Journal of Financial Economics 137 (2020) 272–295

Contents lists available at ScienceDirect

Journal of Financial Economics

journal homepage: www.elsevier.com/locate/jfec

# Mood beta and seasonalities in stock returns[☆]

David Hirshleifer[a], Danling Jiang[b,*], Yuting Meng DiGiovanni[c]

[a] The Paul Merage School of Business, University of California at Irvine and NBER, United States
[b] College of Business, Stony Brook University, United States; School of Economics and Management, Southwest Jiaotong University, China. Mailing address: 306 Harriman Hall, Stony Brook, NY 11794 United States
[c] Muma College of Business, University of South Florida, United States

ARTICLE INFO

*Article history:*
Received 20 March 2018
Revised 19 June 2019
Accepted 7 August 2019
Available online 7 February 2020

*JEL classification:*
G11
G12
G14
G41

*Keywords:*
Return seasonality
Investor mood
Mood beta
Market efficiency
Anomalies

ABSTRACT

Existing research has found cross-sectional seasonality of stock returns—the periodic outperformance of certain stocks during the same calendar months or weekdays. We hypothesize that assets' different sensitivities to investor mood explain these effects and imply other seasonalities. Consistent with our hypotheses, relative performance across individual stocks or portfolios during past high or low mood months and weekdays tends to recur in periods with congruent mood and reverse in periods with noncongruent mood. Furthermore, assets with higher sensitivities to aggregate mood—higher mood betas—subsequently earn higher returns during ascending mood periods and earn lower returns during descending mood periods.

Published by Elsevier B.V.

## 1. Introduction

Extensive research has found 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 et al., 2016), during certain weekdays (Birru, 2018), or during the pre-holiday period (Hirshleifer et al., 2016).[2]

We propose an integrated explanation for these effects based upon investor mood. This explanation covers seasonalities at both the aggregate and cross-sectional levels, and at both monthly and daily return frequencies. We term this explanation the *mood seasonality hypothesis*. Based on this, we test and show an extensive set of new empirical implications for return seasonalities. Consistent with the mood seasonality hypothesis, we find that historical seasonal

☆ 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 Auburn University, Chongqing University, CUNY-Baruch, Florida State University, Fordham University, McMaster University, Southwest Jiaotong University, Stony Brook University, University of South Florida, South University of Missouri at Columbia, the 2017 ASSA-AFE, the 2017 CICF, and the 2018 MFA. Danling Jiang acknowledges financial support from the National Natural Science Foundation of China (NSFC) (Grant #91746109). All errors remain ours.

* Corresponding author.
*E-mail address:* danling.jiang@stonybrook.edu (D. Jiang).

[1] See, e.g., Keim (1983), Lakonishok and Smidt (1988), and Kamstra et al. (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.

https://doi.org/10.1016/j.jfineco.2020.02.003
0304-405X/Published by Elsevier B.V.

return of a security relative to other securities is a positive or negative forecaster of the security's relative future seasonal returns, with direction that depends on whether the investor moods during the historical and forecasting periods are congruent or noncongruent. Also motivated by the mood seasonality hypothesis, we propose a new measure of a stock's return sensitivity to mood variations, which we call mood beta, and show that mood beta is a strong predictor of seasonal asset returns in future periods in which mood is expected to rise or fall.

Mood here refers to emotion-induced variation in investor preferences, beliefs, or risk tolerance. While mood affects economic decision-making through a variety of pathways (Lerner et al., 2015), our focus is on the effects of affective valence—whether the mood is positive or negative (and in changes, improving or deteriorating). Mood can be viewed as a special case of investor sentiment (e.g., Baker and Wurgler, 2006, 2007), which is a general term that includes shifts in beliefs or preferences that can derive from either affective sources (i.e., feelings) or from non-affective sources such as shifts in investor attention (e.g., Hirshleifer and Teoh, 2003; Peng and Xiong, 2006), shifts in confidence (e.g., Daniel et al., 1998, 2001), or extrapolative expectation (e.g., Barberis et al., 2015, 2018).

The key premise of our tests is that there are predictable seasonal variations in investor mood (as motivated by our review of related literature in Section 2). We hypothesize that such seasonal mood shifts cause periodic investor optimism or pessimism in evaluating common factors in returns, which results in seasonal variations in factor mispricing.[3] Accordingly, factor mispricing leads to return seasonality and predictability in the cross-section owing to cross-sectional dispersion in factor loadings. During periods in which mood is improving, both the aggregate market and assets with higher sensitivities to ascending mood earn higher average returns. The reverse holds when mood is deteriorating. High mood sensitivity of an asset results from high loadings on mood-mispriced factors.

We suggest that an asset's sensitivity to seasonal mood shifts can be captured by its average historical returns during different seasonal periods when mood is ascending or descending, or by its return sensitivity to aggregate returns during those periods—the mood beta. We hypothesize that these measures of mood sensitivity predict asset returns in future periods when ascending or descending mood is anticipated.

We test these ideas by selecting calendar months and weekdays that are associated with ascending or descending moods based on various experimental, survey, and empirical research. We hereafter refer to these calendar months or weekdays more briefly as hypothesized high or low mood periods. Specifically, we hypothesize January, March, and Friday to be high mood periods, as these are associated with the highest equal-weighted market returns among all calendar months or weekdays during our sample period 1963–2016. Similarly, we hypothesize September, October, and Monday to be low mood periods, as these are associated with the lowest full sample equal-weighted market returns for the given frequency.

These average return patterns also confirm the seasonal psychology suggested by previous literature. 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 (e.g., Birru,2018).[4] In contrast, September to October 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., Birru, 2018).

The mood seasonality hypothesis first predicts that relative asset performance in the cross-section will recur during congruent-mood periods and reverse during noncongruent-mood periods. For example, if Asset A outperforms Asset B, on average, in January and March, then we expect A to underperform Asset B next September and October (reversal) but to outperform Asset B next January and March (recurrence), and we expect such patterns to repeat for years after the conditioning date. Similarly, if A outperforms B on Friday, we expect this average relative performance to alternate between Mondays and Fridays for months after the conditioning date.

To test for such effects, we use the historical seasonal returns in the past high or low mood periods to forecast returns in future hypothesized high (January, March, and Friday) and low (September, October, and Monday) mood periods in Fama-MacBeth regressions. The seasonal historical return is first proxied by the average asset return in these prespecified high or low mood periods in recent years or weeks.[5] Higher realized returns of the broad market in any month could in part reflect more optimistic mood shifts and lower returns less optimistic mood shifts. Thus we use another proxy for an asset's historical seasonal return: its average return earned during the recent months or weekdays with the highest or lowest equal-weighted market excess return in a given year or week.

We use three sets of test assets over the sample period of 1963–2016: the full cross-section of individuals stocks, the 94 Baker and Wurgler (2006, henceforth BW) portfolios and 79 Keloharju et al. (2016; henceforth KLN) portfolios, with the portfolios formed by sorting individual stocks on various firm characteristics. Consistent with our hypothesis, we show the novel finding that the relative performance across assets during a mood period indeed tends

[3] Shifts in mood may also cause seasonal changes in risk tolerance (e.g., Kamstra et al., 2003), which may also induce factor-wide price changes.

