Pollet (2009) hypothesize that Fridays are associated with more investor inattention. This attention-based hypothesis predicts weaker market reactions to both positive and negative news announced on Fridays, but does not predict an average misreaction. The mood-based hypothesis predicts more favorable market reactions to all news announced on Fridays, implying a positive average misreaction. It is, of course, possible that both attention and mood effects are present.

[5] Consistent with the mood-based theory, we find during our sample period, 1963-2016, that the mean excess return of the equal-weighted market portfolio is highest in January and March and lowest in September and October; and highest on Friday and lowest on Monday.

The test assets include the full cross-section of individuals stocks, the 94 Baker and Wurgler (BW 2006) portfolios and 79 Keloharju, Linnainmaa, and Nyberg (KLN 2016) portfolios, with the two sets of portfolios formed by sorting individual stocks on various firm characteristics. Our tests of cross-sectional return seasonality indicate that the relative performance across assets during a mood state tends to *recur* in future periods when the congruent mood is expected and to *reverse* in future periods with noncongruent mood, supporting the model predictions. We call the former the *congruent-mood recurrence effect* and the latter the *noncongruent-mood reversal effect*.

For example, if Asset A outperforms Asset B on average in January and March, then it tends to underperform Asset B next September and October (reversal), but tends to outperform Asset B next January and March (recurrence), and such patterns repeat for years after the conditioning date. Similarly, if A outperforms B on Friday, this average relative performance alternates between Mondays and Fridays for months after the conditioning date. A long-short portfolio that exploits the mood recurrence or reversal effect generates a monthly risk-adjusted return of 0.33% to 1.80%, or a daily risk-adjusted return of 2 to 10 bps. Similar patterns are found if we measure relative historical performance across assets during the highest or lowest realized mood months or weekdays in recent years or months, the full historical record up to the preceding year or month, or only the odd or even years.

Overall, these mood recurrence and reversal effects prevail between congruent and noncongruent states at different frequencies. These effects differ from existing findings that have documented return seasonalities across the same calendar months (Heston and Sadka 2008) or weekdays (Keloharju, Linnainmaa, and Nyberg 2016). These patterns extend the findings of Birru (2018) by identifying weekday seasonality effects for general stocks rather than Monday versus Friday reversal effects of anomaly portfolios; and by documenting similar general stock seasonality effects at the calendar month level.

Our theoretical predictions are driven by what we call *mood beta*. A security's mood beta is its sensitivity to investor mood variations. In the model, mood beta predicts cross-sectional returns in future seasonal periods based on the foreseeable investor moods in those periods.

Empirically, if mood sensitivity has some stability over time, stocks with high mood betas in the recent past will outperform other stocks during subsequent periods with positive mood shifts (either foreseeable to the econometrician or not) and underperform when there are negative mood shifts. Furthermore, the model implies that mood beta can be measured by the historical sensitivity of an asset's returns to seasonal variations in the equal-weighted market returns across periods with substantial investor mood shifts. Accordingly, we estimate mood beta by regressing an asset's returns on the equal-weighted market returns during periods that we conjecture to be associated with recurring investor mood changes. These periods include months or weekdays with strong positive or negative investor mood swings, as discussed previously.[6]

In our mood beta tests, to forecast cross-sectional returns in the future high or low mood periods, we replace the historical seasonal returns with the estimated mood betas. We find strong evidence that high mood beta stocks tend to outperform in expected future positive mood periods (e.g., Januaries, Marches and Fridays), and underperform in expected future low mood periods (e.g., Septembers, Octobers and Mondays). Furthermore, mood beta varies with firm characteristics and industries in an intuitive pattern: hard-to-value stocks and industries, and those sensitive to high sentiment (in the sense of Baker and Wurgler 2006) have high mood beta while easy-to-value assets and those less subject to sentiment exhibit lower sensitivity to mood.

We form a hedge portfolio that is long on the highest mood beta decile and short the lowest decile during periods when positive mood is expected, and flips the long and short lags during periods when negative mood is expected. This hedge portfolio produces a significant Fama-French 5-factor alpha of 1.5% or more per month and 12 bps or more per weekday. After accounting for the correlation with mood beta, however, historical seasonal returns have substantially reduced ability, sometimes with a reversed sign, to forecast asset returns in future high or low mood periods. Furthermore, the effect of mood beta is robust to controls for market beta estimated using monthly or daily returns as well as the sentiment beta of Baker and Wurgler (2006, 2007). This finding suggests that mood beta offers a unique and integrated explanation for a wide and varied set of seasonal return recurrence and reversal effects.

The tests described so far rely on mood betas estimated in different seasonal periods to forecast seasonal returns. However, since many determinants of return vary seasonally, to sharpen the focus on mood as an explanation we also consider exogenous influences that are more uniquely tied to mood. We therefore turn to what we call *cross-domain tests* of whether mood beta helps forecast returns when there are exogenous variations in investor mood based on anticipations of major holidays,

[6] At the month level, these historical mood months include January, March, September, and October, as well as the two highest and two lowest months in terms of realized equal-weighted market excess returns in a given year. At the weekday level, these historical mood weekdays include Monday and Friday, as well as the highest and the lowest weekdays in terms of realized equal-weighted market excess returns in a given week. Robustness checks select mood periods based on months or weekdays with highest or lowest equal-weighted market excess returns up to the prior year or months or during either odd or even years.

Daylight Saving Time changes and weather conditions (Saunders 1993; Kamstra, Kramer, and Levi 2000; Hirshleifer and Shumway 2003; Frieder and Subrahmanyam 2004).

Specifically, for each stock or portfolio, we construct a composite mood beta as the first principal component of its two mood betas, estimated from month- or weekday-level returns. Our first setting for the cross-domain tests comes from preholiday returns. Previous research suggests that investors experience uplifted mood immediately prior to major holidays. At the aggregate, the market portfolios tend to advance rather than decline during preholiday trading days (Ariel 1990). Adding to this evidence, we show that assets with high mood betas on average earn higher pre-holiday returns than those with low mood betas, although the historical preholiday return remains a positive predictor of future preholiday returns (Hirshleifer, Jiang, Meng, and Peterson 2016).

The next setting pertains to Daylight Saving Time (DST). Extensive evidence from psychology indicates that Spring and Fall DST clock changes have negative effects on individual performance. The joint hypothesis here is that during the weekends of such changes, sleep patterns are disrupted, resulting in downbeat mood (Kamstra, Kramer, and Levi 2000), and that mood betas capture mood sensitivity. Consistent with this hypothesis, we find that stocks with high composite mood beta underperform other stocks during such periods more than that during a typical weekend.

The third setting relies on weather conditions of New York City. We test the joint hypothesis that sunny weather lifts mood, and that mood betas capture sensitivity to mood. Consistent with this joint hypothesis, we find that stocks with high composite mood betas outperform other stocks on seasonally-adjusted sunny days, and do not do so on seasonally-adjusted cloudy days based on weather data from the New York City (on investor mood and sunshine, see Saunders 1993 and Hirshleifer and Shumway 2003).

Across all settings, Fama-MacBeth regressions show that mood beta is a robust positive forecaster of individual stock returns during high mood periods and a robust negative return forecaster when mood is low, even after controls for market beta, sentiment beta, and a wide set of firm characteristics. These cross-domain tests provide corroboration for the hypothesis that mood beta captures mood effects on securities. In particular, the relationships of DST clock changes or weather with asset returns were not tests that derive naturally from non-affective research paradigms; they were first studied precisely because of extensive psychological evidence that sunshine and sleep disruption affect mood.

Overall, regardless of whether the effects documented in this paper derive from investor mood, as we hypothesize, they constitute a rich set of new forms of return predictability that deserves attention. Mood beta provides a possible integrated explanation for this wide range of effects, and it is otherwise far from obvious how to explain them.

Broadly, our study adds to research that explores how investor mood affects financial decision-making and asset prices. The effects of emotion are relatively neglected compared to the large body of research in behavioral finance on cognitive biases and nonstandard preferences such as prospect theory. There has been some past empirical research on feelings and financial decisions. Previous research reports that people in a more positive mood tend to be more risk-tolerant and exhibit a higher demand for risky assets (Bassi, Colacito, and Fulghieri 2013; Kaplanski, Levy, Veld, and Veld-Merkoulova 2015; Breaban and Noussair 2017). Weather conditions, sports outcomes, and aviation disasters are associated with aggregate stock market returns (Saunders 1993; Hirshleifer and Shumway 2003; Edmans, García, and Norli 2007; Kaplanski and Levy 2010), returns of individual stocks, perceived stock overpricing by institutional investors (Goetzmann, Kim, Kumar, and Wang 2015), individuals' sentiment about the economy and life satisfaction (Makridis 2018), and firm hiring and investment decisions as well as hiring and creation of new businesses (Chhaochharia, Kim, Korniotis, and Kumar 2016).

2. The Model

We present a model to illustrate how investor mood may induce return seasonality at both the aggregate and the cross-sectional 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 the mistaken perceptions of mood-prone investors in a setting that excludes risk premia. An alternative modeling approach is to assume that mood variations affect risk aversion.[8] We conjecture that this would lead to similar model predictions, with the role of good-mood-induced greater optimism being replaced with good-mood-induced greater risk tolerance. The model can apply more generally to nonfundamental sources of aggregate and cross-sectional price variations.

[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 investor groups. Either setting yields similar patterns in aggregate and individual stock mispricing. This is a similar approach to that used to tractably model trading behavior and mispricing under investor overconfidence by Daniel, Hirshleifer, and Subrahmanyam (1998, 2001).

[8] Previous literature shows that mood shifts risk aversion (e.g., Kamstra, Kramer, and Levi 2003; Bassi, Colacito, and Fulghieri 2013; Kaplanski , Levy, Veld, and Veld-Merkoulova 2015).

2.1 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, $i = 1,\dots N$, 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:

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

where superscript 1 for signal and noise terms indicates date 1, ς_k^1 is the noise in the k^{th}-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 shift and receive a second set of signals:

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

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 that all signal noises are independent across time and that firm-specific signals are also independent across assets. We also assume that the distributions of signal noise terms are the same for both dates for simplicity.

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 denote the bias induced by a mood shift, γ_f to denote factor 1's sensitivity to the mood shift, and γ_i to denote asset *i*'s specific sensitivity to the mood shift. Thus, at date 2 the *perceived* signals about factor 1 payoffs (S_1^2) and firm-specific payoffs (V_i^2) are

$$S_1^2 = s_1^2 + \gamma_f b \text{ and } V_i^2 = \nu_i^2 + \gamma_i b,$$

where the parameter γ_f is a positive constant. Under positive investor mood shocks, over-optimism prevails and $b > 0$, distributed as $\mathrm{U}(0, 2\bar{b})$, while under negative investor mood shocks over-pessimism prevails and $b < 0$, distributed uniformly as $\mathrm{U}(-2\bar{b}, 0)$, where $\bar{b} > 0$. The optimism/pessimism bias associated with good/bad mood states is consistent with the literature in psychology and experimental finance discussed in Section 3.

The parameter γ_i is fixed for each asset, 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 that firm-specific mood-induced mispricing cancels out in the aggregate, so that the aggregate mood effect is purely driven by the sensitivity of perceived factor 1 payoffs to mood shifts.

2.2 Seasonal return predictability

At date 1, asset prices are correctly priced while at date 2 they are subject to the mood-induced mispricing of the factor and firm-specific expected payoffs. For brevity, we present the pricing equations at date 1 and date 2 in Online Appendix A.1.

Here we are interested in the expected asset price change from date 1 to date 2 for a given mood shift. This corresponds to seasonal returns we examine in the empirical tests, such as high or low mood month or weekday returns, when investor moods shift from being neutral to being positive or negative. 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 shifts:

$$\mathrm{E}(M_i|b) = \mathrm{E}\left(P_i^2 - P_i^1|b\right) = \beta_{i1}\lambda_f\gamma_f b + \lambda_\epsilon\gamma_i b, \tag{2.1}$$

where the term related to $\gamma_f b$ is the inherited factor 1 mispricing and the term related to $\gamma_i b$ is the firm-specific mispricing, both induced by the mood shift b. Here λ_f and λ_ϵ are functions of known parameters and defined in Online Appendix A.1.

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

$$\mathrm{E}(M_A|b) = \lambda_f\gamma_f b + \lambda_\epsilon\bar{\gamma} b = \lambda_f\gamma_f b, \tag{2.2}$$

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 (2.2) suggests that average asset returns in a mood state can be extreme if mood shift is large. This is consistent with prior empirical findings that aggregate markets tend to earn high January and March returns, Friday returns, and pre-holiday returns that significantly dwarf returns earned in ordinary months or on normal days. In contrast, average aggregate returns in early Fall months, Monday, and upon DST clock changes are negative, suggesting that the negative mood shocks can even overpower positive risk premia.

Accordingly, shown in equation (2.1) 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 assets in the cross section is predictable during periods of foreseeable mood shifts.

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

2.3 Cross-sectional seasonal return predictability

Unconditionally, assets 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 ($b > 0$), assets with higher β_1 and/or higher γ_i will outperform assets with lower β_1 and/or lower γ_i. Thus, assets that outperform in the prior mood seasons are expected to continue the outperformance during the next season when the mood shifts are congruent.

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

$$\mathrm{cov}[(P_{2i} - P_{1i}), (P_{2i} - P_{1i})'] = [\beta_{i1}^2 \lambda_f^2 \gamma_f^2 + \lambda_\epsilon^2 \gamma_i^2]\mathrm{cov}(b, b'). \tag{2.3}$$

Across two congruent-mood states, mood shifts are distributed as U$(0, 2\bar{b})$, thus are positive correlated; $\mathrm{cov}(b, b') = \bar{b}^2/3 > 0$. For example, we expect that Friday moods are positively serially correlated even when Friday fundamental news is serially independent. As a result, relative performance recurs from one Friday to the other. Conversely, when mood states are noncongruent (one is drawn from U$(0, 2\bar{b})$, the other from U$(-2\bar{b}, 0)$, mood shocks are negatively correlated;

$\text{cov}(d, d') = -\bar{b}^2/3 < 0$. 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 assets to reverse from Monday to Friday, and from Friday to Monday.

PROPOSITION 2*: Historical seasonal returns of a security will be positively correlated with its future seasonal returns under a congruent-mood state, and negatively related to its future seasonal returns under a noncongruent-mood state.*

In previous research (Heston and Sadka 2008; Keloharju, Linnainmaa, and Nyberg 2016; Birru 2018), what we describe as a congruent-mood state is identified using the same calendar month or weekday and the noncongruent-mood state is identified by Mondays versus Fridays. Thus, Proposition 2 helps to explain existing findings on cross-sectional seasonalities. However, there is a broader implication—that cross-sectional seasonal asset returns will recur under the congruent-mood state and *reverse* under the noncongruent-mood state, regardless of whether the mood state is identified using calendar windows or not. In our empirical tests later, we also identify the historical mood state using the realized, extreme average stock monthly returns in a year or weekday returns in a week.

2.4 Mood beta

An alternative way to predict seasonal returns across assets is to use the mood beta of each asset, where mood beta measures a security's sensitivity to ascending mood. There are potentially many ways to identify mood beta. Here we consider periods of strong mood swings, during which security returns more heavily reflect mood-induced mispricing. 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):

$$\beta_i^{\text{mood}} = \frac{cov(M_i, M_A)}{var(M_A)} = \frac{\beta_{i1}\lambda_f^2\gamma_f^2 + \lambda_\epsilon^2\bar{\gamma}\gamma_i}{\lambda_f^2\gamma_f^2 + \lambda_\epsilon^2\bar{\gamma}^2} = \beta_{i1}\,. \tag{2.4}$$

Intuitively, mood beta measures an asset's average return sensitivity with respect to the returns of the common factor that is being mispriced owing to mood fluctuations. Again, the last equality reflects the simplification coming from $\bar{\gamma} = 0$ when there are many securities. Equation (2.4) predicts that mood beta will be larger for assets with a higher loading on the mood-prone factor (β_{i1}). Thus, assets with a higher mood beta will become more overpriced when factor 1 is becoming overpriced under ascending mood, according to equation (2.1).

PROPOSITION 3: *Mood beta positively predicts the cross-section of security returns during ascending mood states, and negatively predicts the cross-section of security returns during descending mood states.*

Mood beta differs from traditional stock market beta, as in the market model and the CAPM, in that mood beta captures the sensitivity to stock returns with respect to mood-mispriced factors while market beta captures the average stock sensitivity to all common factors. We illustrate this idea in Online Appendix A.2.

3. Tests of cross-sectional seasonal recurrence and reversal effects

Our U.S. sample includes common stocks traded on the NYSE, AMEX, and NASDAQ from January 1963 to December 2016. Daily and monthly stock and market portfolio returns, as well as other trading information, are obtained from the Center for Research in Security Prices (CRSP). Accounting data are obtained from Compustat.