[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 seasonality 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] These return predictors are similar to the historical same-month (Heston and Sadka, 2008) or same-weekday (Keloharju et al., 2016) return variables but differ in that these historical seasonal returns are not confined to the same calendar months; instead they are averaged across different calendar months with congruent mood (such as January and March or September and October).

to recur in future periods of hypothesized congruent mood and to reverse in future periods of hypothesized noncongruent mood. We call the former the congruent-mood recurrence effect and the latter the noncongruent-mood reversal effect. 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 basis points.

In robustness checks, we also identify the hypothesized high or low mood months and weekdays in the future, not by prestipulated periods but by using the historical average equal-weighted market return up to the preceding year or month or the full sample average equal-weighted returns in only odd or even years. These alternative methods identify future hypothesized high and low mood periods out of sample for testing return predictability and therefore help minimize the concern of an in-sample bias. We observe similar cross-sectional return patterns in which relative asset performances flip across high and low mood periods.

A second innovation of this paper is to introduce the concept of mood beta, an asset's return sensitivity to investor mood variations. We estimate an asset's mood sensitivity as the slope coefficient in the regression of the asset's returns earned during the recent high and low mood periods upon the corresponding equal-weighted market returns.[6] We call the slope coefficient the mood beta. Alternatively, the sensitivity of return to mood can be estimated as the difference between mean historical returns in ascending versus descending mood periods normalized by the mean difference in market returns during those periods. For each stock or portfolio, we estimate its mood betas by using its monthly or weekday returns during the high and low mood periods in the latest ten years or six months. We also construct a composite mood beta as the first principal component of the two mood betas.

Our mood sensitivity hypothesis predicts that assets with high mood betas will, on average, outperform during periods with ascending moods and underperform when moods are descending. Consistent with this, we find strong evidence that assets with high mood betas earn higher average future returns during January and March and on Friday and earn lower average future returns during September and October and on Monday. Furthermore, mood betas vary 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 betas, while easy-to-value assets and those less subject to sentiment have low mood betas.

To assess the economic magnitude of the mood beta effect, we form a hedge portfolio. The hedge portfolio goes long the highest mood beta decile and short the lowest decile during periods when mood is expected to rise and flips the long and short sides during periods when mood is expected to fall. This captures the expected positive return spread in both favorable and unfavorable mood periods. This hedge portfolio produces a significant Fama-French five-factor alpha of 1.5% or more per month and 12 basis points or more per day. As predicted, after controlling for mood beta, historical seasonal returns tend to have substantially reduced ability, sometimes with a reversed sign, to forecast returns in future high or low mood periods. These findings suggest that mood beta offers a unique and integrated explanation for a wide and varied set of seasonal return recurrence and reversal effects.

The effect of mood beta is robust to controls for market beta and the sentiment beta of Baker and Wurgler (2007). We perform a horse race between mood beta, market beta, and sentiment beta in Fama-MacBeth regressions. This is important since it would not be surprising if the different betas were correlated across assets. However, this association is far from perfect. We find that mood beta continues to be a strong forecaster of future returns after controlling for these other betas and a set of firm characteristics.

In contrast, in the same regressions, market beta is a negative predictor of future returns, consistent with the documented low-risk anomaly (Baker et al., 2011; Frazzini and Pedersen, 2014). The sentiment beta is a positive return predictor. We also find no evidence that the market beta or the sentiment beta consistently forecasts stock returns in future hypothesized high and low mood periods with opposite signs as predicted by our hypothesis for mood betas. Thus these other betas are not the source of the mood beta effects we identify.

Regardless of whether the effects shown in this paper derive from investor mood, as we hypothesize, they constitute a rich set of newly identified conditional return seasonalities that deserve 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.

## 2. Background and hypotheses

Our mood seasonality hypothesis is motivated by the psychology of mood and by a line of literature on stock return seasonality. The basic month-of-the-year effect refers to 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). Cross-sectionally, Heston and Sadka (2008, 2010) find that relative performance across stocks tends to persist for years in the same calendar month. They rule out various possible explanations based upon volume, volatility, industry, earnings, and dividends but do not propose an explanation for this cross-sectional return seasonality.

We hypothesize that both the aggregate and cross-sectional seasonalities are induced by seasonal variations in investor mood. The strong early January performance of stock markets, especially among small firms (Keim, 1983), may derive from investor optimism at the turn of the year (e.g., Ritter, 1988; Doran et al., 2012;

[6] This is based on the premise that extreme mood periods also have relatively variable mood, improving the signal-to-noise ratio in estimation of mood beta. At the monthly 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.

Bergsma and Jiang, 2016; Kaustia and Rantapuska, 2016). The weak September and October performance may derive from the declining number of hours of daytime sunlight starting in early autumn, which is known to induce the SAD effect (Kamstra et al., 2003). Among all months, Kamstra et al. (2017) show that September to October are associated with the largest net increase in the proportion of SAD-affected individuals and the biggest fund flow from risky to safe assets. They also show that around March, the opposite is observed as the daylight hours start to increase.

The above evidence is consistent with the possibility that investor mood is improving in early January and around March (and quite possibly in February as well) while deteriorating in September to October. Also potentially consistent with this, during our sample period of 1963–2016, the average stock excess return (CRSP equal-weighted index return minus the riskfree rate) is highest in January, followed by March, and lowest in October, followed by September. We therefore use September and October as proxies for investors being in descending moods. For symmetry, we use two months for ascending mood—January and March as suggested by past literature.[7]

Previous literature has also shown 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). Survey evidence suggests a downbeat mood on Mondays and an upbeat mood on Fridays among both the general and the investing populations (e.g., Rossi and Rossi, 1977; McFarlane et al., 1988; Stone et al., 2012; Helliwell and Wang, 2014).

In the cross-section, KLN find that stocks' relative performance on a given weekday persists for subsequent weeks on the same weekday. They hypothesize that cross-sectional return seasonality is a manifestation of seasonal factor premia but do not explore the economic or psychological sources of it. We instead point out the affective psychology behind the seasonal factor premia. Birru (2018) finds that the performance of many major anomaly strategies exhibit opposite return patterns on Monday versus Friday based on whether the short leg is betting on speculative or safe stocks and links these patterns to investor mood. As in Birru's paper, we use Friday to represent improving mood and Monday for deteriorating mood. However, we also study at the monthly frequency and individual stocks as well as mood betas of various test assets.