We use three sets of test assets: the full cross section of individual stocks, the 94 Baker and Wurgler (BW 2006) portfolios and 79 Keloharju, Linnainmaa, and Nyberg (KLN 2016) portfolios. The BW portfolios are formed monthly based on ten firm characteristics: firm age (AGE), book-to-market equity (B/M), dividends to equity (D/BE), external financing (EF/A), market equity (ME), sales growth (SG), tangible assets (PPE/A), Research & Development (R&D/A), return on equity (ROE), and return volatility (SIGMA). As in Baker and Wurgler (2006), we use the NYSE breakpoints for each characteristic to form portfolio deciles and calculate equal-weighted portfolio returns. Non-positive earnings, dividends, PPE, or R&D firms are included in a portfolio separately from the deciles sorted based on positive values of that characteristic.

The KLN portfolios are formed monthly based on six firm characteristics: book-to-market equity (B/M), market equity (ME), price momentum based on cumulative returns from month $t-12$ to $t-2$ (MOM), gross profitability (GP), dividend yield (D/P), and earnings-to-price (E/P). Further added to the KLN portfolios are the Fama-French 17 industry portfolios. As in Keloharju, Linnainmaa, and Nyberg (2016), we use breakpoints based on all firms to form the deciles but we calculate equal-weighted as opposed to value-weighted portfolio returns. This is because we believe that mood should have a stronger impact on small firms than on large firms. Firms with non-positive earnings or dividends firms are included in separate portfolios from the decile portfolios. All definitions of the firm characteristics and portfolio formation are defined in Appendix B. We report the seasonal returns summary statistics in Table 1 with variable definitions presented in Appendix B.

3.1. Month-level mood effects

The basic month-of-the-year effect 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).

Several authors have proposed that the strong early January performance of stock markets, especially among small firms (Keim 1983), may derive from investor optimism at the turn of the new year (e.g., Ritter 1988; Doran, Jiang, and Peterson 2012; Bergsma and Jiang 2016; Kaustia and Rantapuska 2016). It has also been proposed that the weak September and October performance may be caused by the declining number of hours of daytime sunlight starting in early Autumn, which is known to induce the seasonal affective disorder (SAD) effect (Kamstra, Kramer, and Levi 2003). Indeed, among all months, September and October are associated with the largest net increase in the proportion of seasonal-depression-affected individuals while March is associated with the largest net decrease of such population (Kamstra, Kramer, Levi, and Wermers 2017).

During our sample period of 1963-2016, consistent with the above psychology accounts, the average stock excess return (CRSP equal-weighted index return minus the riskfree rate) is highest in January (5.06%), second highest in March (1.26%), lowest in October (−0.84%), and second lowest in September (−0.29%). Thus, in our main tests we use January and March as proxies for the *high* mood months and September and October for the *low* mood months. Later we explore the robustness of our findings to alternative definitions of high and low mood months.

Using these four months, we first test for the return recurrence and reversal effect across congruent and noncongruent-mood month. The return recurrence test is similar to tests of the same-calendar-month effect documented by Heston and Sadka (2008), but we do not differentiate January from March, or September from October as they proxy for the high versus the low mood state, respectively.

3.1.1 The high/low mood-month recurrence effect

Specifically, we run the following Fama-MacBeth (FMB) regressions of the high or low mood month returns across assets on their historical returns earned during congruent-mood months at three sets of annual lags:

$$RET_{\text{high(Low)},t} = \eta_{k,t} + \gamma_{k,t} RET_{\text{high(Low)},t-k} + \varepsilon_t, \tag{3.1}$$

where k = 1, 2-5, and 6-10, $RET_{\text{high(Low)},t}$ is the current mood month (high or low) asset return in year t, and $RET_{\text{high(Low)},t-k}$ is the historical average congruent (high or low) mood month return in year $t-k$ for the same asset. For example, for annual lag k = 1, the independent variable is the average January and March return of an asset of the prior year when forecasting January or March returns of the current year, and it is the average September and October return of the prior year when predicting current September or October returns. For multiple year lags, e.g., 2-5 or 6-10, the annual independent variables are averaged across the designated annual lags before used as an independent variable in the regression.

We run cross-sectional regressions as in equation (3.1) for each mood month 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 congruent-mood months year after year. We follow Heston and Sadka (2008) and call the slope coefficient estimate γ_k the "return response."

Our regression estimates for individual stocks are reported in Table 2, Panel A, Column (1). There is an insignificant coefficient for the first lag, and positive and significant return responses for annual lags 2-5 (coefficient = 1.82%, t = 2.65) and lags 6-10 (coefficient = 4.37%, t = 4.88). The return responses represent significant economic impacts. For example, for the annual lags 2-5 the return response suggests a one-standard-deviation (7.86%) increase in the prior mood month return leads to a 14 bps (7.86%×1.82%) increase in the current congruent-mood return, or a 8.7% increase relative to the mean mood month return (1.64%) in each congruent-mood month during the next two to five years.

Moving to Panels B and C for the BW and KLN portfolios, the return responses are all positive, ranging from 19.20% to 48.75%, and significant at all three sets of lags with t statistics ranging from 4.23 to 7.09. The implied economic effect is larger; a one-standard-deviation increase in the historical return measure implies 60%-86% higher returns relative to the mean in each subsequent congruent-mood month up to ten years. Thus, our evidence confirms that asset returns exhibit recurrence across congruent-mood months for at least ten years after the conditioning date.

3.1.2 The realized high/low mood-month recurrence effect

Next, we expand the high/low mood recurrence effect to considering realized extreme return months to identify high/low past mood periods. We measure realized extreme positive and negative mood periods using the top two and bottom two months ranked based on the equal-weighted CRSP excess returns realized in a given year.[9] 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 assets in these recent realized high and low mood months to forecast the cross-section of returns in subsequent, predictable congruent-mood months:

$$RET_{\text{High(Low)},t} = \eta_{k,t} + \gamma_{k,t} RET_{\text{RHigh(Rlow)},t-k} + \varepsilon_t, \tag{3.2}$$

where $RET_{\text{RHigh(Rlow)},t-k}$ is the historical return during the two highest (lowest) market return month realized in year $t-k$. The return responses are reported in Column (2) of Table 2. For individual stocks, we obtain positive and significant return responses for all three sets of annual lags, significant at the 10%, 1% and 1% levels, respectively. The average return response for lags 2-5 is 3.20%, implying that a one-standard-deviation (3.05%) return increase in the historical realized, extreme mood month leads to a 10 bps, or a 6%, higher returns relative to the mean in each of the future congruent-mood months of the subsequent five years.

For the BW and KLN portfolios, the return responses are all positive, ranging from 18% to 36%, and significant at the 1% level. The implied economic impact is considerably larger; a one-standard-deviation change in the historical return measure leads to 101% to 227% higher returns relative to the mean in each of future mood months. This evidence supports our conjecture that cross-sectional returns recur across the congruent-mood months even when we identify mood swings using realized average stock returns.

3.1.3 The high/low mood-month reversal effect

Next, we test for the cross-sectional reversal effect across noncongruent, recurrent mood states, again proxied by January and March for high moods and September and October for low moods. In such regressions, we simply switch the independent variables in regression (3.1) when forecasting future high or low mood month returns. That is, we test whether the historical high mood month returns reverse during future low mood months and vice versa.

In Column (3) of Table 2, we report the regression estimates. For individual stocks, the return responses are all negative and significant at the 1% for the three sets of lags. The coefficient for annual

[9] Our results hold if we focus on only the highest and lowest realized-market-return months. Further, we believe that the equal-weighted market index can more accurately reflect the collective mood effect for individual stocks than the value-weighted index as individual investors are more prone to the mood influence and prefer trading small stocks.

lags 2-5 is −5.63% (t = −5.77), suggesting that a one-standard-deviation increase in the most recent noncongruent-month return leads to a 27% lower return relative to the mean in each of the noncongruent-mood months in the subsequent five years.

The return response is negative and significant for annual lags up to five for the BW portfolios and only for lags 2-5 for the KLN portfolios. In both cases, the economic impact represents a 41% to 53% return reduction resulted from a one-standard-deviation increase in the historical return. Most interestingly, for k = 1, reversal is observed for individual stocks and the BW portfolios, despite the fact that monthly returns in the prior year typically exhibit a momentum effect (Jegadeesh and Titman 1993). The evidence thus shows that a cross-sectional reversal effect takes place across noncongruent-mood states at least for a few subsequent years.

3.1.4 The realized high/low mood-month reversal effect

The reversal effect can also be identified using recent realized mood states proxied by extreme historical equal-weighted CRSP excess returns. The regressions are done by switching the independent variables in regression (3.2). In Column (4) of Table 2, we report the estimates from regressions of the current high or low mood month returns across stocks on their own historical returns in prior years during the recent realized low or high mood months, respectively.

We obtain significant negative return responses across all lags for all three sets of test assets. For lags 2-5, the return response is −8.65% (t = −5.95) for individual stocks, −26.2% (t = −4.27) for the BW portfolios, and −27.0% (t = −4.30) for the KLN portfolios. These return responses represent a 16% to 108% lower monthly return relative to the mean for a one-standard-deviation increase in the historical noncongruent-mood month return. This is again a remarkably strong return reversal effect at a time when investor mood is expected to reverse.

Taken together, our results in Table 2 suggest the existence of strong congruent-mood recurrence effects and noncongruent-mood reversal effects at the monthly frequency, regardless whether we identify historical mood months using average or realized market performances. The estimated economic effect is stronger for portfolios than for individual stocks. These effects connect seemingly independent cross-sectional seasonalities across different calendar months with the congruent or noncongruent mood.

3.2. Weekday-level mood effects

At a higher frequency, we explore whether the cross-sectional recurrence and reversal effects are present across weekdays with identifiable moods. 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). There is also evidence of downbeat mood on Mondays and upbeat mood on Fridays among both the general and the investing populations (e.g., Rossi and Rossi 1977; McFarlane, Martin, and Williams 1988; Stone, Schneider, Harter 2012; Helliwell and Wang 2014).[10]

In the cross section, Keloharju, Linnainmaa, and Nyberg (2016) find that stocks' relative performance on a given weekday recurs in subsequent weeks on the same weekday. Birru (2018) identifies a different kind of cross-sectional weekday return predictability—opposite performance of anomaly portfolios on Mondays versus Fridays based on whether the short leg is betting on speculative or safe stocks. At least one possible source of these patterns is that stocks or portfolio strategies that do well on the past good (bad) mood days will continue doing so under future good (bad) mood days—a mood congruence effect, and will do poorly under noncongruent-mood days.

We verify the findings from previous studies that stocks as a whole earn higher returns on Fridays and lower returns on Monday during our sample period 1963-2016. We then go beyond previous findings to document weekday congruent-mood recurrence and noncongruent-mood reversal effects.

3.2.1 The high/low mood-weekday recurrence effect

We examine the congruent-mood recurrence effect at the daily frequency using FMB regressions, similar to Keloharju, Linnainmaa, and Nyberg (2016) but using only Monday and Friday stock return. We rerun regression (3.1) at the weekday level, in which high mood is identified by Friday and low mood is identified by Monday.

For individual stocks, Column (1) in Table 3 shows that historical Monday/Friday weekday returns across stocks are strong positive predictors of their subsequent congruent-mood-weekday returns beyond the 1st lag, which has an insignificant return response. The return responses for week lags 2-10 and 11-20 are 1.96% (t = 9.90) and 2.53% (t = 13.22), statistically significant at the 1% level, implying a 52% to 62% higher future Monday/Friday return for a one-standard-deviation increase in

[10] See Birru (2018) for an excellent review of this line of literature.

the historical congruent-mood-weekday return.[11] The insignificance at the 1st lag is also observed by Keloharju Linnainmaa, and Nyberg (2016), owing to the short-term reversal effect of one-month return (Jegadeesh 1990) that appears to be unusually strong during the first week.[12]

For the BW and KLN portfolios, the return responses are all positive and significant at the 1% level across the three sets of lags. The size of the return response implies a 101% to 160% higher future Monday/Friday portfolio return for a one-standard-deviation increase in the historical congruent weekday return.[13] Thus, our evidence confirms recurrent relative performances across stocks or portfolios across congruent-mood weekdays for a sample with only Monday and Friday returns.

3.2.2 The realized high/low mood-weekday recurrence effect

We extend the high/low mood recurrence effect to identifying daily mood states by using the two days with the highest or the lowest CRSP equal-weighted excess return realized in a given week. Then we test whether cross-sectional performance in prior realized extreme mood periods recurs on subsequent weekdays with predictable, congruent moods (Friday and Monday), similar to regression (3.2).

Column (2) of Table 3 report the estimates. Across the three panels, the return responses are all significantly positive across assets and week lags except for the first lag of individual stocks, again likely owing to the short-term return reversal effects at the individual stock level. For week lags 2-10, the return responses are 1.43% (t = 5.39), 14.30% (t = 12.93), 14.77% (t = 13.05), for individual stocks, the BW and the KLN portfolios, respectively. These return responses represent a 44% to 243% higher returns for a one-standard-deviation increase in the predictor for each Monday and Friday during the next 2 to 10 weeks.

3.2.3 The high/low mood-weekday reversal effect

For the reversal effect across noncongruent weekdays, we regress Friday or Monday returns across stocks on their noncongruent-mood-weekday returns (Monday or Friday, respectively) in prior weeks. That is, we switch the independent variables in regression (3.1). As reported in Column (3) of

[11] Untabulated tests show that the predictive power of the same-weekday return persists for at least 50 weeks at the individual stock level.
[12] Keloharju, Linnainmaa, and Nyberg (2016) show that past daily returns are in general 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.
[13] Untabulated tests show that the predictive power of the congruent-mood-weekday return persists for at least 50 weeks at the portfolio level.

Table 3 Panel A, we observe a significant negative return response for all three sets of lags for individual stocks. For lags 2-10, the return response is −1.80% (t = −9.15), suggesting a 48% higher return relative to the mean is expected during Mondays and Fridays of the next 2 to 10 weeks for a one-standard-deviation increase in the highest- or lowest-market-weekday return. In Panels B and C, the significant negative return response is present for lags 2-10 and 11-20 for the BW portfolios and only for lags 11-20 for the KLN portfolios, suggesting a weaker return reversal effect across noncongruent-mood weekdays at the portfolio level.

3.2.4 The realized high/low mood-weekday reversal effect

Analogous to the monthly returns, a stronger reversal effect is also observed across noncongruent-mood weekdays identified using historical, realized extreme equal-weighted CRSP excess returns. We regress high (low) mood weekday (i.e., Friday or Monday) returns across assets on their historical returns realized on the lowest-market-return (highest-market-return) weekday of the prior weeks for three sets of week lags, k = 1, 2-10, 6-20, when mood is noncongruent.

For individual stocks, the return responses reported in Column (4) of Table 3, Panel A are all negative and significant at the 5% level or better. The economic impact is large; a one-standard-deviation increase in the daily highest- or lowest-market-weekday return corresponds to a 146%, 56%, and 27% lower noncongruent-mood-weekday return relative to the mean, respectively, for each of the next one, ten, and twenty Monday and Fridays.

When we move to Panels B and C, however, for the BW and KLN portfolios, the return response is positive for the 1st lag. It turns negative and significant when we move to longer lags, suggesting the reversal effects take place only after the first few weeks. Overall, this evidence indicates that when investor mood switches between noncongruent states in a predictable way, cross-sectional return reversals occur strongly at the individual stock level and to some extent at the portfolio level.

4. Mood Beta and Mood Return Effects

The evidence in Tables 2 and 3 provides support for our model predictions that relative stock performance tends to recur between congruent-mood periods and to reverse between noncongruent-mood periods across the cycle of calendar months, weekdays, and market states. We next employ mood beta to integrate the various seasonality effects.

4.1 Mood-month-return-estimated mood beta

To forecast future mood month (e.g., January, March, September, and October) asset returns, we estimate mood beta for each asset from regressions of a stock's historical high, low, realized high and low mood returns in excess of the riskfree rate ($XRET_{i,\text{MoodMonth}}$) on the contemporaneous equal-weighted CRSP excess returns ($XRET_{A,\text{MoodMonth}}$), using a 10-year rolling window by requiring a minimum of 40 observations.[14]

$$XRET_{i,\text{MoodMonth}} = \alpha_i + \beta_{i,\text{month}}^{\text{Mood}} XRET_{A,\text{MoodMonth}} + \varepsilon_i. \tag{4.1}$$

The estimated $\beta_{i,\text{month}}^{\text{Mood}}$ is called "mood-month-return-estimated mood beta." It measures the average return change of an asset in response to a one-percent aggregate return change in the identified historical mood months, during which we hypothesize that mood swings likely dictate the systematic return fluctuations.