We hypothesize that these seasonal mood variations cause seasonal factor mispricing, resulting from mood-induced overoptimism or overpessimism about future expected factor payoffs. The factor-wide mispricing is inherited by the cross-section of stocks and portfolios according to their factor loadings. The general idea that factor-level mispricing predicts the cross section is modeled explicitly by Daniel et al. (2001) in the context of investor overconfidence. Differences in cross-sectional mispricing can also be induced by cross-stock differences in cost of arbitrage. Baker and Wurgler (2006, 2007) provide evidence that shifts in general market sentiment influence stocks with different characteristics such as valuation uncertainty and cost of arbitrage. In our context, assets with higher loadings on the mispriced factor are more sensitive to mood shocks and will inherit greater factor mispricing. Thus, when a factor gets overpriced or underpriced upon seasonal mood shifts, assets with greater mood sensitivity will earn higher or lower returns accordingly.[8]

This effect manifests in the following two mood seasonality hypotheses that we test:

*Hypothesis 1*. (The mood recurrence and reversal effects): In the cross-section, a security's historical seasonal returns are positively correlated with its future seasonal returns under a congruent-mood period and negatively related to its future seasonal returns under a noncongruent-mood period.

*Hypothesis 2*. (The mood beta effect): Mood beta, which measures an asset's return sensitivity to mood, positively predicts the cross-section of security returns during ascending mood periods and negatively predicts the cross-section of security returns during descending mood periods.

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 et al., 2013; Kaplanski et al., 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 et al., 2007; Kaplanski and Levy, 2010), returns of individual stocks, perceived stock overpricing by institutional investors (Goetzmann et al., 2015), market reactions to earnings announcements (deHaan et al., 2017; Jiang et al., 2019), individuals' sentiment about the economy and life satisfaction (Makridis 2018), and firm hiring and investment decisions as well as hiring and creating new businesses (Chhaochharia et al., 2019).

## 3. Mood recurrence and reversal effects

Our US 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.

[7] Untabulated robustness checks show that results are very similar if we instead use January and February for ascending mood. Also, we find qualitatively similar effects if we use only January to proxy for a high mood state.

[8] Mood can also induce shifts in risk tolerance. This has similar implications to the shifts in optimism and pessimism that we focus on since the returns of riskier stocks will be more sensitive to shifts in mood than less risky stocks. However, it is not clear that mood will affect risk tolerance at the high frequency of our daily tests.

We use three sets of test assets: the full cross section of individual stocks, the 94 BW portfolios and 79 KLN 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 BW, we use the NYSE breakpoints for each characteristic to form portfolio deciles and to calculate equal-weighted portfolio returns. Nonpositive 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: B/M, 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 KLN, we use breakpoints based on all firms to form the deciles, but we calculate equal-weighted, as opposed to value-weighted, portfolio returns because we believe that mood should have a stronger impact on small firms than on large firms. Firms with nonpositive earnings or dividend firms are included in separate portfolios from the decile portfolios. All definitions of the seasonal returns, firm characteristics, and portfolio formation are defined in the Data Appendix. Table 1 reports the seasonal returns summary statistics.

### 3.1. Month-level mood effects

During our sample period of 1963–2016, consistent with the psychology accounts reviewed in Section 2, 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 hypothesized high mood months and September and October for the hypothesized low mood months. Later we explore the robustness of our findings to alternative definitions of hypothesized 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 found by Heston and Sadka (2008), but we do not differentiate January from March or September from October, as they proxy for the past high versus the low mood state, respectively.

#### 3.1.1. The mood recurrence effect: returns during prespecified mood months as predictors

Specifically, we estimate the following Fama-MacBeth (FMB) regressions of the hypothesized high (January and March) or low (September and October) mood month returns across assets on their historical seasonal returns earned during these prespecified congruent-mood months at three sets of annual lags:

$$RET_{\mathrm{high(Low)},\ t} = \eta_{k,t} + \gamma_{k,t} RET_{\mathrm{high(Low)},\ t-k} + \varepsilon_t, \qquad (1)$$

where $k = 1$, 2–5, and 6–10, and $RET_{\mathrm{high(Low)},t}$ is the current mood month (high or low) asset return in year $t$, and $RET_{\mathrm{high(Low)},\ t-k}$ 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 being used as an independent variable in the regression.

We run cross-sectional regressions as in regression (1) for each mood month, and the estimates of $\gamma_{k,\ t}$ are averaged across the full sample period to yield the estimate for $\gamma_k$, 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 $\gamma_k$ 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 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 basis points (7.86%×1.82%) increase in the current congruent-mood return, or an 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 mood recurrence effect: returns during realized mood months as predictors

Next, we expand the mood recurrence effect predicted based upon prespecified mood months by considering historical seasonal returns during realized mood months. We measure realized positive and negative mood periods using the top two and bottom two months, ranked by the equal-weighted CRSP excess returns realized in a given year.[9] The

[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.

**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 the Data Appendix. 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 |
| $\beta^{Mood}$ | 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 |
| $\beta^{SENT}$ | 0.24 | 0.20 | 2.91 | −2.55 | −0.99 | 1.44 | 3.11 |
| *Baker and Wurgler (BW) 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 |
| $RET_{RLow}$ | −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 |
| $\beta^{Mood}{}_{Month}$ | 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 |
| $\beta^{Mood}$ | 0.00 | −0.04 | 1.00 | −1.18 | −0.58 | 0.62 | 1.26 |
| $\beta^{MKT}{}_{Month}$ | 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 |
| $\beta^{SENT}$ | 0.20 | 0.18 | 0.38 | −0.25 | −0.04 | 0.42 | 0.69 |
| *Keloharju, Linnainmaa, and Nyberg (KLN) 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 |
| $RET_{RHigh}$ | 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 |
| $\beta^{Mood}{}_{Month}$ | 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 |
| $\beta^{Mood}$ | 0.00 | 0.00 | 0.99 | −1.15 | −0.63 | 0.61 | 1.21 |
| $\beta^{MKT}{}_{Month}$ | 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 |
| $\beta^{SENT}$ | 0.23 | 0.20 | 0.45 | −0.30 | −0.06 | 0.49 | 0.81 |

(*continued on next page*)

**Table 1** (*continued*)

*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* | 0.10 | 0.09 | 0.09 | 0.00 | 0.00 | 0.15 | 0.21 |
| *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. $\text{RET}_{\text{High(Low)}}$ refers to the high (or low) mood months identified using the full sample equal-weighted market excess returns: January and March (September and October). $\text{RET}_{\text{RHigh(RLow)}}$ 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 are corrected for heteroskedasticity 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 the Data Appendix. The sample period is from January 1963 to December 2016.

| *Dep. var.* | *Congruent-mood recurrence* $\text{RET}_{\text{High(Low)}}$ | | *Noncongruent-mood reversal* $\text{RET}_{\text{High(Low)}}$ | |
|---|---|---|---|---|
| *Indep. var. (Lagged)* | $\text{RET}_{\text{High(Low)}}$ | $\text{RET}_{\text{RHigh(RLow)}}$ | $\text{RET}_{\text{Low(High)}}$ | $\text{RET}_{\text{RLow(RHigh)}}$ |
| *Year lag (k)* | (1) | (2) | (3) | (4) |
| *Panel A: Individual stocks* | | | | |
| *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 (BW) portfolios* | | | | |
| 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 (KLN) portfolios* | | | | |
| *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) |

rationale, as discussed previously, relies on the assumption that extreme realized average returns are 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, hypothesized congruent-mood months:

$$RET_{\text{High(Low)},\ t} = \eta_{k,t} + \gamma_{k,t} RET_{\text{RHigh(Rlow)},\ t-k} + \varepsilon_t, \qquad (2)$$

where $RET_{\text{RHigh(Rlow)},\ t-k}$ is the historical return during the two highest (lowest) market return months 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 10 basis points, or a 6%, higher returns relative to the mean in each of the future hypothesized 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 in the past using realized average stock returns.