In unreported tests, we use an alternative mood beta measure, defined as the ratio, $(\overline{XRET}_{i,\text{HighRHigh}} - \overline{XRET}_{i,\text{LowRLow}})/(\overline{XRET}_{A,\text{HighRHigh}} - \overline{XRET}_{A,\text{LowRLow}})$, where each variable indicates average returns in excess of the riskfree rate across the positive (e.g. high or realized high) mood months or the negative (e.g. low or realized low) mood months. The ratio-based mood beta also captures the average return change for an asset when the average aggregate return increases by one percentage point from periods with declining moods to periods with ascending moods. The results using this ratio are qualitatively similar to those using the regression-based mood beta.

In the second stage, we run Fama-MacBeth regressions of assets' future high or low mood month returns in the cross section on their own mood beta, estimated using prior return information ending in year $t-5$ to $t-2$, the lags for which we observe robust congruent-mood recurrence and noncongruent-mood reversal effects in Table 2. Mood betas are averaged across multiple annual lags for use as a regressor. Estimates for lags of $t=1$ or 6-10 are unreported and similar to the baseline regressions.

Our theory predicts that higher mood beta stocks will do better in subsequent high mood months and worse in subsequent low mood months. Thus, our cross-sectional regressions flip the sign of the mood beta (equivalent to flipping the sign of estimated slope coefficient) when forecasting low mood month returns. In consequence, the estimated coefficient ($\lambda_{k,t}$) is expected to be positive. We call λ_k the *mood premium*, which captures the average size of the positive return spread between the

[14] These include eight months in a year, four high/low months and four realized high/low months. If a calendar month appears in both measures, it is counted twice, implying a higher weight given to the month when estimating mood beta.

high and low mood beta assets in high mood periods and that of the negative return spread when moods are low.

Furthermore, to explore the extent to which the congruent-mood recurrence effects are explained by mood beta, we orthogonalize the historical high and low mood month returns on mood beta. The orthogonalized high or low mood month returns, denoted as $RET^{\perp}_{\text{High(Low)}}$, may proxy for firm-specific mood sensitivity or a component that is totally unrelated to mood.

$$RET_{\text{High},t} = \eta_{k,t} + \lambda_{k,t}\beta^{\text{Mood}}_{i,\text{Month},t-k} + \gamma_{k,t}RET^{\perp}_{\text{High},t-k} + \varepsilon_t, \text{ and}$$
$$RET_{\text{Low},t} = \eta_{k,t} - \lambda_{k,t}\beta^{\text{Mood}}_{i,\text{Month},t-k} + \gamma_{k,t}RET^{\perp}_{\text{Low},t-k} + \varepsilon_t. \tag{4.2}$$

As reported in Column (1) of Table 4, Panel A, for individual stocks (year lag 2-5), the estimated mood premium is 1.47% ($t = 4.83$), implying that a one-standard-deviation increase in mood beta (0.69) leads to an average 101 bps (= 1.47%*0.69) return increase (decrease) in each of the next ten Januaries and Marches (Septembers and Octobers).

After accounting for the correlation with mood beta, the coefficient of $RET^{\perp}_{\text{High(Low)}}$ becomes insignificant. 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. For the BW and KLN portfolios, the mood premium estimates reported in Panels B and C nearly double, 2.73% and 2.95% per month, significant at the 1% level. $RET^{\perp}_{\text{High(Low)}}$, however, continues to carry a significant positive coefficient for individual stocks.

Replacing $RET^{\perp}_{\text{High(Low)}}$ with $RET^{\perp}_{\text{RHigh(RLow)}}$ in Column (2) of Table 4 has no effect on the forecasting power of mood beta but tends to diminish and sometimes flip the sign of the coefficient on the past congruent-mood month returns.

To test whether mood beta explains the noncongruent-mood reversal effect, we add both mood beta and the orthogonalized historical returns earned during noncongruent-mood month ($RET^{\perp}_{\text{Low(high)}}$) to the Fama-MacBeth regressions as below:

$$RET_{\text{High},t} = \eta_{k,t} + \lambda_{k,t}\beta^{\text{Mood}}_{i,\text{Month},t-k} + \gamma_{k,t}RET^{\perp}_{\text{Low},t-k} + \varepsilon_t, \text{ and}$$
$$RET_{\text{Low},t} = \eta_{k,t} - \lambda_{k,t}\beta^{\text{Mood}}_{i,\text{Month},t-k} + \gamma_{k,t}RET^{\perp}_{\text{High},t-k} + \varepsilon_t. \tag{4.3}$$

Shown in Column (3) of Table 4, $RET^{\perp}_{\text{Low(high)}}$ tends to exhibit considerably diminishing predictive power; it is statistically significant for individual stocks and marginally significant for two sets of portfolios. In contrast, the mood premium ($\lambda_{k,t}$) estimates remain positive and significant at the 1% level for all three cases.

Next, we replace $RET^{\perp}_{\text{Low(high)}}$ in regressions (4.3) by the orthogonalized historical returns earned during the realized high or low mood months ($RET^{\perp}_{\text{RLow(RHigh)}}$). The estimates are reported under Columns (4) in Table 4. These orthogonalized historical return measures lose their predictive power for two of the three test assets. In contrast, the mood premium estimates remain virtually unchanged. The findings overall suggest that mood beta accounts for a majority, if not all, of the month-level recurrence and reversal return seasonalities.

4.2 Mood-weekday-return-estimated mood beta

Moving to weekday seasonality, we estimate mood beta for each asset from regressions of a stock's excess return during the high (Friday), low (Monday), realized high and low mood weekdays in prior weeks on the corresponding equal-weighted market excess returns using a 6-month rolling window (by requiring a minimum of 50 observations), for which we have verified earlier that the congruent-mood recurrence effect is present at the weekday level.

$$XRET_{i,\text{MoodWeekday}} = \alpha_i + XRET_{A,\text{MoodWeekday}} + \varepsilon_i. \tag{4.4}$$

The estimated coefficient on the market excess return is called the "mood-weekday-return-estimated mood beta." We obtain qualitatively similar results if we define mood beta as a ratio, $(\overline{XRET}_{i,\text{HighRHigh}} - \overline{XRET}_{i,\text{LowRLow}})/(\overline{XRET}_{A,\text{HighRHigh}} - \overline{XRET}_{A,\text{LowRLow}})$.

We next use the estimated $\beta^{\text{Mood}}_{i,\text{Weekday}}$ to forecast future high/low mood weekday (Friday and Monday) returns together with the orthogonalized historical returns earned during congruent-mood weekday ($RET^{\perp}_{\text{High(Low)}}$).

$$RET_{\text{High},t} = \eta_{k,t} + \lambda_{k,t}\beta^{\text{Mood}}_{i,\text{Weekday},t-k} + \gamma_{k,t}RET^{\perp}_{\text{high},t-k} + \varepsilon_t, \text{ and}$$
$$RET_{\text{Low},t} = \eta_{k,t} - \lambda_{k,t}\beta^{\text{Mood}}_{i,\text{Weekday},t-k} + \gamma_{k,t}RET^{\perp}_{\text{Low},t-k} + \varepsilon_t. \tag{4.5}$$

We focus on the mood betas estimated using prior return information ending in week $t-10$ to $t-2$. Mood betas across multiple lags are averaged before used as a regressor. Estimates for lags of t = 1 or 11-20 are unreported and similar to the baseline regressions. As reported in Column (1) of Table 4 (week lag 2-10), the estimated mood beta premium is positive and significant at the 1% for all three sets of test assets, with the size of the daily premium at 5 bps for individual stocks, 12 bps for the BW portfolios, and 10 bps for the KLN portfolios. The estimated return response on $RET^{\perp}_{\text{High(Low)}}$ remains positive and significant for three sets of test assets.

In Column (2) of Table 4, we report the estimates for a similar specification as in regression (4.5), in which we replace $RET^{\perp}_{\text{High(Low)}}$ with the orthogonalized realized high/low weekday returns ($RET^{\perp}_{\text{RHigh(RLow)}}$), identified from realized weekday returns of the equal-weighted market. We again observe all mood beta premia are positive and significant at the 1% level, while only one out of three coefficients of $RET^{\perp}_{\text{RHigh(RLow)}}$ is significant.

Next we replace $RET^{\perp}_{\text{High(Low)}}$ in regression (4.5) by those earned during the noncongruent-mood weekdays, either using $RET^{\perp}_{\text{Low(High)}}$ or $RET^{\perp}_{\text{RLow(RHigh)}}$, to assess how the cross-sectional mood reversal effect is related to mood beta. The estimates are reported under Columns (3) and (4) of Table 4. Mood beta premia remain positive and significant in all cases. But only two out of six coefficients on $RET^{\perp}_{\text{Low(High)}}$ and $RET^{\perp}_{\text{RLow(RHigh)}}$ remain negative and significant. After accounting for the mood beta, the noncongruent-mood reversal effects tend to weaken or disappear, and even turn into a return recurrence effect.

This evidence suggests that mood beta explains much of the noncongruent reversal effects at the weekday level. Since betas are estimated with error, it is possible that true mood beta is the entire source of these effects.

4.3 Mood beta, market beta and sentiment beta

We next consider whether the mood beta effects that we document derive from traditional beta. Under rational risk-based asset pricing theory, the market premium should be positive, which implies that market beta should be positively related to expected returns in pre-designated months or days. This prediction, however, is contradicted by our estimates of negative premia on mood beta during Septembers, Octobers, and Mondays (see Panels A and B of Figure 2, which will be discussed later).

Nevertheless, to further address the possibility that the mood beta effects may derive in part from market beta, we perform tests that control for market beta in our regressions with mood beta, where market beta is estimated in a fashion analogous to the corresponding mood beta (using monthly or daily returns) except that all month or weekday returns are used in the estimation.

Another possible concern is that mood beta may be a proxy for the sentiment beta proposed by Baker and Wurgler (2006, 2007). The purpose of studying mood beta is to capture stock sensitivity to shifts in investor emotions, which we view as a special case of investor sentiment. Sentiment is a more general term that applies to any common shifts in investor attitudes toward assets other than fully rational updates in beliefs, which may derive from either affective or non-affective sources.

But as a distinctive aspect of investor sentiment, investor mood can potentially behave differently from other aspects of sentiment. So we do not expect mood beta to be perfectly correlated sentiment beta over time or across securities. Furthermore, mood varies across months as well as weekdays, a frequency which is higher than that used to construct the Baker and Wurgler sentiment index, or to measure its components, such as IPO volume, aggregate equity versus issuance, and dividend premium.

To verify whether mood beta has incremental explanatory power, we include sentiment beta in the regression, where sentiment beta is estimated using the most recent 60 (at least 36) monthly returns regressed on the monthly change in the Baker and Wurgler (2006) sentiment index (orthogonalized to macroeconomic variables) together with the CRSP value-weighted index return. An alternative measure of the sentiment index estimated using the principal component of the monthly changes in five sentiment index components yields qualitatively similar results.

Our regressions are designed to forecast future asset returns during the high or low mood periods (months or weekdays) using mood beta with controls for market beta or sentiment beta. Again, we focus on the year lags 2-5 for month-level return regressions and week lags 2-10 for weekday return regressions. The estimates reported in Table 5 indicate that, across all three test assets and specifications, the mood premium remains positive and significant in the presence of market beta or sentiment beta.

In contrast, market beta tends to carry a significantly negative premium, contrary to the theoritcal prediction. This phenomenon is referred to as the low-risk anomaly (Baker, Bradley, and Wurgler 2011; Frazzini and Pedersen 2014). Sentiment beta tends to carry a positive coefficient, suggesting that high sentiment beta stocks tend to earn higher average returns during ascending mood periods. In conclusion, neither market beta nor sentiment beta subsumes the ability of mood beta to predict returns.

4.4 Composite mood beta

So far for each asset we have two mood betas, estimated from monthly and weekday returns during high and low mood periods. To further reduce noise and to develop out-of-sample tests, we form a composite mood beta (β_i^{Mood}) as the first principal component of the two mood betas: $\beta_{i,\mathrm{month}}^{\mathrm{Mood}}$

and $\beta_{i,\text{Weekday}}^{\text{Mood}}$, extracted month by month in the cross section of individual stocks or portfolios. $\beta_{i,\text{month}}^{\text{Mood}}$ is updated annually, so the monthly variation for a given stock comes solely from the variation in $\beta_{i,\text{Weekday}}^{\text{Mood}}$.

The composite mood beta has an average eigenvalue of 1.34, 1.60, and 1.47, respectively for the three sets of test assets, and by construction, zero mean and unit standard deviation. The average weight is roughly equal on the two mood beta components in the composite mood beta. The evidence suggests that there is important commonality among the two mood betas that is picked up by the composite mood beta.

We report the summary statistics of the composite mood beta on Table 1, and depict the time-series average of the composite beta for each of the BW and KLN portfolios in Figure 1. The figure shows a set of interesting observations. Mood beta tends to be higher for younger firms than older firms, growth firms than value firms, non-dividend payers than payers, small firms than larger firms, high R&D firms than low R&D firms, high volatility firms than low volatility firms, low dividend-yield firms than high dividend-yield firms, low earnings-to-price firms than high earnings-to-price firms.

Some other attributes exhibit a V-shaped or inverse V-shaped relationship with mood beta. For example, mood beta is higher for both extreme winners and extreme losers, firms with extremely high or extremely low return on equity, firms with the highest or the lowest external financing, and firms with the fastest or the slowest sales growth. Mood beta is lower for firms with zero or extremely high tangible assets. Across industries, the highest mood beta is observed for the Machinery industry, and by far the lowest mood beta is seen for the Utilities industry.

Many of these patterns about mood beta are similar to those associated with the sentiment beta of Baker and Wurgler (2006). These patterns support the notion that hard-to-value firms and attention-grabbing firms are more heavily influenced by investor mood swings than easy-to-value or easy-to-neglect firms. In subsequent tests, we use the composite mood beta to assess the profitability of trading strategies as well as to conduct the cross-domain tests.

4.5 Long-short portfolios based on mood returns and mood beta

Our Fama-MacBeth regression results presented earlier in Sections 4.1 and 4.2 suggest that historical congruent-mood returns, noncongruent-mood returns, and mood beta all have the ability to forecast cross-sectional returns in future high or low mood periods. We next examine the profitability of various trading strategies derived from these findings.

We form a long-short portfolio for each predictor based on the portfolio deciles sorted each month according to the predictor. If the historical mood return is used as the predictor, the hedge portfolio always goes long the highest decile and short the lowest decile. If mood beta is used instead, the hedge portfolio goes long the highest decile and short the lowest decile during the subsequent high mood periods, and flips the long and short legs when low moods are anticipated.

Table 6, Panel A reports the mean monthly long-short returns from seven strategies based on historical congruent and noncongruent-mood month returns (high, low, realized high, realized low), as well as the three mood betas: mood-month-return estimated, mood-weekday-return estimated, and the composite mood beta. The strategies are implemented for forecasting the high and low mood months only (January, March, September, and October) and use only the signals measured with annual lags 2-5 or weekly lags 2-10, for which we observe robust return predictability in previous tests. In addition to mean returns, we report the estimated risk-adjusted returns (i.e., alphas) for these long-short portfolios based on the Fama-French-Carhart 4-factor model (Carhart 1997) and the Fama and French (2015) 5-factor model.

Across the three sets of test assets, the trading strategies that capture the congruent-mood recurrence effects work better for the BW and KLN portfolios, with a 5-factor alpha ranging from 1.47% (t = 5.06) to 1.80% (t = 5.81) per month. Those based on the noncongruent-mood reversal effects work better for individual stocks, with a 5-factor alpha of −1.40% (t = −5.63) and −1.74% (t = −4.44) per month.

The trading strategies based on three mood betas tend to be more profitable for individual stocks. The monthly 5-factor alphas for the mood beta strategies across three sets of assets range from 0.61% (t = 1.90) to 2.85% (t = 5.23). The composite-mood-beta-based strategies work well for all three sets of test assets, generating a monthly 5-factor alpha ranging from 1.59% to 2.37%, all significant at the 5% level or better. It is particularly profitable for individuals stocks.

Moving to Panel B, the trading strategies now apply to forecasting future mood weekday returns (Mondays and Fridays). Here we see significant alphas for strategies based on the congruent-mood recurrence effect; the alphas range from 3 to 12 bps per day across the three assets, nearly all significant at the 5% level or better. The strategies based on the noncongruent-mood reversal effect are profitable for individual stocks (8 to 10 bps per day) and for the BW portfolios (2 to 3 bps per day), but unprofitable for the KLN portfolios.

In contrast, mood-beta-based strategies are highly profitable throughout all measures, with alphas ranging from 8 to 17 bps a day, all significant at the 5% level or better. Overall, mood beta implies more stable and profitable trading strategies across three assets over the full sample periods.[15]

One may wonder whether the long-short mood beta portfolio's profit comes from both high and low mood periods. Consistent with our model prediction, as depicted in Panels A and B of Figure 2, the three high-minus-low portfolios based on the composite mood beta yield positive returns during high mood months and weekdays but negative returns during low mood months and weekdays. This is in contrast to the prediction of rational risk theory that higher loadings on fundamental risk factors should consistently receive risk premia of the same sign.

In Figures 3 and Figure A1 of the Online Appendix, we present the high-minus-low portfolios based on the market beta and sentiment beta across the various high and low mood periods. The figures show that neither market beta nor the sentiment beta consistently overperform during high mood periods and underperform during low mood periods. Thus, neither market beta nor sentiment beta fully captures the mood sensitivity captured by mood beta.

4.6 Alternative definitions of mood periods

One possible concern is that our results may be driven by a look-ahead or in-sample bias and the fact that mood beta correlates with market beta. Rational factor pricing models imply that ex ante the market ex ante risk premium is positive on all months or days. In long enough samples, return predictability should reflect such positive ex ante premia for market beta; systematic patterns with negative daily or monthly premia for market beta would be ruled out.

Consider now the hypothesis that our mood beta effects are driven by market beta. Then our finding that in some seasonal periods there is a negative premium associated with mood beta should be limited to specific samples (especially when the seasonal periods are selected based upon look-ahead bias). In contrast, in our mood-based theory, such effects should be observable out of sample as mood varies predictably across months and weekdays.

To address this issue, we conduct four robustness checks in Table 7 by changing the predictable future mood periods from the originally pre-designated January, March, September, October, Monday, and Friday.

[15] Figure A2 of the Online Appendix indicates that the long-short profits exhibit diminishing returns since 2001, which may be caused by the rising importance of sophisticated investors such as hedge funds.

Instead, we identify future mood periods based on the extreme, average monthly or weekday equal-weighted market excess returns (1) from 1927 to the preceding year before the forecast is made; (2) over the rolling 50-year window for monthly returns ending in the prior year or the rolling 10-year window for weekday returns ending in the prior month; (3) of even years only to forecast returns in odd years during 1963-2016; and (4) of odd years only to forecast returns in even years during 1963-2016. The commonality in the four tests is that the future mood months or weekdays are identified using only historical or split-sample data that exclude the return information of the mood months or weekday being forecasted.

As in Table 6, we report the long-short portfolio returns based on historical mood returns or mood beta. The estimates in Panel A of Table 7 are for the month-level tests with year lags 2-5. The results indicate strong congruent-mood recurrence effects for portfolios and strong noncongruent-mood reversal effects for individual stocks, a pattern generally similar to our baseline results in Table 6.

Moving to weekday level tests, the congruent-mood recurrence effects are general strong across three sets of tests assets. The noncongruent-mood reversal effects are generally strong for individual stocks and the Baker and Wurlger (2006) portfolios, but weak for the Keloharju, Linnainmaa, and Nyberg (2016) portfolios, again similar to the baseline results in Table 6.

Lastly, the long-short mood beta portfolio returns are reported in Table 7, Column (5). Across four approaches of identifying future mood periods and three sets of test assets, mood beta-based long-short portfolios earn positive and significant average returns in 8 out of 12 cases, and marginally significant average returns in 2 out of 12 cases, leaving only two cases insignificant. The long-short strategies produce an average return of about 1% per mood month or above 10 bps per mood day, a magnitude that is slightly smaller at the monthly level, and similar at the weekday level, to the baseline strategies based on pre-designated mood months or weekdays.

Overall, using the alternative definitions of future predictable mood periods leads to qualitatively similar, and quantitatively comparable results. Thus, our findings of the congruent-mood recurrence and noncongruent-mood reversal effects and the predictive power of mood beta are unlikely to be driven by a look-ahead or in-sample bias.

4.7 Is January Special?

Heston and Sadka (2008) show that January is associated with a stronger same-month return persistence effect. In Table A1 of the Online Appendix, we extend their analysis to the congruent-mood recurrence and noncongruent-mood reversal effects by separately reporting the Fama-MacBeth regression coefficients for January and non-January months.

Indeed, both month-level mood effects are visibly stronger during January months. While some of the historical congruent-mood or noncongruent-mood returns lose predictive power in non-January mood months, however, mood beta retains its significant power in the forecasts for all three test assets.

Moving to Table A2 for the weekday-level tests, however, we find that congruent-mood recurrence and noncongruent-mood reversal effects are slightly stronger in non-January months. So is the forecast power of mood beta; the coefficient of mood beta in non-January months is several times that in January. Taken together, the mood effects are especially strong in January for monthly-level tests but not so for weekday-level tests.

5. Cross-Domain Mood Beta Tests

So far our tests of mood beta have been confined to the domains of predicting seasonal returns from which mood beta is derived. A powerful test of the predictive power of mood beta is to go beyond the original domain to settings that have at best weak relation to seasonalities by month or weekday. We therefore seek to perform deeply out-of-sample tests of our hypothesis.

Furthermore, this approach allows us to focus on exogenous shifts that are more uniquely linked to *mood* changes rather than other economic changes. In particular we consider how mood beta affects returns of general and different sets of stocks at times of anticipations of major holidays, Daylight Savings Time changes, and in relation to weather conditions.

5.1 Preholiday returns

We first examine whether mood beta helps to forecast the cross-section of preholiday returns. 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; Autore, Bergsma, and Jiang 2015). Furthermore, individual stocks that historically have earned higher pre-holiday returns tend to continue doing so for the same holiday over the next ten years (Hirshleifer, Jiang, Meng, and Peterson 2016).

Our theory explains both the aggregate and cross-sectional pre-holiday effects. It further predicts that high mood beta assets will outperform low mood beta assets during preholiday periods when moods are ascending. For the holiday related analyses, we include thirteen major holidays in the U.S. that have been celebrated for over 100 years: 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.[16]

We verify the pre-holiday effect (e.g. Ariel 1990) using our sample from 1963-2016. In this period the average pre-holiday daily return is 20 bps, roughly 5 times that earned in other trading days. Hirshleifer, Jiang, Meng, and Peterson (2016) find that the relative pre-holiday performance across stocks tends to recur year after year on the same holiday, across different holidays, and to reverse immediately after the same holiday. We add mood beta to such analyses.

We test for the mood beta effect on preholiday returns through FMB regressions. The dependent variable is the daily pre-holiday stock return. In Table 8, the return predictor in regression (1) is the pre-holiday return of the stock for the k^{th} lagged holiday to test the link across different holidays, in regression (2) is the composite mood beta, and in regression (3) includes both, as follows

$$RET_{\text{Preholiday},t} = \alpha_{k,t} + \lambda_{k,t}\beta_{t-k}^{\text{Mood}} + \gamma_{k,t}RET_{\text{Preholiday},t-k} + \varepsilon_t, \tag{5.1}$$

where k = 1, 2-7, 8-13, where holiday-level independent variables are first averaged across multiple holiday lags, wherever applied, before used as the predictor for regressions. 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 recurrence of the relative pre-holiday returns for an average holiday over a one-year horizon that follows the holiday.

In Column (1) in Table 8, we report the return responses for the historical preholiday returns, which are positive and significant in 7 out of 9 cases at the 5% level or better. This preholiday return recurrence effect is consistent with findings of Hirshleifer, Meng, Jiang, and Peterson (2016). In Column (2), we use the composite mood beta to forecast the pre-holiday returns in the cross section.

[16] 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.

The estimated coefficient on mood beta is positive and significant in all 9 cases at the 1% level, ranging from a 4 to 8 bps daily premium.

Controlling for mood beta, estimates in Column (3) show that the coefficients on the orthogonalized historical pre-holiday return remain similar for lags 1 and 2-7 to the baseline regressions but become weaker for lags 8-13, especially for the two sets of portfolios. The evidence suggests that high mood beta stocks indeed outperform during pre-holiday periods. However, mood beta seems to reduce the power of the historical pre-holiday return to forecast future historical pre-holiday returns in the intermediate term.

Furthermore, as plotted in Panel C of Figure 2, the long-short portfolios based on the composite mood beta yield a daily average preholiday return of 12 to 20 bps. This contrasts with less than one basis point average daily return in other trading days. Thus, mood beta helps capitalize ascending investor mood in anticipation of major holidays.

5.2 Daylight Saving Time changes

Our second test setting is based on the Daylight Saving Time (DST) changes (collected from www.timeandate.com) in the U.S. from 1967 to 2016. The start and end of summer time involve changing the clock in two pre-designated weekends each year. Clock change disrupts sleep routines, leading to temporary depressed mood and low stock market returns (Kamstra, Kramer, and Levi 2000).

We replicate the finding by Kamstra, Kramer, and Levi in this updated sample period from their original study (1967-1997); Indeed, the stock market as a whole tends to experience abnormally low returns over the Spring and Fall DST change weekends—from Friday close to Monday close.[17] Our estimates in Table 9, the top two rows, show that the DST weekends are associated with an average excess return of −0.235% and −0.293%, respectively for the value- and equal-weighted market portfolios, which are significantly below the average weekend returns observed in ordinary weeks (−0.036% and −0.070%).

More importantly, we report in Table 9 that high mood beta assets significantly underperform low mood beta assets during the DST clock change weekends. For individual stocks, the Fama-MacBeth regression of the DST weekend stock returns on their mood beta yields a significant negative coefficient of −0.147% (*t*–statistic = −2.65) for the DST clock change weekends, which is 0.091% lower than the coefficient on mood betas during the regular weekends.

[17] Tuesday close is used to replace Monday close if Tuesday is the first trading day of the week following the time change.

This pattern of a more negative mood beta coefficient is observed for the BW portfolios, with a differential mood beta coefficient of −0.037% (t–statistic = −1.98). For the KLN portfolios, the differential is insignificant (−0.036%, t–statistic = −1.62). As plotted in Panel D of Figure 2, the three long-short portfolios based on the composite mood beta yield an average return that is twice negative during the DST weekends relative to other weekends.

Overall, the evidence supports our hypothesis that individual stocks and the BW portfolios with high mood beta tend to decline more than low beta assets on weekends with usually low moods induced by the DST clock changes.

5.3 Weather conditions

A third setting for out-of-sample testing of mood beta effects is based on weather-induced investor mood. We identify mood days using seasonally-adjusted cloud cover in New York City and focus on early morning measure as we use it as a forecaster of stock returns (e.g., Hirshleifer and Shumway 2003).

We obtain the hourly station-level weather data from the National Oceanic and Atmospheric Administration (NOAA) ISD-Lite dataset (e.g., deHaan, Madsen, and Piotroski 2016) from January 1963 through May 2016. We first identify stations that are located within 50 miles to the centroid of the New York Stock Exchange (NYSE) zip code (10005). Then we aggregate the hourly cloud cover (ranging from 0 to 8, with 0 indicating the least cloud cover and 8 the most cloud cover) from 5AM to 8AM each day for each station. Next for each day we average the station-level measures to yield the daily New York City cloud cover index. As in previous literature, to eliminate the seasonal variation in weather, we deseasonalize the daily cloud cover index by subtracting the mean level index for the same week across the entire sample period.

We define sunny (cloudy) days as the 25% of trading days with the least (most) amount of deseasonalized cloud cover, and the remaining days (50% of the sample days) as moderate days. We first confirm the finding of Hirshleifer and Shumway (2003) in the updated sample period of 1963-2016 that sunny days in New York City are associated with significantly higher average market returns than cloudy days. For example, in Table 10, the average return of the value-weighted market index on sunny days is 6.8 bps, which is nearly ten-fold the mean return (0.7 bps) on cloudy days, a statistically significant difference of 6.1 bps per day (t = 2.51). A similar pattern is present for the equal-weighted market index as well.

We further find that high mood beta assets significantly outperform in sunny days. For individual stocks, the estimated coefficient on the composite mood beta is 1.7 bps (t = 2.08). The coefficient is reduced in size to 1.4 bps per day for moderate days and becomes insignificant in cloudy days (−0.4 bps), suggesting no differential return performance across mood betas during cloudy days. The estimated mood beta coefficient is marginally significantly different between sunny and cloudy days, with the difference of 2.2 bps per day (t–statistic = 1.93).

The same patterns are observed for the BW and KLN portfolios, with the differential mood beta coefficient between the sunny and cloudy days of 1 bps to 1.1 bps per day, both significant at the 5% level. Panel E of Figure 2 plots the long-short portfolio returns based on the composite mood beta. It shows that the portfolios yield an average daily return of three to five bps during sunny days and *negative* one to three bps during cloudy days.

5.4 Fama-MacBeth regressions spanning all the domains

Lastly, we combine all test domains in firm-level Fama-MacBeth regressions to assess the incremental predictive power of mood beta relative to other return predictors. In Table 11, we report the Fama-MacBeth regression estimates for the mood month and mood day regressions, in which lagged mood beta is used to forecast stock returns in future mood months (January, March, September, or October) or mood days (Mondays, Fridays, preholidays, sunny days, cloudy days, or DST changes weekends).

We include only the composite mood beta (regressions 1 and 4), add market beta and sentiment beta (regressions 2 and 5), and additionally control for a set of firm characteristics used to form the BW and KLN portfolios (regressions 3 and 6), including firm size (*ME*), book-to-market equity (*B/M*), momentum (Mom), external financing (*EF/A*), gross profitability (*GP*), tangible assets (PPE/A), sales growth (*SG*), and return volatility (*SIGMA*). We exclude several potential controls that are too closely related to the preceding ones: firm age, dividend-to-price, earnings-to-price, dividend-to-book equity, ROE and R&D. Like the included controls, these measure or correlate with firm size, fundamental-to-price ratio, profitability, or asset tangibility.

To account for the opposite relationship between mood beta and future returns in high versus low mood periods, we add a negative sign to the dependent variable realized in low mood months or days so that mood beta has an expected positive coefficient for both mood states. This sign adjustment is equivalent to flipping signs of all independent variables, from market beta and sentiment beta to firm characteristics, between the high and low mood periods.

The regression estimates reported in Table 11 show that mood beta has a positive and significant coefficient throughout all regressions; the coefficient ranges from 0.59% to 1.80% per mood month and from 2.15 bps to 4.07 bps per mood day, all significant at the 5% level or better. Including all other forecasters (Regressions 3 and 6) roughly halves the size of the coefficient on mood beta.

In contrast, market beta and sentiment beta have mixed or insignificant coefficient, exhibiting no clear pattern. Among other firm characteristics, only size, momentum, and gross profitability exhibit a consistent and significant relationship with future mood returns, which suggests that their relationship with future returns also tend to flip between high and low mood periods.

Overall, the evidence in the three cross-domain tests is consistent with the predictions of the mood-based theory. Mood beta positively predicts stock returns when investors experience ascending moods and negatively predict returns when investors experience descending moods. This forecasting power is robust to controls for market beta, sentiment beta, and a host of firm characteristics. This is the case even though the domains of the mood shifts are very different from the seasonal calendar variations used to estimate mood betas.

6. Conclusion

We offer a theory predicting that investor mood seasonal variations are in part responsible for both aggregate and cross-sectional return seasonalities. Consistent with the mood-based theory, we document a variety of strong, novel cross-sectional mood recurrence and reversal effects across calendar months, weekdays, and market states. Assets that outperform in the past periods when investors are in upbeat moods tend to outperform in future seasons when an upbeat mood is expected, and to underperform in future periods when a downbeat mood is expected.

Our theory and empirical results also highlight the role of mood beta, which measures a security's mood sensitivity to factor-wide mispricing and is estimated during strong mood seasons, in integrating various mood recurrence and reversal effects, as well as cross-sectional returns under mood states induced by anticipation of major holidays, Daylight Saving Time changes and weather conditions. Across the board, we observe that high mood beta stocks outperform low mood beta stocks during future high mood states, underperform during future low mood states, and its predictive power is incremental to market beta, sentiment beta, and a host of firm characteristics.

It is unclear how to reconcile our findings with a rational risk-based story, in which 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. The evidence in Keloharju, Linnainmaa, and Nyberg (2016) provides the insight that both aggregate and cross-sectional return seasonalities are manifestations of seasonal factor premia—though not necessarily rational risk premia. Here we test one possible source of such seasonal factor return premia: seasonal variations in investor moods that induce corresponding seasonal variation in factor mispricing. The evidence we provide collectively suggests that investor mood is an important contributor to stock return seasonalities at the aggregate as well as in the cross section.

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Appendix A: Model derivation and more implications

A. 1 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,

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

where again 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 (A.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:

$$P_i^2 = \bar{\theta}_i + \sum_{k=1}^{K} \beta_{i1} \mathrm{E}\left[\theta \middle| s_k^1, S_1^2, s_2^2\right] + \mathrm{E}\left[\epsilon_i \middle| v_i^1, V_i^2\right]$$
$$= \bar{\theta}_i + \beta_{i1}\left[\lambda_f s_1^1 + \lambda_f\left(s_1^2 + \gamma_f b\right)\right] + \beta_{i2}\left[\lambda_f s_2^1 + \lambda_f s_2^2\right] + \left[\lambda_\epsilon v_i^1 + \lambda_\epsilon\left(v_i^2 + \gamma_i b\right)\right], \quad \text{(A.2)}$$

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 at date 2, relative to rational pricing (b = 0), factor 1 and firm-specific payoffs are inflated (deflated) by γb. Therefore, equation (A.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 (A.2) can explain why the aggregate market outperforms during periods of positive moods (e.g., during January, March, Friday, pre-holiday trading days, sunny days), and underperforms during periods of negative moods (e.g., September, October, Monday, cloudy days, and Daylight Saving Time change weekends), as well as why some assets consistently outperform others when positive or negative mood swings occur.