#### *3.1.3. The mood reversal effect: returns during prespecified mood months as predictors*

Next, we test for the cross-sectional reversal effect across prespecified, noncongruent, recurrent mood periods, 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 (1) when forecasting future high or low mood month returns, through which 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 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 effect represents a 41% to 53% return reduction resulting 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 prespecified, noncongruent-mood states, at least for a few subsequent years.

#### *3.1.4. The mood reversal effect: returns during realized mood months as predictors*

The reversal effect can also be identified by using recent realized mood periods identified 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 hypothesized 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 realized 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 of 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 seemingly connect 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 days of the week with hypothesized moods: Mondays and Fridays. In untabulated tests, we first verify the findings from previous studies that stocks as a whole, measured by the equal-weighted market portfolio, earn higher returns on Fridays (19 basis points) and lower returns on Monday (−10 basis points) during our sample period 1963–2016. We then go beyond previous findings to examine weekday congruent-mood recurrence and noncongruent-mood reversal effects.

#### *3.2.1. The mood recurrence effect: returns during prespecified mood weekdays as predictors*

We examine the congruent-mood recurrence effect at the weekday frequency using FMB regressions, similar to KLN but using only Monday and Friday stock returns. We rerun regression as in regression (1) for Mondays, proxying hypothesized low moods, and Fridays, proxying hypothesized high moods.

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 first 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 the historical congruent-mood-weekday return.[10] The insignificance at the first lag is also observed by KLN, owing to the short-term reversal effect of one-month returns (Jegadeesh, 1990) that appears to be unusually strong during the first week.[11]

[10] Untabulated tests show that the predictive power of the same-weekday return persists for at least 50 weeks at the individual stock level.

[11] Keloharju et al. (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 are much less negative or slightly positive.

**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 are corrected for heteroskedasticity 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 the Data Appendix. The sample period is from January 1963 to December 2016.

| *Dep. var.* | *Congruent-mood recurrence* $RET_{High(Low)}$ | | *Noncongruent-mood reversal* $RET_{High(Low)}$ | |
|---|---|---|---|---|
| Indep. var. (Lagged) | $RET_{High(Low)}$ | $RET_{RHigh(RLow)}$ | $RET_{Low(High)}$ | $RET_{RLow(RHigh)}$ |
| *Week lag (k)* | (1) | (2) | (3) | (4) |
| *Panel A: Individual stocks* | | | | |
| *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 (BW) portfolios* | | | | |
| *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 (KLN) portfolios* | | | | |
| *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) |

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.[12] Thus, our evidence confirms recurrent relative performances across stocks or portfolios across prespecified congruent-mood weekdays: Monday and Friday.

### 3.2.2. The mood recurrence effect: returns during realized mood weekdays as predictors

We extend the mood-weekday recurrence effect to identifying realized mood weekdays by using the two days with the highest or 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 hypothesized congruent moods (Friday and Monday), similar to regression (3.2).

Column (2) of Table 3 reports 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 portfolios and the KLN portfolios, respectively. These return responses represent 44% to 243% higher returns for a one standard deviation increase in the predictor for each Monday or Friday during the next two to ten weeks.

### 3.2.3. The mood reversal effect: returns during prespecified mood weekdays as predictors

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 (1) when forecasting returns on the hypothesized future high and low weekdays.

As reported in Column (3) of 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% lower return relative to the mean is expected during Mondays (Fridays) of the next two to ten weeks for a one standard deviation increase in the average Friday (Monday) return over

[12] Untabulated tests show that the predictive power of the congruent-mood-weekday return persists for at least 50 weeks at the portfolio level.

the past two to ten weeks. 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 prespecified noncongruent-mood weekdays at the portfolio level.

#### *3.2.4. The mood reversal effect: returns during realized mood weekdays as predictors*

Analogous to the monthly returns, a stronger reversal effect is also observed across noncongruent-mood weekdays when the prior mood is identified using historical, realized extreme equal-weighted CRSP excess returns. We regress hypothesized high or low mood weekday (i.e., Friday or Monday) returns across assets on their historical returns realized on the weekday with the lowest or highest market return of the prior weeks for three sets of week lags, $k$ = 1, 2–10, 6–20, when mood is presumably 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 past average noncongruent-mood-weekday return corresponds to a 146%, 56%, and 27% lower return relative to the mean, respectively, for each of the next 1, 10, and 20 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 first 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 effect

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

We measure mood beta by an asset's return sensitivity to the equal-weighted market excess returns during the past high and low mood periods. This approach starts from the idea that shifts in mood are manifested in both returns on the equal-weighted market portfolio as well as on individual assets. Unfortunately, regressing asset returns on aggregate returns reflects both variation in mood and in fundamentals. However, it is likely that extreme mood periods also have relatively variable mood. Thus restricting the regression to extreme mood periods can potentially improve the signal-to-noise ratio in estimation of mood beta. As a robustness check, we alternatively estimate mood sensitivity using mean return differences between high and low mood periods.

### *4.1. Monthly mood beta*

The first mood beta is estimated by using monthly returns during the past high and low mood periods. Specifically, using a 10-year rolling window by requiring a minimum of 40 observations, we estimate mood beta for each asset from time-series regressions of the asset's historical excess returns earned during prespecified and realized high and low mood months ($XRET_{i,\text{ MoodMonth}}$) on the contemporaneous equal-weighted CRSP excess returns ($XRET_{A,\text{ MoodMonth}}$).

$$XRET_{i,\text{MoodMonth}} = \alpha_i + \beta^{\text{Mood}}_{i,\text{ month}} XRET_{A,\text{MoodMonth}} + \varepsilon_i. \quad (3)$$

The regression thus includes eight months in a year: four prespecified (January, March, September, and October) and four realized high and low mood months (the top two and bottom two months with the highest and lowest realized equal-weighted market returns).[13] The estimated $\beta^{\text{Mood}}_{i,\text{ month}}$ is called the monthly mood beta. It measures the average return change of an asset in response to a 1% aggregate return change in the identified historical mood months.

In unreported tests, we obtain similar results if we estimate mood beta using only four months a year based on either prespecified or realized moods. We also 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 excess returns across the high or 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 improving moods. The results using this ratio are qualitatively similar to those using the regression-based mood beta.

Moving to the second stage, we run FMB regressions of asset returns in the current hypothesized high (January and March) or low mood month (September and October) on their mood beta, estimated using prior return information ending in year $t-5$ to $t-2$, the lags for which we observe robust mood recurrence and 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 are similar to the baseline regressions.