A. 2 Market Beta versus Mood Beta

Our model in Section 2 implies that market beta is different from mood beta. Market beta measures an asset'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 (2.1) and (2.2) 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

$$\beta_i^A = \frac{cov[(P_{2i} - P_{1i})^R,\ (P_{2A} - P_{1A})^R]}{var(P_{2A} - P_{1A})^R} = \frac{\beta_{i1} + \beta_{i2}}{2}, \tag{A.3}$$

That is, market beta is an average loading across all factors, as opposed to only the loading on the mood-prone factor. This implies that if β_{i1} and β_{i2} are not perfectly correlated, and after controlling for market beta, mood beta still has incremental power to forecast future returns under the congruent, or noncongruent, mood state.

PROPOSITION 4: *Market beta does not subsume the power of mood beta to explain the cross-section of seasonal returns during states with mood shifts.*

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 asset mispricing induced by mood and help to forecast future returns of the asset under the congruent and noncongruent-mood states. 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 effects (recurrence and reversal) in the cross section. We next test these new predictions.

Appendix B: Variable Definition

B.1 Returns and betas of test assets

Variables	Definitions
RET_{High}	Monthly or weekday return during the *high mood* months or weekdays identified by high full-sample average equal-weighted market excess returns. The high mood state refers to January and March at the month level and Friday at the weekday level. When used as an independent variable or sorting variable at the month level tests, it is the average return during January and March in a given year. Reported in percentages.
RET_{Low}	Monthly or weekday return during the *low mood* months or weekdays identified by low full-sample average equal-weighted market excess returns. The low mood state refers to September and October at the month level and Monday at the weekday level. When used

	as an independent or sorting variable at the month level tests, it is the average return during September and October in a given year. Reported in percentages.
RET_{RHigh}	Monthly or weekday return during the *high mood* months or weekdays identified by *realized* high equal-weighted market excess returns. The realized high mood state refers to the two months in a year or the one day in a week with the highest equal-weighted CRSP excess return. When used as an independent or sorting variable at the month level tests, it is the average return during the two realized high mood months in a given year. Reported in percentages.
RET_{RLow}	Monthly or weekday return during the *low mood* months or weekdays identified by *realized* low equal-weighted market excess returns. The realized low mood state refers to the two months in a year or the one day in a week with the lowest equal-weighted CRSP excess return. When used as an independent or sorting variable at the month level tests, it is the average return during the two realized low mood months in a given year. Reported in percentages.
$RET_{Preholiday}$	Daily return during the pre-holiday period, which refers to the (−2, 0) trading day window, where day 0 is one of the 13 major holidays that have been celebrated in the United States for at least 100 years, including 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. If a holiday is a trading day, the holiday itself is included. When used as an independent variable, it is the average daily return during the pre-holiday period for a given holiday of a year. Reported in percentages.
β^{Mood}_{Month}	Monthly-return-estimated mood beta, estimated by regressing an asset's excess returns during the four high and four low mood months (as defined for the mood state returns) on the equal-weighted CRSP excess return over a 10-year rolling window ending in the prior year, updated annually. A minimum of 40 observations are required.
$\beta^{Mood}_{Weekday}$	Weekday-return-estimated mood beta, estimated by regressing an asset's excess returns during the two high and two low mood weekdays (as defined for the mood state returns) on the equal-weighted CRSP excess return over a 6-month rolling window ending in the prior month, updated monthly. A minimum of 50 observations are required.
β^{Mood}	Composite mood beta, defined as the principal component of β^{Mood}_{Month} and $\beta^{Mood}_{Weekday}$, extracted monthly. It is normalized to have zero mean and unit standard deviation.
β^{MKT}_{Month}	Monthly-return-estimated market beta, estimated from a market model using monthly returns over a 10-year rolling window ending in the prior year, updated annually. The market portfolio is proxied by the value-weighted CRSP index.
$\beta^{MKT}_{Weekday}$	Weekday-return-estimated market beta, estimated from a market model using daily returns over a 6-month rolling window ending in the prior month, updated monthly. The market portfolio is proxied by the value-weighted CRSP index.
β^{SENT}	Sentiment beta, estimated from regressions of monthly returns (in percentages) over a 60-month rolling window (requiring at least 36 monthly observations) on the monthly changes in the Baker and Wurgler (2006) orthogonalized sentiment index, controlling for the CRSP value-weighted returns, updated monthly.

B.2 Firm characteristics

B.2.1 Baker and Wurgler (2006) Portfolios

Variables	Definitions
AGE	Firm age as measured by the number of months since the firm's first appearance on CRSP, measured as of the most recent month.
B/M	Book-to-market equity. We define book equity (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 B/M, we match BE for the fiscal year ending in calendar year $t-1$ with the firm's market equity at the end of December of year $t-1$ and then match this B/M to returns from July of year t through June of year $t+1$. This variable is winsorized annually at the 0.5% and 99.5% levels.
D/BE	Dividends to equity, defined as dividends per share at the ex date (DVPSX_F) of fiscal year end times Compustat shares outstanding (CSHO) dividend by book equity. Zero dividend firms are included in a separate portfolio from the deciles. We match D/BE for the fiscal year ending in calendar year $t-1$ to returns from July of year t through June of year $t+1$. This variable is winsorized annually at the 0.5% and 99.5% levels.
EF/A	External finance, defined as the change in total assets (AT) minus the change in retained earnings (RE) divided by assets (AT). If retained earnings is missing, it is replaced by net income (NI) minus common stock dividends (DVC). We match EF/A in June of year t to returns from July of year t through June of year $t+1$.This variable is winsorized annually at 0.5% and 99.5% levels.
ME	Market equity, measured by price (PRC) times shares outstanding (SHROUT) from the end of the latest June. We match ME in June of year t to returns from July of year t through June of year $t+1$.
SG	Sales growth, defined as the change in net sales (SALE) divided by prior-year net sales. We match SG for the fiscal year ending in calendar year $t-1$ to returns from July of year t through June of year $t+1$. This variable is winsorized annually at the 0.5% and 99.5% levels.
PPE/A	Tangible assets, defined as property, plant and equipment (PPEGT) over assets (AT). Zero PPEGT firms are included in a separate portfolio from the deciles. We match PPE/A for the fiscal year ending in calendar year $t-1$ to returns from July of year t through June of year $t+1$. This variable is winsorized annually at the 0.5% and 99.5% levels.
R&D/A	Research and development expense (XRD) over assets (AT). We do not consider this variable prior to 1972, following Baker and Wurgler (2006). Zero XRD firms are included in a separate portfolio from the deciles. We match R&D/A for the fiscal year

	ending in calendar year $t - 1$ to returns from July of year t through June of year $t + 1$. This variable is winsorized annually at the 0.5% and 99.5% levels.
ROE	Return on equity, defined as earnings dividend by book equity. Earning is income before extraordinary items (IB) plus income statement deferred taxes (TXDB) minus preferred dividends (DVP). Book equity (BE) is as defined as for B/M. ROE is set to zero if earning is negative. Zero ROE firms are included in a separate portfolio from the deciles. We match D/BE for the fiscal year ending in calendar year $t - 1$ to returns from July of year t through June of year $t + 1$. This variable is winsorized annually at the 0.5% and 99.5% levels.
SIGMA	Return volatility, measured by the standard deviation of monthly returns over the 12 months ending in June. We match SIGMA measured as of June of year t to monthly returns from July of year t through June of year t+1.

B.2.2 Keloharju, Linnainmaa, and Nyberg (2016) Portfolios

Variables	Definitions
ME	As defined in Appendix B.2.1.
B/M	As defined in Appendix B.2.1.
Mom	Price momentum measured by the cumulative return from month $t - 12$ through $t - 2$, matched to return in month t.
GP	Gross profitability, defined as annual revenues (REVT) minus cost of goods sold (COGS), divided by book equity (BE) for the last fiscal year end in $t - 1$, where BE is as defined in Appendix B.2.1 for B/M. We match GP for the fiscal year ending in calendar year $t - 1$ to returns from July of year t through June of year $t + 1$. This variable is winsorized annually at the 0.5% and 99.5% levels.
D/P	Dividend yield, defined as ex-date dividends per share (DVPSX_F) scaled by ex-date price per share (PRCC_F) at the fiscal year end. Zero dividend firms are included in a separate portfolio from the deciles. We match D/P for the fiscal year ending in calendar year $t - 1$ to returns from July of year t through June of year $t + 1$. This variable is winsorized annually at the 0.5% and 99.5% levels.
E/P	Earnings yield, defined as earnings per share including extraordinary items (EPSFI) scaled by price per share (PRCC_F) at the fiscal year end. Zero earnings firms are included in a separate portfolio from the deciles. We match E/P for the fiscal year ending in calendar year $t - 1$ to returns from July of year t through June of year $t + 1$. This variable is winsorized annually at the 0.5% and 99.5% levels.
Industries	We use the Fama-French 17 industry portfolios formed at the end of June each year based on its four-digit SIC code at that time. The industries include Food, Mines, Oil, Clothes, Durables, Chemicals, Consumer goods, Construction, Steel, Fabricated products, Machinery, Automobiles, Transportation, Utilities, Retail stores, Financial, and Other.

Table 1: Summary Statistics

This table reports the summary statistics of the main variables. The analyses include common stocks traded on the NYSE, AMEX, or NASDAQ. All variables are defined in Appendix B. The sample period is from January 1963 to December 2016.

Panel A: Returns and Betas of Test Assets

Variables	Mean	Median	Standard Deviation	10% Percentile	25% Percentile	75% Percentile	90% Percentile
Individual Stocks							
Month-Level							
RET_{High}	3.65	1.11	20.67	-13.46	-5.36	9.38	21.69
RET_{Low}	-0.38	-0.22	17.38	-17.95	-8.08	6.29	16.00
$RET_{High/Low}$	1.64	0.00	19.20	-15.75	-6.67	7.83	18.85
RET_{RHigh}	8.59	5.17	22.24	-8.51	-1.10	14.38	27.78
RET_{RLow}	-6.37	-5.30	15.50	-23.53	-13.34	0.49	7.53
$RET_{RHigh/RLow}$	1.09	0.00	20.57	-17.96	-8.19	8.00	19.74
Weekday-Level							
RET_{High}	0.22	0.00	4.45	-3.17	-1.1	1.23	3.64
RET_{Low}	-0.09	0.00	4.58	-3.77	-1.43	1.04	3.37
$RET_{High/Low}$	0.07	0.00	4.51	-3.45	-1.26	1.14	3.51
RET_{RHigh}	0.83	0.00	4.69	-2.50	-0.43	1.98	4.60
RET_{RLow}	-0.71	-0.08	4.46	-4.49	-2.08	0.26	2.46
$RET_{Rhigh/Rlow}$	0.06	0.00	4.64	-3.66	-1.36	1.23	3.70
$\beta^{Mood}{}_{Month}$	1.02	0.93	0.69	0.30	0.58	1.34	1.81
$\beta^{Mood}{}_{Weekday}$	1.06	0.96	1.08	0.01	0.41	1.58	2.28
β^{Mood}	0.00	-0.12	1.00	-1.13	-0.68	0.56	1.30
$\beta^{MKT}{}_{Month}$	1.09	1.04	0.65	0.35	0.65	1.45	1.89
$\beta^{MKT}{}_{Weekday}$	0.74	0.66	3.95	-0.06	0.23	1.17	1.70
β^{SENT}	0.24	0.20	2.91	-2.55	-0.99	1.44	3.11
Baker and Wurgler (2006) Portfolios							
Month-Level							
RET_{High}	3.25	2.44	6.41	-3.33	-0.50	6.51	10.39
RET_{Low}	-0.02	0.77	6.52	-7.36	-3.03	3.61	7.02
$RET_{High/Low}$	1.61	1.61	6.67	-5.35	-1.72	4.92	8.95
RET_{RHigh}	8.01	7.15	4.90	3.20	4.99	9.93	13.24
RET_{RLow}	-5.75	-4.52	5.05	-11.76	-7.66	-2.47	-0.93
$RET_{RHigh/RLow}$	1.13	0.94	8.49	-8.68	-4.52	7.15	10.79
Weekday-Level							
RET_{High}	-0.07	0.00	1.07	-1.15	-0.48	0.42	0.92
RET_{Low}	0.18	0.21	0.85	-0.72	-0.19	0.59	1.03
$RET_{High/Low}$	0.06	0.11	0.97	-0.95	-0.34	0.52	0.98
RET_{RHigh}	0.85	0.68	0.86	0.09	0.35	1.13	1.75

Variables	Mean	Median	Standard Deviation	10% Percentile	25% Percentile	75% Percentile	90% Percentile
RET_{RLow}	-0.73	-0.51	0.98	-1.82	-1.08	-0.13	0.15
$RET_{RHigh/RLow}$	0.06	0.12	1.21	-1.27	-0.53	0.69	1.28
β^{Mood}_{Month}	0.95	0.95	0.22	0.68	0.83	1.08	1.20
$\beta^{Mood}_{Weekday}$	1.05	1.06	0.21	0.78	0.93	1.18	1.30
β^{Mood}	0.00	-0.04	1.00	-1.18	-0.58	0.62	1.26
β^{MKT}_{Month}	1.09	1.10	0.22	0.82	0.96	1.23	1.36
$\beta^{MKT}_{Weekday}$	0.82	0.81	0.25	0.52	0.63	1.00	1.13
β^{SENT}	0.20	0.18	0.38	-0.25	-0.04	0.42	0.69
Keloharju, Linnainmaa, and Nyberg (2016) Portfolios							
Month-Level							
RET_{High}	3.45	2.60	6.86	-3.54	-0.54	6.75	10.92
RET_{Low}	-0.14	0.58	6.76	-7.72	-3.23	3.58	7.08
$RET_{High/Low}$	1.65	1.59	7.04	-5.72	-1.84	5.16	9.27
RET_{Low}	8.15	7.20	5.47	2.96	4.88	10.19	13.96
RET_{RLow}	-5.91	-4.71	5.30	-12.31	-8.03	-2.44	-0.81
$RET_{RHigh/RLow}$	1.12	0.80	8.85	-9.05	-4.72	7.21	11.13
Weekday-Level							
RET_{High}	0.19	0.22	0.88	-0.71	-0.19	0.61	1.06
RET_{Low}	-0.08	-0.01	1.1	-1.16	-0.49	0.42	0.93
$RET_{High/Low}$	0.06	0.11	1.00	-0.96	-0.34	0.53	1.00
RET_{RHigh}	0.84	0.66	0.90	0.06	0.33	1.12	1.77
RET_{RLow}	-0.71	-0.50	1.02	-1.85	-1.08	-0.11	0.18
$RET_{RHigh/RLow}$	0.06	0.12	1.24	-1.27	-0.52	0.68	1.28
β^{Mood}_{Month}	0.98	0.99	0.23	0.70	0.86	1.10	1.21
$\beta^{Mood}_{Weekday}$	1.04	1.05	0.25	0.74	0.89	1.19	1.33
β^{Mood}	0.00	0.00	0.99	-1.15	-0.63	0.61	1.21
β^{MKT}_{Month}	1.09	1.10	0.24	0.79	0.95	1.25	1.38
$\beta^{MKT}_{Weekday}$	0.80	0.78	0.29	0.45	0.58	1.00	1.18
β^{SENT}	0.23	0.20	0.45	-0.30	-0.06	0.49	0.81

Panel B: Firm Characteristics

Variables	Mean	Median	Standard Deviation	10% Percentile	25% Percentile	75% Percentile	90% Percentile
AGE	155	97	168	15	39	208	384
B/M	0.91	0.67	0.92	0.19	0.36	1.13	1.81
D/BE	0.02	0.00	0.04	0.00	0.00	0.04	0.06
D/P	0.02	0.00	0.02	0.00	0.00	0.02	0.05
ROE	0.13	0.09	2.87	0.00	0.00	0.15	0.22
EF/A	0.09	0.05	0.24	-0.08	-0.01	0.15	0.32
E/P	-0.03	0.05	0.44	-0.21	-0.01	0.09	0.15
GP	0.32	0.29	0.30	0.03	0.12	0.48	0.69

SG	0.21	0.10	0.78	-0.14	-0.01	0.23	0.48
ME	1.42	0.08	9.84	0.01	0.02	0.40	1.76
MOM	0.13	0.05	0.60	-0.46	-0.21	0.33	0.72
PPE/A	0.53	0.45	0.39	0.09	0.22	0.77	1.08
R&D/A	0.04	0.00	0.10	0.00	0.00	0.03	0.11
SIGMA	0.14	0.11	0.10	0.05	0.08	0.17	0.24

Table 2: Mood Month Return Recurrence and Reversal Effects

This table reports the estimates of Fama-MacBeth regressions to test for return recurrence and reversal effects across mood months in the cross section. For the congruent-mood recurrence effect, we regress high (low) mood month returns across assets on their own past high (low) mood month returns or their own past returns during the two realized high (low) mood months. $RET_{High(Low)}$ refers to the high (or low) mood months identified using the full-sample equal-weighted market excess returns: January and March (September and October). $RET_{RHigh(RLow)}$ refers to the high (or low) mood months identified using the realized equal-weighted excess market returns in a given year. For the noncongruent-mood reversal effect, the independent variables are flipped to forecast the future high (low) mood month returns. The reported coefficient is the time series average of the return responses, reported in percentages for annual lags up to ten. For regressions with year lags 2-5 or 6-10, the annual independent variables are averaged across the designated lags before used in the regression. The reported Fama-MacBeth *t* statistics are in parentheses and corrected for heteroscedasticity and autocorrelation using Newey and West (1987). The symbols *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively, based on two-tailed tests. All variables are defined in Appendix B. The sample period is from January 1963 to December 2016.

Panel A: Individual Stocks

	Congruent-mood Recurrence		Noncongruent-mood Reversal	
Dep. Var.	$RET_{High(Low)}$		$RET_{High(Low)}$	
Indep. Var. (Lagged)	$RET_{High(Low)}$	$RET_{RHigh(RLow)}$	$RET_{Low(High)}$	$RET_{RLow(RHigh)}$
Year Lag (k)	(1)	(2)	(3)	(4)
1	1.05	1.37*	-3.00***	-3.99***
	(1.54)	(1.76)	(-3.01)	(-3.38)
2~5	1.82***	3.20***	-5.63***	-8.65***
	(2.65)	(2.64)	(-5.77)	(-5.95)
6~10	4.37***	5.44***	-2.65***	-6.38***
	(4.88)	(3.65)	(-3.58)	(-4.55)

Panel B: Baker and Wurgler (2006) Portfolios

Year Lag (k)				
1	20.63***	20.39***	-11.30*	-16.70***
	(4.23)	(4.41)	(-1.76)	(-3.00)
2~5	43.03***	29.35***	-30.0***	-26.2***
	(4.74)	(4.70)	(-3.53)	(-4.27)
6~10	48.75***	35.89***	2.04	-28.7***
	(6.38)	(5.29)	(0.18)	(-3.86)

Panel C: Keloharju, Linnainmaa, and Nyberg (2016) Portfolios

Year Lag (k)				
1	19.20***	17.96***	-5.55	-11.50**
	(4.52)	(4.45)	(-1.12)	(-2.24)
2~5	32.40***	26.39***	-22.0***	-27.00***
	(4.36)	(4.32)	(-3.09)	(-4.30)
6~10	47.08***	33.23***	-3.11	-25.10***
	(7.09)	(5.40)	(-0.42)	(-3.91)

Table 3: Mood Weekday Return Recurrence and Reversal Effects

This table reports the estimates of Fama-MacBeth regressions to test for return recurrence and reversal effects across mood weekdays in the cross section. The dependent variable is the asset return on Friday or Monday. For the congruent-mood recurrence effect, we regress high (Friday) or low (Monday) mood weekday returns across assets on their own past average Friday or Monday returns or their own past returns during the realized high or low mood weekdays. $RET_{High(Low)}$ refers to the high (low) mood weekdays identified using the full-sample equal-weighted market excess returns: Friday (Monday). $RET_{RHigh(RLow)}$ refers to the high and low mood weekdays identified using the realized equal-weighted market excess returns in a given week. For the noncongruent-mood reversal effect, the independent variables are switched to forecast the future high (low) mood weekday returns. The reported coefficient is the time series average of the return responses, reported in basis points for weekly lags up to 20. For regressions with week lags 2-10 or 11-20, the weekly independent variables are averaged across the lags before used in the regression. The reported Fama-MacBeth *t* statistics are in parentheses and corrected for heteroscedasticity and autocorrelation using Newey and West (1987). The symbols *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively, based on two-tailed tests. All variables are defined in Appendix B. The sample period is from January 1963 to December 2016.

Panel A: Individual Stocks

	Congruent-mood Recurrence		Noncongruent-mood Reversal	
Dep. Var.	$RET_{High(Low)}$		$RET_{High(Low)}$	
Indep. Var. (Lagged)	$RET_{High(Low)}$	$RET_{RHigh(RLow)}$	$RET_{Low(High)}$	$RET_{RLow(RHigh)}$
Week Lag (k)	(1)	(2)	(3)	(4)
1	0.01	-0.62***	-4.87***	-1.90***
	(0.07)	(-6.67)	(-31.6)	(-17.2)
2~10	1.96***	1.43***	-1.80***	-1.53***
	(9.90)	(5.39)	(-9.15)	(-5.59)
11~20	2.53***	2.28***	-0.92***	-1.34***
	(13.22)	(8.67)	(-4.65)	(-5.14)

Panel B: Baker and Wurgler (2006) Portfolios

Week Lag (k)				
1	7.00***	6.61***	2.38***	0.84*
	(13.94)	(13.93)	(4.44)	(1.77)
2~10	22.36***	14.30***	-5.80***	-4.63***
	(17.30)	(12.93)	(-4.30)	(-4.05)
11~20	17.13***	12.09***	-9.14***	-7.69***
	(11.94)	(10.61)	(-6.77)	(-6.79)

Panel C: Keloharju, Linnainmaa, and Nyberg (2016) Portfolios

Week Lag (k)				
1	8.40***	8.20***	4.91***	2.37***
	(15.31)	(16.17)	(8.52)	(4.67)
2~10	24.63***	14.77***	-1.17	-1.46
	(18.37)	(13.05)	(-0.85)	(-1.28)
11~20	19.51***	11.65***	-5.57***	-4.68***
	(13.41)	(10.23)	(-4.00)	(-4.13)

Table 4: Mood Beta as a Predictor in the Cross Section of Seasonal Returns

This table examines the predictive power of mood beta to forecast future mood month or weekday returns in Fama-MacBeth regressions. The monthly-return-estimated mood beta (β^{Mood}_{Month}) is used to forecast mood month returns and the weekday-return-estimated mood beta ($\beta^{Mood}_{Weekday}$) is used to forecast mood weekday returns. When forecasting future returns during a high mood state, the independent variable is the stock's historical β^{Mood}, and when forecasting future returns during a low mood state, it is $-\beta^{Mood}$. The other independent variable is the residual return earned during congruent or noncongruent-mood months or weekdays in the past, which is orthogonalized to β^{Mood}. Estimates for regressions with year lags 2-5 and week lags 2-10 are reported. Mood betas and residual returns are averaged across the designated year or week lags before used as a regressor. Regression estimates are reported percentages. The reported Fama-MacBeth *t* statistics are in parentheses and corrected for heteroscedasticity and autocorrelation using Newey and West (1987). The symbols *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively, based on two-tailed tests. All variables are defined in Appendix B. The sample period is from January 1968 to December 2016.

	Congruent-mood Recurrence				*Noncongruent-mood Reversal*			
Dep. Var.	$RET_{High(Low)}$				$RET_{High(Low)}$			
Indep. Var.	(1)		(2)		(3)		(4)	
	$\pm\beta^{Mood}$	$RET^{\perp}_{High(Low)}$	$\pm\beta^{Mood}$	$RET^{\perp}_{RHigh(RLow)}$	$\pm\beta^{Mood}$	$RET^{\perp}_{Low(High)}$	$\pm\beta^{Mood}$	$RET^{\perp}_{RLow(RHigh)}$
Panel A: Individual Stocks								
Year Lag	1.47***	0.76	1.48***	-4.91***	1.47***	-3.87***	1.48***	-0.31
2~5	(4.83)	(1.06)	(4.84)	(-4.67)	(4.83)	(-4.01)	(4.84)	(-0.35)
Week Lag	0.05***	1.66***	0.05***	0.27	0.05***	-1.64***	0.05***	-0.69***
2~10	(7.59)	(8.72)	(7.61)	(1.32)	(7.59)	(-8.94)	(7.56)	(-3.30)
Panel B: Baker and Wurgler (2006) Portfolios								
Year Lag	2.73***	30.47***	2.73***	9.52**	2.73***	-10.30*	2.73***	10.91**
2~5	(5.26)	(6.00)	(5.26)	(2.00)	(5.26)	(-1.95)	(5.26)	(2.06)
Week Lag	0.12***	19.30***	0.12***	6.07***	0.12***	-1.68	0.12***	9.95***
2~10	(11.11)	(18.53)	(11.13)	(5.67)	(11.11)	(-1.54)	(11.10)	(9.27)
Panel C: Keloharju, Linnainmaa, and Nyberg (2016) Portfolios								
Year Lag	2.95***	24.94***	2.95***	8.35	2.95***	-12.4*	2.95***	2.06
2~5	(6.03)	(4.45)	(6.03)	(1.61)	(6.03)	(-1.95)	(6.03)	(0.36)
Week Lag	0.10***	24.76***	0.10***	10.61***	0.10***	0.90	0.10***	10.50***
2~10	(9.43)	(21.23)	(9.42)	(9.33)	(9.43)	(0.73)	(9.39)	(8.95)

Table 5: Mood Beta, Market Beta, and Sentiment Beta as Predictors in the Cross Section of Returns

This table examines the predictive power of mood beta, market beta, and sentiment beta to forecast future mood month or weekday returns in Fama-MacBeth regressions. The mood betas (β^{Mood}_{Month}, $\beta^{Mood}_{Weekday}$) are estimated using monthly or weekday returns during the historical mood states, as defined as in Table 4. The market betas (β^{Mkt}_{Month}, $\beta^{Mkt}_{Weekday}$) are estimated analogously but using all historical monthly or weekday returns during a rolling window. The sentiment beta (β^{Sent}) is estimated by regressing the monthly stock returns on the monthly changes in the Baker and Wurgler (2006) sentiment index together with the value-weighted CRSP index over a rolling 60-month window. When forecasting future returns during a high mood month or weekday, the independent variable is the stock's historical β^{Mood}. When forecasting future returns during a low mood month or weekday, it is $-\beta^{Mood}$. Regression estimates are reported in percentages. The reported Fama-MacBeth *t* statistics are in parentheses corrected for heteroscedasticity and autocorrelation using Newey and West (1987). The symbols *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively, based on two-tailed tests. All variables are defined in Appendix B. The sample period is from January 1964 or January 1968 to December 2014 or 2016 depending on the availability of the independent variables.

	Month Return					*Weekday Return*			
Dep. Var.	$RET_{High(Low)}$				*Dep. Var.*	$RET_{High(Low)}$			
Indep. Var.	(1)		(2)		*Indep. Var.*	(3)		(4)	
Year Lag (k)	$\pm\beta^{Mood}_{Month}$	β^{Mkt}_{Month}	$\pm\beta^{Mood}_{Month}$	β^{Sent}	*Week Lag (k)*	$\pm\beta^{Mood}_{Weekday}$	$\beta^{Mkt}_{Weekday}$	$\pm\beta^{Mood}_{Weekday}$	β^{Sent}
Panel A: Individual Stocks									
2~5	1.98***	-0.87***	1.52***	-0.01	*2~10*	0.07***	-0.09***	0.05***	0.005***
	(5.78)	(-3.99)	(4.86)	(-0.65)		(8.97)	(-7.69)	(6.08)	(4.83)
Panel B: Baker and Wurgler (2006) Portfolios									
2~5	5.49***	-3.56***	2.61***	0.91***	*2~10*	0.42***	-0.39***	0.11***	0.05***
	(6.62)	(-5.06)	(5.09)	(4.41)		(13.14)	(-8.09)	(9.34)	(7.38)
Panel C: Keloharju, Linnainmaa, and Nyberg (2016) Portfolios									
2~5	6.00***	-3.28***	3.10***	0.55**	*2~10*	0.44***	-0.41***	0.11***	0.05***
	(7.65)	(-4.44)	(5.69)	(2.55)		(12.65)	(-7.40)	(9.04)	(7.55)

Table 6: Long-Short Portfolio Returns Based on Mood Returns and Mood Beta

Panel A reports the mean and abnormal returns on the long-short portfolios sorted based on historical congruent, noncongruent-mood month returns or mood betas. Each month, we sort stocks into deciles based on the average historical congruent ($RET_{High(Low)}$, $RET_{Bhigh(RLow)}$), noncongruent ($RET_{Low(High)}$, $RET_{RLow(Rhigh)}$) mood month returns, or mood beta ($\beta^{Mood}{}_{Month}$, $\beta^{Mood}{}_{Weekday}$, and β^{Mood}) during years $t-2$ through $t-5$ and calculate equal-weighted portfolio returns. The long-short portfolios based on historical returns go long the highest decile and short the lowest decile. The long-short portfolios based on mood beta go long the highest decile and short the lowest mood beta decile during the high mood months (January and March) and flip the long and short lags during the low mood months (September and October). Panel B reports the mean and abnormal returns on the long-short portfolios sorted based on historical congruent or noncongruent weekday returns and mood betas. Each day, we sort stocks into deciles based on the average historical congruent or noncongruent-mood weekday returns, or mood beta during weeks $t-2$ through $t-10$ and calculate equal-weighted portfolio returns. The long-short portfolios based on historical returns go long the highest decile and short the lowest decile. The long-short portfolios based on mood beta are long the highest decile and short the lowest mood beta decile during the high mood weekday (Friday) and reverses the long and short lags during the low mood weekday (Monday). The abnormal returns are estimated using the 4-factor model (Fama-French-Carhart 1997) and the Fama-French (2015) 5-factor model. Estimates are reported in percentage points. In parentheses reported are the Newey-West t statistics. All variables are defined in Appendix B. The sample period starts from January 1963, 1964, or 1968, depending on the availability of the sorting variable, and ends in December 2016.

Panel A: Month-Level Strategies

Test Assets	Dependent Variable: Month-Level $RET_{High(Low)}$						
Sorting Variables	$RET_{High(Low)}$	$RET_{RHigh(RLow)}$	$RET_{Low(High)}$	$RET_{RLow(RHigh)}$	$\beta^{Mood}{}_{Month}$	$\beta^{Mood}{}_{Weekday}$	β^{Mood}
Individual Stocks	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Mean Return	0.26*	0.24	-1.48***	-1.74***	2.74***	1.15**	2.23***
	(1.78)	(0.78)	(-6.90)	(-5.36)	(5.08)	(2.58)	(3.95)
4-Factor-Adjusted	0.33*	0.46	-1.40***	-1.65**	2.69***	1.03**	2.15***
	(1.85)	(1.34)	(-5.75)	(-4.27)	(5.04)	(2.12)	(3.75)
5-Factor-Adjusted	0.33*	0.54	-1.40***	-1.74**	2.85***	1.22**	2.37***
	(1.76)	(1.55)	(-5.63)	(-4.44)	(5.23)	(2.51)	(4.07)
Baker and Wurgler (2006) Portfolios							
Mean Return	1.43***	1.50***	-0.77***	-1.39***	1.74***	1.00***	1.58***
	(5.68)	(4.78)	(-3.52)	(-4.49)	(4.92)	(3.21)	(4.38)
4-Factor-Adjusted	1.42***	1.57**	-0.74***	-1.53**	1.72***	0.99***	1.56***
	(5.23)	(4.34)	(-3.03)	(-4.29)	(4.62)	(3.09)	(4.13)
5-Factor-Adjusted	1.47***	1.65**	-0.77***	-1.62**	1.82***	1.08***	1.67***
	(5.06)	(4.47)	(-3.10)	(-4.44)	(4.79)	(3.30)	(4.32)

Keloharju, Linnainmaa, and Nyberg (2016) Portfolios							
Mean Return	1.67***	1.45***	-0.69***	-1.34***	1.87***	0.46	1.45***
	(6.27)	(4.36)	(-2.71)	(-4.11)	(5.44)	(1.54)	(4.12)
4-Factor-Adjusted	1.69***	1.57**	-0.80***	-1.41**	1.90***	0.52	1.49***
	(5.51)	(4.31)	(-3.48)	(-3.87)	(4.99)	(1.65)	(3.94)
5-Factor-Adjusted	1.80***	1.66**	-0.82***	-1.47**	1.99***	0.61*	1.59***
	(5.81)	(4.45)	(-3.49)	(-3.93)	(5.14)	(1.90)	(4.13)