Our mood seasonality Hypothesis 2 predicts that high mood beta stocks will do better in subsequent high mood months and will do 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 ($\lambda_{k,\,t}$ in regression (4) below) in the cross-sectional regressions is expected to be positive. As phase two of the FMB regressions, we average $\lambda_{k,\,t}$ across time to yield $\lambda_k$, which

[13] If a month appears twice in a year based on the two identification criteria, then it counts as two observations in the regressions. This of course induces residual correlation in the regression, but this is not a concern for our purposes. We use these regressions to estimate the mood beta for use in other tests, not to evaluate its statistical significance.

**Table 4**
Mood beta to predict cross section of returns.

This table examines the predictive power of mood beta to forecast future mood month or weekday returns in Fama-MacBeth regressions. The key independent variable ($\beta^{Mood}$) refers to the monthly mood beta (${\beta^{Mood}}_{Month}$) when we forecast mood month returns and the weekday mood beta (${\beta^{Mood}}_{Weekday}$) when we forecast mood weekday returns. When forecasting future returns during a high mood state, the independent variable is the stock's historical $\beta^{Mood}$, 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 $\beta^{Mood}$. 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 are corrected for heteroskedasticity 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 the Data Appendix. The sample period is from January 1968 to December 2016.

| *Dep. var.* | *Congruent-mood recurrence* $RET_{High(Low)}$ | | | | *Noncongruent-mood reversal* $RET_{High(Low)}$ | | | |
|---|---|---|---|---|---|---|---|---|
| *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 (BW) 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 (KLN) 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) |

we call the mood premium and captures the average size of the positive return spread between the high and low mood beta assets in high mood periods and that of the negative return spread in low mood periods.

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

$$RET_{High,t} = \eta_{k,t} + \lambda_{k,t}\beta^{Mood}_{i,Month,t\text{–}k} + \gamma_{k,t}RET^{\perp}_{High,t-k} + \varepsilon_t, \text{ and}$$
$$RET_{Low,t} = \eta_{k,t} - \lambda_{k,t}\beta^{Mood}_{i,Month,t-k} + \gamma_{k,t}RET^{\perp}_{Low,t-k} + \varepsilon_t. \quad (4)$$

As reported in Column (1) of Table 4, Panel A, for individual stocks (year lag 2–5), the estimated mood premium ($\gamma_k$) is 1.47% ($t = 4.83$), implying that a one standard deviation increase in mood beta (0.69) leads to an average 101 basis points (= 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 $RET^{\perp}_{High(Low)}$ 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. $RET^{\perp}_{High(Low)}$, however, continues to carry a significant positive coefficient for the portfolios. Replacing $RET^{\perp}_{High(Low)}$ with $RET^{\perp}_{RHigh(RLow)}$ 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 $RET^{\perp}_{RHigh(RLow)}$.

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

$$RET_{High,t} = \eta_{k,t} + \lambda_{k,t}\beta^{Mood}_{i,Month,t\text{–}k} + \gamma_{k,t}RET^{\perp}_{Low,t-k} + \varepsilon_t, \text{ and}$$
$$RET_{Low,t} = \eta_{k,t} - \lambda_{k,t}\beta^{Mood}_{i,\ Month,t-k} + \gamma_{k,t}RET^{\perp}_{High,t-k} + \varepsilon_t. \quad (5)$$

Shown in Column (3) of Table 4, $RET^{\perp}_{Low(high)}$ tends to exhibit considerably diminished 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 $RET^{\perp}_{Low(high)}$ in regressions (4.3) with the orthogonalized historical returns earned during the realized high or low mood months ($RET^{\perp}_{RLow(RHigh)}$). 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 return recurrence and reversal effects.

### 4.2. Weekday mood beta

Moving to weekday returns, we estimate mood beta for each asset from time-series regressions of a stock's excess return during the prespecified and realized high and low mood days of the week on the corresponding equal-weighted market excess returns using a six-month rolling window (by requiring a minimum of 50 observations):

$$XRET_{i,\text{MoodWeekday}} = \alpha_i + \beta_{i,\ \text{weekday}}^{\text{Mood}} XRET_{A,\text{MoodWeekday}} + \varepsilon_i. \quad (6)$$

The regression thus includes Fridays, Mondays, and the weekdays with the highest and lowest equal-weighted market excess returns realized in a week. The estimated coefficient on the market excess return is called the weekday 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 $\beta_{i,\ \text{Weekday}}^{\text{Mood}}$ to forecast future returns on hypothesized high and low mood weekdays (Fridays and Mondays) by controlling for the orthogonalized historical seasonal returns earned during congruent-mood weekday ($RET_{\text{High(Low)}}^{\perp}$).

$$RET_{\text{High},t} = \eta_{k,t} + \lambda_{k,t}\beta_{i,\text{Weekday},t\text{–}k}^{\text{Mood}} + \gamma_{k,t} RET_{\text{high},t-k}^{\perp} + \varepsilon_t, \ \text{and}$$
$$RET_{\text{Low},t} = \eta_{k,t} - \lambda_{k,t}\beta_{i,\text{Weekday},t-k}^{\text{Mood}} + \gamma_{k,t} RET_{\text{Low},t-k}^{\perp} + \varepsilon_t. \quad (7)$$

We focus on the mood betas estimated using prior six-month weekday returns ending in week $t-10$ to $t-2$. Mood betas across the multiple lags are averaged to generate the mood beta regressor. Estimates for lags of $t = 1$ or 11–20 are unreported and are 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% level for all three sets of test assets, with the size of the daily premium at 5 basis points for individual stocks, 12 basis points for the BW portfolios, and 10 basis points for the KLN portfolios. The estimated return response on $RET_{\text{High(Low)}}^{\perp}$ remains positive and significant for all 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 $RET_{\text{High(Low)}}^{\perp}$ with $RET_{\text{RHigh(RLow)}}^{\perp}$, identified from realized weekday returns of the equal-weighted market portfolio. Again, all mood beta premia are positive and significant at the 1% level, while only one out of three coefficients of $RET_{\text{RHigh(RLow)}}^{\perp}$ is significant.

Next we replace $RET_{\text{High(Low)}}^{\perp}$ in regression (4.5) by those earned during the noncongruent-mood weekdays, either using $RET_{\text{Low(High)}}^{\perp}$ or $RET_{\text{RLow(RHigh)}}^{\perp}$, to assess how the noncongruent-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 $RET_{\text{Low(High)}}^{\perp}$ and $RET_{\text{RLow(RHigh)}}^{\perp}$ 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 a considerable portion of the noncongruent reversal effects at the weekday level. Since betas are estimated with error, it is possible that the 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 find derive from traditional market 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 predesignated 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 Fig. 2, which will be discussed later in Section 5.3).

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 asset returns and value-weighted market returns are used in the estimation.

Another possible concern is that mood beta may be a proxy for the sentiment beta (Baker and Wurgler 2007). The purpose of studying mood beta is to capture stock sensitivity to shifts in investor emotions—the affective aspect of investor sentiment. Investor emotions can potentially behave differently from other aspects of sentiment (such as, for example, swings in investor attention between different aspects of the economic environment). Thus we do not expect mood beta to be perfectly correlated with sentiment beta over time or across securities.

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 changes in the BW sentiment index (orthogonalized to macroeconomic variables) together with the CRSP value-weighted index returns. An alternative measure of the sentiment index that is 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 hypothesized high and low mood periods (months or weekdays) using mood beta with controls for market beta or sentiment beta. Again, we focus on 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 significant in the presence of market beta or sentiment beta.

In contrast, during the hypothesized high and low mood periods, market beta tends to carry a significantly negative premium, contrary to the prediction of the rational risk-based theory. This phenomenon is referred to as the low-risk anomaly (Baker et al., 2011; Frazzini and Pedersen, 2014). We also find that sentiment beta tends to carry a positive coefficient, suggesting that high-sentiment

**Table 5**
Mood beta, market beta, and sentiment beta.

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 ($\beta^{Mood}{}_{Month}$, $\beta^{Mood}{}_{Weekday}$) are estimated using monthly or weekday returns during the historical mood states, as defined as in Table 4. The market betas ($\beta^{Mkt}{}_{Month}$, $\beta^{Mkt}{}_{Weekday}$) are estimated by regressing all historical monthly or weekday asset returns on the corresponding returns on the value-weighted CRSP index during a rolling window. The sentiment beta ($\beta^{Sent}$) is estimated by regressing the monthly asset returns on the monthly changes in the Baker and Wurgler (2006) sentiment index together with the value-weighted CRSP index returns over a rolling 60-month window. When forecasting future returns during a high mood month or weekday, the independent variable is the asset's historical $\beta^{Mood}$. 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 and are corrected for heteroskedasticity 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 the Data Appendix.

| *Dep. var.* | *Mood month return* $RET_{High(Low)}$ | | | | *Dep. var.* | *Mood weekday return* $RET_{High(Low)}$ | | | |
|---|---|---|---|---|---|---|---|---|---|
| *Indep. var.* | (1) | | (2) | | *Indep.* var. | (3) | | (4) | |
| *Year lag (k)* | $\pm\beta^{Mood}{}_{Month}$ | $\beta^{Mkt}{}_{Month}$ | $\pm\beta^{Mood}{}_{Month}$ | $\beta^{Sent}$ | *Week lag (k)* | $\pm\beta^{Mood}{}_{Weekday}$ | $\beta^{Mkt}{}_{Weekday}$ | $\pm\beta^{Mood}{}_{Weekday}$ | $\beta^{Sent}$ |
| *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 (BW) 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 (KLN) 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) |

beta stocks tend to earn higher average returns in these periods. In conclusion, neither market beta nor sentiment beta subsumes the ability of mood beta to predict returns across high and low mood periods in the very specific way in which it does—with opposite signs.

### 4.4. Composite mood beta

So far, for each asset, we have two mood betas, estimated from monthly and weekday returns during the historical high and low mood periods. To further reduce noise, we form a composite mood beta ($\beta_i^{Mood}$) as the first principal component of the monthly mood beta ($\beta_{i,\ month}^{Mood}$) and the weekday mood beta ($\beta_{i,\ Weekday}^{Mood}$), extracted month by month in the cross-section of individual stocks or portfolios. The monthly mood beta $\beta_{i,\ month}^{Mood}$ is updated annually, so the within-year variation for a given stock comes solely from the variation in $\beta_{i,\ Weekday}^{Mood}$.

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 across 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.

In Table 1 we report the summary statistics of the composite mood beta, and in Fig. 1 we plot the time-series average of the composite beta for each of the BW and KLN portfolios. Fig. 1 reveals that mood beta tends to be higher for younger firms than older firms, growth firms than value firms, nondividend 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, and low earnings-to-price firms than high earnings-to-price firms.

Some other attributes exhibit a V-shaped or inverse V-shaped relation 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, with the highest or lowest external financing, and 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 and business equipment industry, and by far the lowest mood beta is seen for the utilities industry.

Many of these patterns for mood beta are similar to those associated with the BW sentiment beta. 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 multivariate tests.

### 4.5. Long-short portfolios based on historical seasonal returns and mood beta

Our FMB regression results presented in the previous sections suggest that historical congruent-mood returns, noncongruent-mood returns, and mood beta all have the ability to forecast cross-sectional returns in future hypothesized high (January, March, and Friday) and low (September, October, and Monday) mood periods. To quantify the economic magnitude of these effects, we next examine the profitability of various trading strategies derived from these findings.

We form a long-short portfolio for each predictor based on portfolio deciles sorted each month according to the predictor. If the historical seasonal return is used as the predictor, the hedge portfolio always goes long the highest and short the lowest decile. If mood beta is used