Panel B: Weekday-Level Strategies

Test Assets	Dependent Variable: Weekday-Level $RET_{High(Low)}$						
Sorting Variables	$RET_{High(Low)}$	$RET_{RHigh(RLow)}$	$RET_{Low(High)}$	$RET_{RLow(RHigh)}$	$\beta^{Mood}{}_{Month}$	$\beta^{Mood}{}_{Weekday}$	β^{Mood}
Individual Stocks	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Mean Return	0.07***	0.03**	-0.10***	-0.07***	0.17***	0.13***	0.17***
	(7.55)	(2.03)	(-11.32)	(-5.31)	(12.77)	(7.25)	(9.40)
4-Factor-Adjusted	0.06**	0.03*	-0.10***	-0.08***	0.17***	0.13**	0.17***
	(7.12)	(1.70)	(-13.06)	(-5.37)	(11.28)	(6.86)	(8.73)
5-Factor-Adjusted	0.07***	0.03**	-0.10***	-0.08***	0.17***	0.13***	0.17***
	(7.84)	(1.97)	(-12.11)	(-5.17)	(11.27)	(6.86)	(8.70)
Baker and Wurgler (2006) Portfolios							
Mean Return	0.09***	0.08***	-0.02***	-0.02***	0.13***	0.08***	0.13***
	(15.06)	(10.83)	(-3.04)	(-3.35)	(19.22)	(11.23)	(16.98)
4-Factor-Adjusted	0.09***	0.08***	-0.03***	-0.03***	0.13***	0.08***	0.12***
	(14.54)	(10.12)	(-4.68)	(-3.43)	(16.66)	(10.38)	(14.82)
5-Factor-Adjusted	0.09***	0.08***	-0.03***	-0.02***	0.13***	0.08***	0.12***
	(14.93)	(10.35)	(-4.23)	(-3.23)	(16.60)	(10.29)	(14.85)
Keloharju, Linnainmaa, and Nyberg (2016) Portfolios							
Mean Return	0.12***	0.09***	-0.00	-0.01	0.12***	0.08***	0.12***
	(15.15)	(9.71)	(-0.47)	(-1.10)	(15.78)	(8.43)	(13.78)
4-Factor-Adjusted	0.12**	0.09***	-0.01	-0.01	0.12***	0.08**	0.12***
	(15.87)	(9.03)	(-1.53)	(-1.32)	(13.36)	(7.73)	(12.03)
5-Factor-Adjusted	0.12**	0.09***	-0.01	-0.01	0.12***	0.08**	0.12***
	(16.33)	(9.28)	(-0.89)	(-1.18)	(13.37)	(7.73)	(12.16)

Table 7: Long-Short Portfolio Returns: Robustness

Panel A reports the mean returns on the long-short portfolios sorted based on congruent, noncongruent-mood month returns or mood betas. Panels A employs a similar methodology as used in that of Table 6 except that the future high (low) mood months are identified using the highest (lowest) mean equal-weighted market excess monthly returns (1) from 1927 to the most recent year (Expanding Window), (2) over the most recent 50 years (Rolling Window), (3) during even years to forecast only odd years from 1963 to 2016 (Odd Years); (4) during odd years to forecast only even years from 1963 to 2016 (Even Years). Panels B reports the long-short portfolio mean returns during high (low) mood weekdays, which are identified using the highest (lowest) mean equal-weighted market weekday excess returns (1) from 1927 to the most recent year (Expanding Window), (2) over the most recent 10 years (Rolling Window), (3) during even years to forecast only odd years from 1963 to 2016 (Odd Years); (4) during odd years to forecast only even years from 1963 to 2016 (Even Years). Regression estimates are reported in percentages. In parentheses reported are the Newey-West *t* statistics. All variables are defined in Appendix B. The sample period starts from January 1963, 1964, or 1968, depending on the availability of the sorting variable, and ends in December 2016.

Panel A: Month-Level Strategies

Test Assets	Dependent Variable: Month-Level $RET_{High(Low)}$				
Sorting Variable	$RET_{High(Low)}$	$RET_{RHigh(RLow)}$	$RET_{Low(High)}$	$RET_{RLow(RHigh)}$	β^{Mood}
Individual Stocks	(1)	(2)	(3)	(4)	(5)
Expanding Window	0.32**	0.21	-1.37***	-1.43***	1.82***
	(2.30)	(0.71)	(-6.92)	(-4.62)	(3.33)
Rolling Window	-0.29	-0.00	-1.32***	-1.58***	1.20**
	(-1.63)	(-0.01)	(-6.67)	(-4.84)	(2.26)
Odd Years	-0.08	-0.55	-1.50***	-1.40***	0.77
	(-0.37)	(-1.06)	(-4.66)	(-2.63)	(1.01)
Even Years	0.29	0.12	-1.33***	-1.34***	1.84**
	(1.54)	(0.28)	(-4.83)	(-2.95)	(2.28)
Baker and Wurgler (2006) Portfolios					
Expanding Window	1.27***	1.31***	-0.67***	-1.13***	1.32***
	(5.14)	(4.27)	(-3.30)	(-3.75)	(3.79)
Rolling Window	0.90***	0.86**	-0.13	-0.62*	0.90**
	(3.94)	(2.58)	(-0.53)	(-1.82)	(2.36)
Odd Years	1.11***	0.94**	-0.20	-0.63	0.88*
	(3.23)	(2.19)	(-0.61)	(-1.56)	(1.82)
Even Years	1.21***	1.37***	-0.87***	-1.32***	1.26***
	(3.23)	(3.53)	(-2.64)	(-3.12)	(2.71)
Keloharju, Linnainmaa, and Nyberg (2016) Portfolios					
Expanding Window	1.49***	1.23***	-0.64**	-1.06***	1.19***
	(5.30)	(3.74)	(-2.58)	(-3.19)	(3.37)
Rolling Window	1.38***	0.78**	0.11	-0.63*	0.72*
	(5.45)	(2.35)	(0.43)	(-1.77)	(1.81)
Odd Years	1.62***	0.84*	-0.05	-0.73*	0.78
	(4.40)	(1.76)	(-0.12)	(-1.66)	(1.53)
Even Years	1.12***	1.31***	-0.89***	-1.33***	1.17***
	(2.63)	(3.18)	(-2.74)	(-3.13)	(2.72)

Panel B: Weekday-Level Strategies

Test Assets	Dependent Variable: Weekday-Level $RET_{High(Low)}$				
Sorting Variable	$RET_{High(Low)}$	$RET_{RHigh(RLow)}$	$RET_{Low(High)}$	$RET_{RLow(RHigh)}$	β^{Mood}
Individual Stocks	(1)	(2)	(3)	(4)	(5)
Expanding Window	0.06***	0.04***	-0.09***	-0.07***	0.16***
	(7.10)	(2.84)	(-10.29)	(-5.16)	(8.64)
Rolling Window	0.06***	0.04***	-0.08***	-0.08***	0.16***
	(6.79)	(2.83)	(-9.11)	(-5.35)	(8.23)
Odd Years	0.08***	0.01	-0.06***	-0.13***	0.16***
	(7.11)	(0.51)	(-5.94)	(-6.41)	(6.33)
Even Years	0.06***	0.00	-0.12***	-0.17***	0.20***
	(4.46)	(0.04)	(-8.92)	(-7.72)	(6.99)
Baker and Wurgler (2006) Portfolios					
Expanding Window	0.08***	0.07***	-0.02***	-0.02***	0.12***
	(13.39)	(10.01)	(-2.70)	(-3.21)	(15.22)
Rolling Window	0.08***	0.07***	-0.01	-0.02***	0.11***
	(13.02)	(9.93)	(-0.99)	(-2.85)	(14.08)
Odd Years	0.10***	0.08***	-0.00	-0.02**	0.12***
	(13.19)	(8.50)	(-0.18)	(-2.54)	(12.35)
Even Years	0.09***	0.08***	-0.02**	0.08***	0.13***
	(8.81)	(7.59)	(-2.36)	(7.59)	(11.61)
Keloharju, Linnainmaa, and Nyberg (2016) Portfolios					
Expanding Window	0.12***	0.09***	0.00	-0.01	0.11***
	(14.15)	(9.45)	(0.05)	(-0.86)	(12.72)
Rolling Window	0.11***	0.09***	0.01*	-0.00	0.10***
	(13.81)	(9.34)	(1.70)	(-0.37)	(11.60)
Odd Years	0.13***	0.09***	0.02**	0.00	0.10***
	(13.50)	(6.81)	(2.14)	(0.35)	(8.88)
Even Years	0.11***	0.11***	-0.01	-0.02	0.14***
	(8.73)	(6.92)	(-1.00)	(-1.25)	(10.12)

Table 8: Pre-Holiday Return Recurrence Effects and Mood Beta in the Cross Section

This table reports the estimates of Fama-MacBeth regressions to test for pre-holiday return recurrence effects and the predictive power of mood beta in the cross section. We include 13 major holidays each year, as defined in Appendix B. In regression (1), we regress daily pre-holiday returns ($RET_{Preholiday}$) across assets on their own past average daily pre-holiday returns during prior holidays, including the immediate preceding holiday (k =1), averaged across holidays $t-2$ through $t-7$, and across holidays $t-8$ through $t-13$. In regression (2), we use the composite mood beta (β^{Mood}) to forecast future pre-holiday returns in the cross section. In regression (3), we add the residual historical preholiday return ($RET^{\perp}_{Preholiday}$) as an independent variable, orthognolaized to the composite mood beta. For regressions with holiday lags 2-7 or 8-13, the holiday-level independent variables are averaged across the designated lags before used in the regression. We report the time series average of the return responses (in basis points) and that of mood beta (in percentages) as the coefficients and the Fama-MacBeth t statistics in parentheses. The symbols *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively, using two-tailed tests. All variables are defined in Appendix B. The sample period is from January 1968 to December 2016.

Dependent Variable	$RET_{Preholiday}$			
Independent Variable (Lagged)	(1)	(2)	(3)	
Holiday Lag (k)	$RET_{Preholiday}$	β^{Mood}	β^{Mood}	$RET^{\perp}_{Preholiday}$
Individual Stocks				
1	0.15	0.08***	0.08***	0.17
	(0.74)	(6.73)	(6.75)	(0.86)
2~7	2.48***	0.08***	0.08***	2.18***
	(5.92)	(6.77)	(6.77)	(5.40)
8~13	1.65***	0.08***	0.08***	1.36***
	(3.44)	(7.07)	(7.07)	(2.92)
Baker and Wurgler (2006) Portfolios				
1	12.69***	0.04***	0.04***	11.93***
	(4.46)	(8.82)	(8.82)	(3.88)
2~7	23.42***	0.04***	0.04***	22.69***
	(4.27)	(8.33)	(8.33)	(3.90)
8~13	10.77*	0.04***	0.04***	6.89
	(1.75)	(8.94)	(8.94)	(1.06)
Keloharju, Linnainmaa, and Nyberg (2016) Portfolios				
1	10.74***	0.04***	0.04***	10.65***
	(4.72)	(8.25)	(8.25)	(4.47)
2~7	25.13***	0.05***	0.05***	24.88***
	(5.46)	(7.90)	(7.90)	(5.15)
8~13	13.68**	0.04***	0.04***	10.83*
	(2.45)	(8.25)	(8.25)	(1.85)

Table 9: Aggregate Returns and Mood Beta as a Predictor of the Cross Section of Returns under Daylight Saving Time Change

This table presents estimates of the average market excess returns and the Fama-MacBeth regression coefficient on the composite mood beta (β^{Mood}) in forecasting future weekend returns under mood states induced by the Daylight Saving Time change. We report the average weekend excess returns of the market portfolios, proxied by the CRSP value-weighted and equal-weighted portfolios, under the Daylight Saving Time change as compared to other weekends. The weekend return is the return from the Friday close to Monday close (or Tuesday close if it is the first trading day of that week). We also forecast future stock returns during the Daylight Saving Time weekend using Fama-MacBeth regressions, where the dependent variable is the weekend asset return and the independent variable is the asset's composite mood beta (β^{Mood}) measured as of the most recent month. Market excess returns and mood beta coefficients are reported in percentages and *t* statistics are in parentheses. The symbols *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively, based on two-tailed tests. All variables are defined in Appendix B. The sample period is from January 1963 (for aggregate returns) or 1968 (for mood beta) to December 2016.

	Spring Daylight Saving Time Weekends (N=50)	*Fall Daylight Saving Time Weekends (N=50)*	*All Daylight Saving Time (All DST) Weekends (N=100)*	*Other Weekends (N=2509)*	t-*test (All DST – Other)*
	Mean Excess Return				
CRSP value-weighted	-0.203	-0.267	-0.235	-0.036	-0.200* (t = 1.70)
CRSP equal-weighted	-0.321	-0.264	-0.293	-0.070	-0.223** (t = 2.21)
	Mood Beta (β^{Mood}) Coefficient in FMB Regressions				
Individual Stocks	-0.197**	-0.097	-0.147***	-0.056***	-0.091*
	(-2.59)	(-1.20)	(-2.65)	(-6.09)	(-1.92)
Baker and Wurgler (2006) Portfolios	-0.088**	-0.040	-0.064***	-0.028***	-0.037**
	(-2.42)	(-1.25)	(-2.65)	(-7.75)	(-1.98)
Keloharju, Linnainmaa, and Nyberg (2016) Portfolios	-0.107***	-0.025	-0.066**	-0.030***	-0.036
	(-2.73)	(-0.81)	(-2.61)	(-6.81)	(-1.62)

Table 10: Aggregate Returns and Mood Beta as a Predictor of the Cross Section of Returns under New York City Weather Condition

This table presents estimates of the average market excess returns and the Fama-MacBeth regression coefficient on the composite mood beta (β^{Mood}) in forecasting future daily returns under mood states induced by weather conditions in New York City. We report the average daily excess returns of the market portfolios, proxied by the CRSP value-weighted and equal-weighted portfolios, sorted based on the early morning (5am. to 8am.) deseasonalized cloud cover index of New York City. Sunny (cloudy) days consist of the 25% of trading days with the least (most) amount of deseasonalized cloud cover with the remaining days classified as moderate days. Deseasonalized cloud cover is the cloud cover index of the day minus the average of the daily index for the same calendar week across the full sample period. We also forecast the future asset returns in the cross section conditional on weather conditions using Fama-MacBeth regressions, where the dependent variable is the daily asset return under a given weather condition, and the independent variable is the stock's composite mood beta (β^{Mood}) measured as of the most recent month. Market excess returns and mood beta coefficients are reported in percentages and *t* statistics are in parentheses. The symbols *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively, using two-tailed tests. All variables are defined in Appendix B. The sample period is from January 1963 (for aggregate returns) or 1968 (for mood beta) to May 2016.