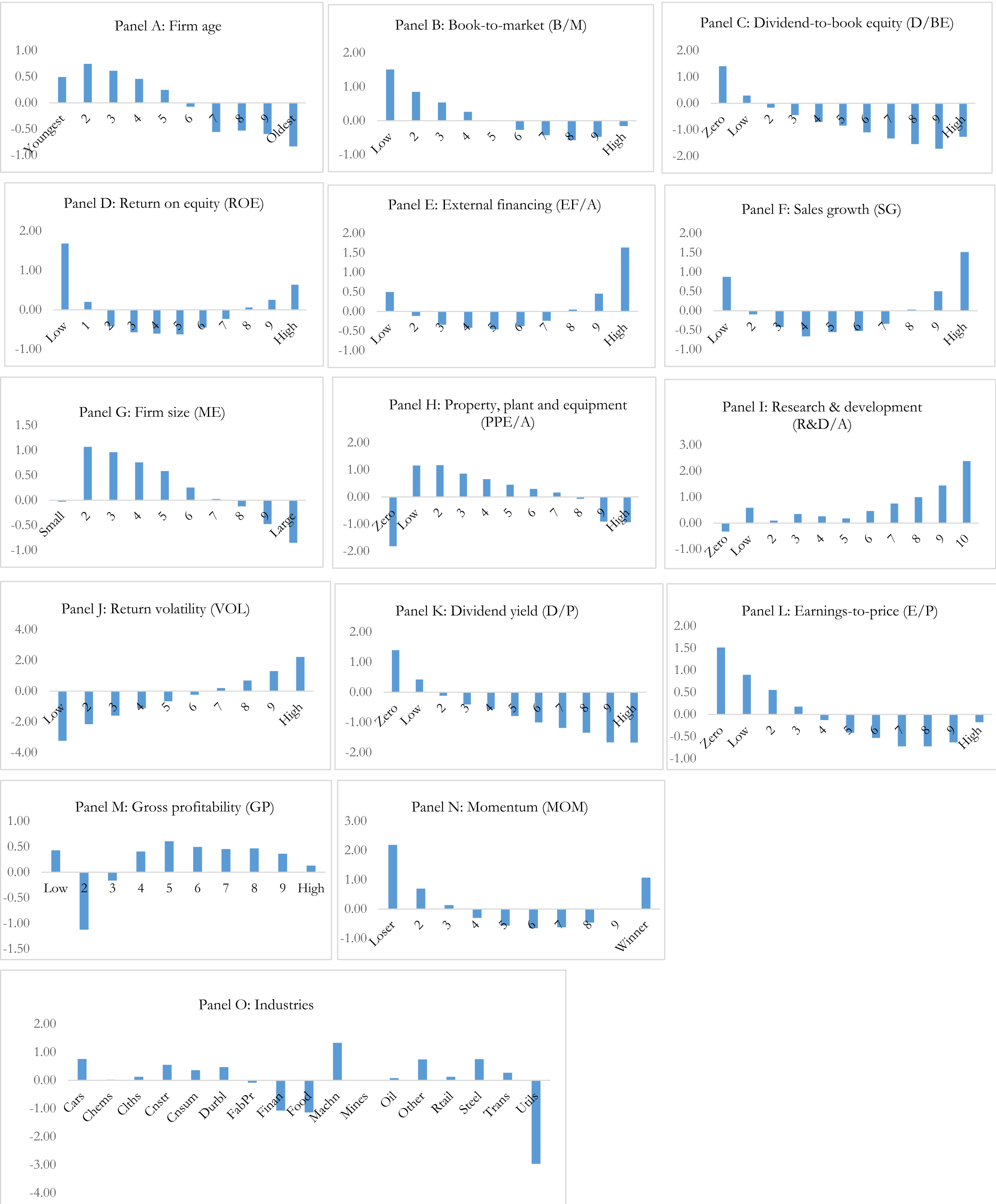


**Fig. 1.** Mood betas of characteristics-sorted portfolios.
This figure reports the average composite mood beta ($\beta^{\text{Mood}}$) for portfolios sorted based on firm characteristics used by Baker and Wurgler (2006) (Panels A through J) and Keloharju et al. (2016) (Panels K through O excluding size and book-to-market portfolios, which are reported in Panels B and G). All variables are defined in the Data Appendix.

**Table 6**
Long-short portfolios based on historical seasonal returns and mood beta: month-level tests.

This table 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 betas ($\beta^{Mood}{}_{Month}$, $\beta^{Mood}{}_{Weekday}$, and $\beta^{Mood}$) 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). The abnormal returns are estimated using the four-factor model (Fama-French-Carhart 1997) and the Fama-French (2015) five-factor model. Estimates are reported in percentage points. The Newey-West $t$-statistics are reported in parentheses. All variables are defined in the Data Appendix.

| Sorting variables | $RET_{High(Low)}$ (1) | $RET_{RHigh(RLow)}$ (2) | $RET_{Low(High)}$ (3) | $RET_{RLow(RHigh)}$ (4) | $\beta^{Mood}{}_{Month}$ (5) | $\beta^{Mood}{}_{Weekday}$ (6) | $\beta^{Mood}$ (7) |
|---|---|---|---|---|---|---|---|
| *Panel A: Individiual stocks* | | | | | | | |
| *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) |
| *Panel B: Baker and Wurgler (BW) 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) |
| *Panel C: Keloharju, Linnainmaa, and Nyberg (KLN) 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) |

instead, the hedge portfolio goes long the highest and short the lowest decile during the hypothesized high mood periods and flips the long and short legs when low moods are anticipated.

Table 6 reports results at the month level. We employ four strategies based on historical seasonal returns earned during the prespecified high and low and the realized high and low mood months and three mood beta strategies based on the monthly, the weekday, and the composite mood betas. The strategies are implemented by using the signals measured with annual lags 2–5. In addition to reporting mean returns, we report the estimated risk-adjusted returns (i.e., alphas) for these long-short portfolios based on the Fama-French-Carhart four-factor model (Carhart 1997) and the Fama and French (2015) five-factor model.

Across the three sets of test assets, Table 6 shows that the trading strategies that capture the congruent-mood recurrence effects (Columns (1) and (2)) work better for the BW and KLN portfolios, with a five-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 (Columns (3) and (4)) work better for individual stocks, with a five-factor alpha of −1.40% ($t=-5.63$) and −1.74% ($t=-4.44$) per month.

The trading strategies based on three mood betas (Columns (5)-(7)) tend to be more profitable for individual stocks. The monthly five-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 (Column (7)) work well for all three sets of test assets, generating a monthly five-factor alpha ranging from 1.59% to 2.37%, all significant at the 5% level or better. It is particularly profitable for individuals stocks. This contrasts with the relatively weaker results based on the return recurrence effects in (1) and (2).

Next, in Table 7 we apply the trading strategies to forecasting future mood weekday returns (Mondays and Fridays) using predictors with weekly lags 2–10. Here we observe all positive alphas for strategies based upon the congruent-mood recurrence effect (Columns (1) and (2)); the alphas range from 3 to 12 basis points per day across the three assets, nearly all significant at the 5% level or better. The strategies based on the noncongruent-mood reversal effect (Columns (3) and (4)) are profitable for individual stocks (8 to 10 basis points per day) and for the BW portfolios (2 to 3 basis points per day), but are unprofitable for the KLN portfolios.

In contrast, mood-beta-based strategies (Columns (5)-(7)) are highly profitable throughout all measures, with alphas ranging from 8 to 17 basis points a day, all significant at the 5% level or better. Overall, mood beta implies more stable and profitable trading strategies across all three assets over the full sample period.[14]

[14] Fig. A1 in the Online Appendix indicates that the long-short profits exhibit diminishing returns since 2001, which may derive from the rising influence of sophisticated investors such as hedge funds.

**Table 7**
Long-short portfolios based on historical seasonal returns and mood beta: weekday-level tests.

This table reports the mean and abnormal returns on the long-short portfolios sorted based on historical congruent ($RET_{High(Low)}$, $RET_{Bhigh(RLow)}$), noncongruent ($RET_{Low(High)}$, $RET_{RLow(Rhigh)}$) mood weekday returns, or mood betas ($\beta^{Mood}{}_{Month}$, $\beta^{Mood}{}_{Weekday}$, and $\beta^{Mood}$). Each day of the week, 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 four-factor model (Fama-French-Carhart 1997) and the Fama-French (2015) five-factor model. Estimates are reported in percentage points. The Newey-West t-statistics are reported in parentheses. All variables are defined in the Data Appendix.

| Sorting variables | $RET_{High(Low)}$ (1) | $RET_{RHigh(RLow)}$ (2) | $RET_{Low(High)}$ (3) | $RET_{RLow(RHigh)}$ (4) | $\beta^{Mood}{}_{Month}$ (5) | $\beta^{Mood}{}_{Weekday}$ (6) | $\beta^{Mood}$ (7) |
|---|---|---|---|---|---|---|---|
| *Panel A: Individual stocks* | | | | | | | |
| *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) |
| *Panel B: Baker and Wurgler (BW) 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) |
| *Panel C: Keloharju, Linnainmaa, and Nyberg (KLN) 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) |

### *4.6. Multivariate Fama-MacBeth regressions*

Last, we conduct multivariate tests using firm-level FMB regressions to assess the incremental predictive power of mood beta relative to a set of firm characteristics and return predictors—after accounting for the possible ability of these return predictors to forecast returns with opposing signs across the high and low mood periods. In Table 8, we report the estimates separately for the mood month and mood day regressions, in which lagged mood beta is used to forecast stock returns in future hypothesized high and low mood months (January, March, September, and October) or mood days (Monday and Friday).