	Sunny Days (N=3393)	*Moderate Days (N=6688)*	*Cloudy Days (N=3393)*	*t-test (Sunny – Cloudy)*
	Mean Excess Return			
Value-weighted Market Returns	0.068	0.047	0.007	0.061*** (t = 2.51)
Equal-weighted Market Returns	0.102	0.083	0.037	0.065*** (t = 3.11)
	Mood Beta (β^{Mood}) Coefficient			
Individual Stocks	0.017**	0.014**	-0.004	0.022*
	(2.08)	(2.57)	(-0.59)	(1.93)
Baker and Wurgler (2006) Portfolios	0.009***	0.006***	-0.000	0.010**
	(2.95)	(2.65)	(-0.16)	(2.23)
Keloharju, Linnainmaa, and Nyberg (2016) Portfolios	0.008**	0.005**	-0.003	0.011**
	(2.00)	(2.11)	(-0.88)	(2.06)

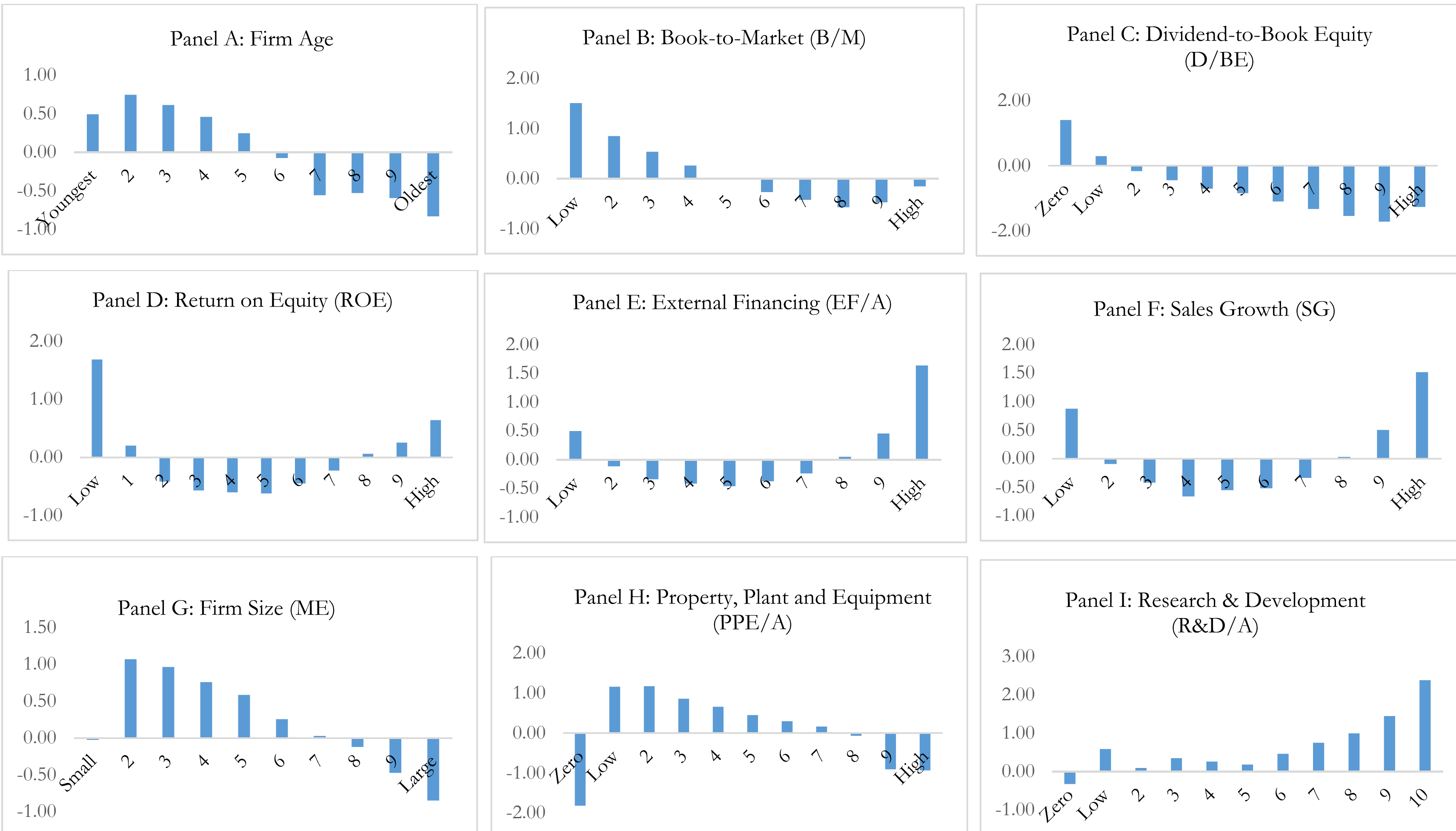
Table 11: Fama-MacBeth Regression at the Firm Level

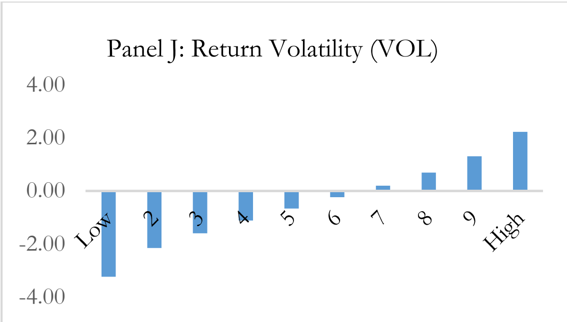
This table reports Fama-MacBeth regression estimates on mood beta, market beta, sentiment beta, and a host of firm characteristics in forecasting future mood month or mood day returns. The test assets are the full cross section of individual stocks. Columns (1), (2), and (3) report the estimates for the regressions that forecast the positive January and March (high mood months) returns and the negative September and October (low mood months) returns. Columns (4), (5), and (6) report the estimates for the regressions that forecast the positive high mood day (Friday, preholiday, sunny days) returns and the negative low mood day (Monday, Daylight Savings Time change weekend, cloudy days) returns. In parentheses reported are the Newey-West *t* statistics. All independent variables are lagged. They are also standardized to have zero mean and unit variance and are defined in Appendix B. The dependent variable is the mood-month return in percentages or mood-weekday return in basis points. The sample period starts from January 1963 and ends in December 2016.

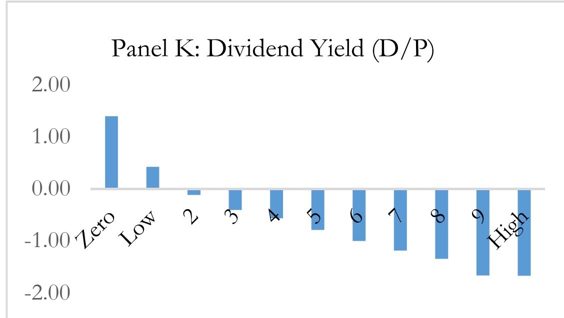
Dep. Var.	$+\ \mathrm{RET}_{\mathrm{High}}$ and $-\ \mathrm{RET}_{\mathrm{Low}}$					
	Mood Month			Mood Day		
Indep. Var.	(1)	(2)	(3)	(4)	(5)	(6)
β^{Mood}	1.15***	1.80***	0.59**	4.07***	3.61***	2.15***
	(3.70)	(3.83)	(2.19)	(8.32)	(13.07)	(8.15)
$\beta^{Mkt}{}_{Weekday}$		-0.74*	-0.56		0.59	1.54***
		(-1.85)	(-0.80)		(1.12)	(3.16)
β^{Sent}		-0.03	0.13		0.41***	0.08
		(-0.16)	(0.57)		(2.65)	(0.50)
Log(ME)			-1.01***			-3.47***
			(-5.66)			(-11.2)
Log(B/M)			0.05			-1.09***
			(0.21)			(-6.26)
Mom			-1.63***			-2.26***
			(-2.77)			(-8.90)
EF/A			0.03			-0.14
			(0.15)			(-0.88)
GP			-0.47**			-0.92***
			(-2.04)			(-5.87)
PPE/A			-0.08			0.34**
			(-0.61)			(2.07)
SG			-0.24			-0.18
			(-0.81)			(-1.27)
SIGMA			0.30			1.94***
			(0.87)			(8.30)
# of mons/days	196	188	188	7,967	7,017	7,017
Avg.# of stocks	2,577	2,814	2,577	2,701	2,847	2,610
Adj. R2	0.25%	0.36%	1.23%	1.07%	1.64%	2.66%

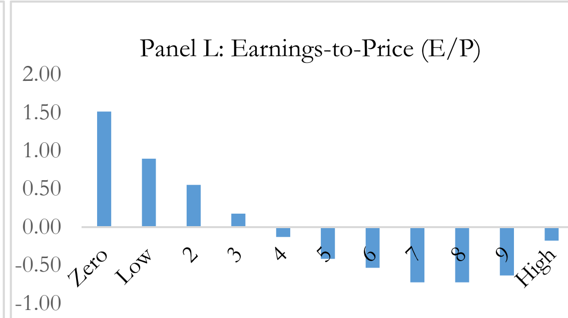
Figure 1: Mood Betas of Characteristics-Sorted Portfolios

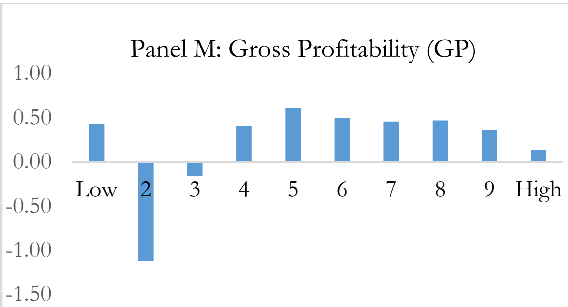
This figure reports the average composite mood beta (β^{Mood}) for portfolios sorted based on firm characteristics used by Baker and Wurgler (2006) (Panels A through J) and Keloharju, Linnainmaa, and Nyberg (2016) (Panels K through O excluding size or book-to-market portfolios, which are reported in Panels B and G). All variables are defined in Appendix B. The sample period is from January 1968 to December 2016.

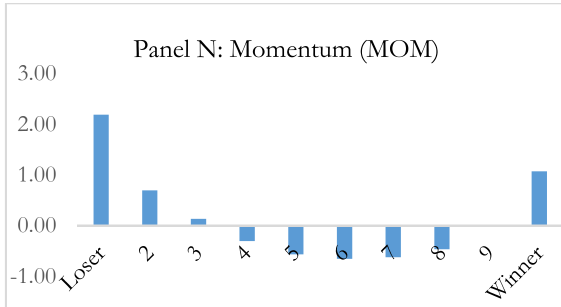



Panel J: Return Volatility (VOL)
4.00
2.00
0.00
-2.00
-4.00
Low
2
3
4
5
6
7
8
9
High


Panel K: Dividend Yield (D/P)
2.00
1.00
0.00
-1.00
-2.00
Zero
Low
2
3
4
5
6
7
8
9
High


Panel L: Earnings-to-Price (E/P)
2.00
1.50
1.00
0.50
0.00
-0.50
-1.00
Zero
Low
2
3
4
5
6
7
8
9
High


Panel M: Gross Profitability (GP)
1.00
0.50
0.00
-0.50
-1.00
-1.50
Low
2
3
4
5
6
7
8
9
High


Panel N: Momentum (MOM)
3.00
2.00
1.00
0.00
-1.00
Loser
2
3
4
5
6
7
8
9
Winner

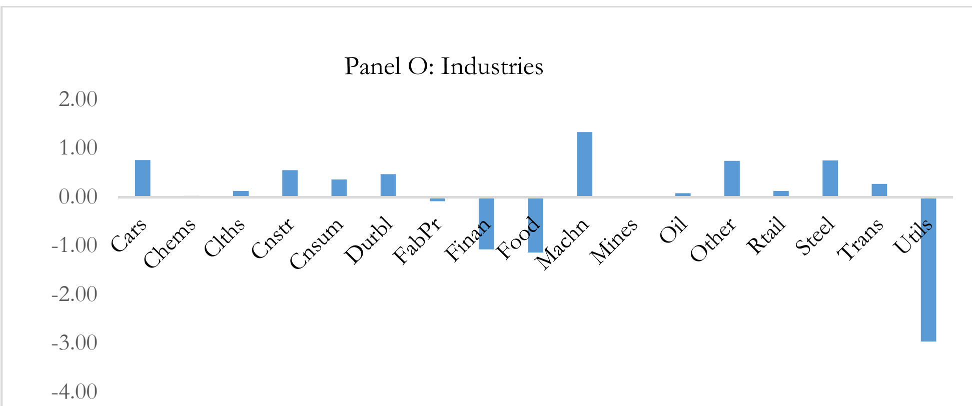

Panel O: Industries
2.00
1.00
0.00
-1.00
-2.00
-3.00
-4.00
Cars
Chems
Clths
Cnstr
Cnsum
Durbl
FabPr
Finan
Food
Machn
Mines
Oil
Other
Rtail
Steel
Trans
Utils

Figure 2: High-Minus-Low Mood Beta Returns across High and Low Mood States

This figure reports the average high-minus-low portfolio returns sorted based on the composite mood beta (β^{Mood}) across high and low mood states. The high-minus-low portfolio is long the top decile of assets with the highest mood beta and short the bottom decile of assets with the lowest mood beta. High mood state is proxied by January and March (Panel A), Friday (Panel B), Preholiday (Panel C) and Sunny Day (Panel E) Low mood state is proxied by September and October (Panel A), Monday (Panel B), Daylight Saving Time (DST) Weekends (Panel D) and Cloudy Day (Panel E). The three sets of test assets include the full cross section of individual stocks, the 94 Baker and Wurgler (2006) portfolios (BW) and the 79 Keloharju, Linnainmaa, and Nyberg (2016) portfolios (KLN). The average returns of the long-short portfolios are expressed in percentage points in Panel A and in basis points in all other panels. The composite mood beta is defined in Appendix B. The sample period is from January 1968 to December 2016 for Panels A to D and May 2016 for Panel E.

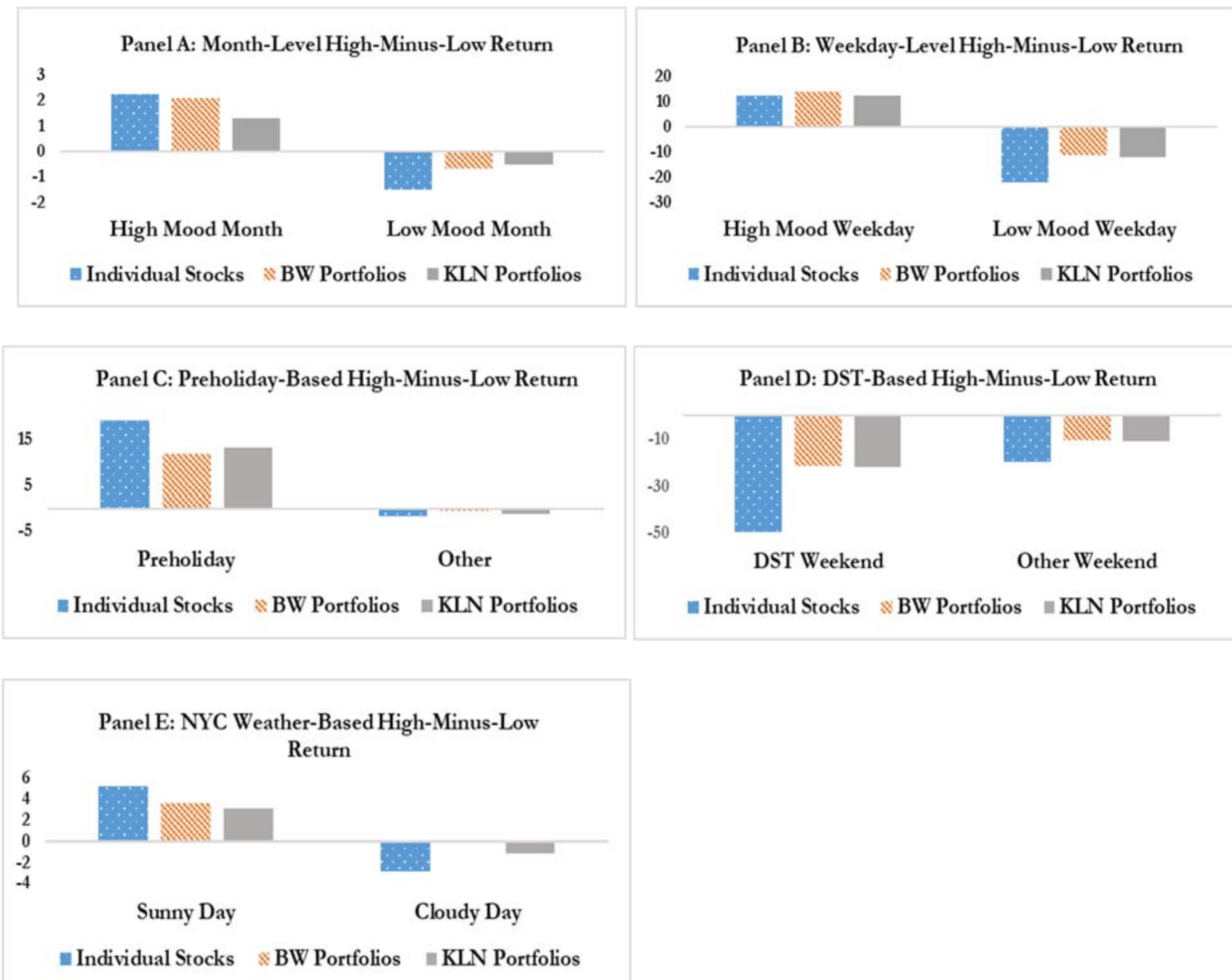


Figure 3: Long-Short Market Beta Portfolios across High and Low Mood States

This figure reports the average long-short portfolio returns sorted based on the market beta ($\beta^{Mkt}_{weekday}$) across high and low mood states, where $\beta^{Mkt}_{weekday}$ is estimated using a 6-month rolling window of daily returns. The long-short portfolio is long the top decile of assets with the highest market beta and short the bottom decile of assets with the lowest market beta. High mood state is proxied by January and March (Panel A), Friday (Panel B), Preholiday (Panel C) and Sunny Day (Panel E) Low mood state is proxied by September and October (Panel A), Monday (Panel B), Daylight Saving Time (DST) Weekends (Panel D) and Cloudy Day (Panel E). The three sets of test assets include the full cross section of individual stocks, the 94 Baker and Wurgler (2006) portfolios (BW) and the 79 Keloharju, Linnainmaa, and Nyberg (2016) portfolios (KLN). The average returns of the long-short portfolios are expressed in percentage points in Panel A and in basis points in all other panels. Market beta is estimated using daily stock returns over a 6-month rolling window and defined in the Appendix. The sample period is from January 1968 to December 2016 for Panels A to D and May 2016 for Panel E. The figure shows that high market beta assets do not necessarily outperform low market beta assets during high mood periods but they tend to underperform during low mood periods.