We include regressions with only the composite mood beta (regressions 1 and 4), with market beta and sentiment beta (regressions 2 and 5), and additionally controlling for a set of firm characteristics used to form the BW and KLN portfolios (regressions 3 and 6). The characteristics include *ME, B/M, MOM, EF/A, GP*, PPE/A, *SG*, and *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 relation 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 weekdays 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 anticipated high and low mood periods.

The regression estimates reported in Table 8 show that mood beta has a positive and significant coefficient throughout all regressions; the coefficient ranges from 0.59% to 1.80% per month and from 2.37 basis points to 4.65 basis points per 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 coefficients, exhibiting no clear pattern. Among other firm characteristics, only size, momentum, and gross profitability exhibit a consistent and significant relation 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 multivariate FMB regressions supports our prior finding that mood beta positively predicts stock returns when investors experience ascending moods and negatively do so when descending moods occur. The forecasting power is robust to controls for market beta, sentiment beta, and a host of firm characteristics.

## **5. Additional tests and robustness checks**

This section presents additional tests and robustness checks to address several possible concerns about our main

**Table 8**
Fama-MacBeth regression at the firm level.

This table reports Fama-MacBeth regression estimates on lagged mood beta, market beta, sentiment beta, and a host of firm characteristics in forecasting future returns during the high and low mood month or weekdays. The test assets are the full cross-section of individual stocks. The dependent variable is the monthly return in percentagess or the weekday return in basis points. 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) returns and the negative low mood day (Monday) returns. The Newey-West *t*-statistics are reported in parentheses. All independent variables are lagged. They are also standardized to have zero mean and unit variance and are defined in the Data Appendix.

| *Dep. var.* | $+\ \mathrm{RET}_{\mathrm{High}}$ and $-\ \mathrm{RET}_{\mathrm{Low}}$ | | | | | |
|---|---|---|---|---|---|---|
| | Mood month | | | Mood day | | |
| *Indep. var.* | (1) | (2) | (3) | (4) | (5) | (6) |
| $\beta^{Mood}$ | 1.15*** | 1.80*** | 0.59** | 4.65*** | 4.14*** | 2.37*** |
| | (3.70) | (3.83) | (2.19) | (9.39) | (12.69) | (7.38) |
| $\beta^{Mkt}{}_{Weekday}$ | | −0.74* | −0.56 | | 0.61 | 1.38** |
| | | (−1.85) | (−0.80) | | (0.98) | (2.39) |
| $\beta^{Sent}$ | | −0.03 | 0.13 | | 0.58*** | 0.38** |
| | | (−0.16) | (0.57) | | (3.07) | (1.99) |
| *Log(ME)* | | | −1.01*** | | | −3.69*** |
| | | | (−5.66) | | | (−9.49) |
| *Log(B/M)* | | | 0.05 | | | −1.88*** |
| | | | (0.21) | | | (−9.06) |
| *MOM* | | | −1.63*** | | | −0.70** |
| | | | (−2.77) | | | (−2.44) |
| *EF/A* | | | 0.03 | | | 0.25 |
| | | | (0.15) | | | (1.24) |
| *GP* | | | −0.47** | | | −1.59*** |
| | | | (−2.04) | | | (−8.53) |
| *PPE/A* | | | −0.08 | | | 0.42** |
| | | | (−0.61) | | | (2.13) |
| *SG* | | | −0.24 | | | 0.07 |
| | | | (−0.81) | | | (0.37) |
| *SIGMA* | | | 0.30 | | | 2.43*** |
| | | | (0.87) | | | (8.02) |
| *# of mons/days* | 196 | 188 | 188 | 4816 | 4621 | 4621 |
| *Avg.# of stocks* | 2577 | 2814 | 2577 | 2639 | 2780 | 2555 |
| *Adj. R2* | 0.25% | 0.36% | 1.23% | 0.78% | 1.62% | 2.61% |

findings of the mood recurrence, reversal, and mood beta effects.

### 5.1. Alternative definitions of hypothesized mood periods

A possible concern is that our results may be driven by a look-ahead or in-sample bias. Our hypothesized high and low mood periods are identified by the average highest and lowest aggregate returns in the full sample period. Thus market beta will be strongly positively related to returns in the high market return periods and will be negatively related to returns during the periods when realized market returns are, on average, negative. If mood beta is correlated with market beta, then such patterns may apply to mood beta as well.

The evidence opposes this explanation. We show in Table 8 (discussed in Section 4.6) and Fig. 2 (further discussed in Section 5.3) that market beta does not predict returns with opposite signs in the hypothesized high and low mood periods. In contrast, the mood beta does. Thus market beta does not capture this key mood beta effect.[15]

We also raise a conceptual objection to this explanation and present a set of robustness checks. Conceptually, rational factor pricing models imply that the ex ante market risk premium is positive on all months or days. In long enough samples, systematic patterns of negative daily or monthly premia for market beta would be ruled out. Suppose that our mood beta is a proxy for the true market beta, then there should typically be a positive premium for mood beta. This is dissonant with our finding that in some seasonal periods there is a negative premium associated with mood beta. At best, such a finding would be limited to specific subsamples (especially when the high and low mood periods are selected by also using information from the periods being predicted). This contrasts with our mood seasonality hypothesis that predicts such effects will systematically occur in sample as mood varies predictably across months and weekdays.

We also conduct a set of robustness checks in Tables 9 and 10 by changing the predictable future mood periods from the originally predesignated January, March, September, October, Monday, and Friday to others based on alternative identifications. The purpose of these tests is to ascertain whether our findings are limited to specific periods.

We consider four alternative identifications of mood periods based on the extreme, realized monthly or weekday equal-weighted market excess returns observed in four windows, which include (1) from 1927 to the preceding year before the forecast is made (*Expanding window*); (2) over the rolling 50-year (10-year) window for monthly (weekday) returns ending in the prior year (month) (*Rolling window*); (3) during even years when we forecast returns in odd years (*Even years to forecast odd years*); and (4) during odd years when we forecast returns in even years (*Odd years to forecast even* years). 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.

At the month level, Table 9 reports the long-short portfolio returns based on historical mood month returns. 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 7. Moving to weekday-level tests in Table 10, the congruent-mood recurrence effects generally remain strong across three sets of tests assets. The noncongruent-mood reversal effects are strong for individual stocks and the BW portfolios but weak for the KLN portfolios, again similar to the baseline results in Table 7.

More importantly, the long-short returns of the composite mood beta portfolios, reported in Tables 9 and 10, Column (5), exhibit similar patterns to our baseline tests.

[15] So this mood beta effect could only be driven by market beta if one believes that mood beta is a more accurate proxy for the true market beta than market beta directly estimated from recent monthly or daily returns. It is not clear why this would be the case.

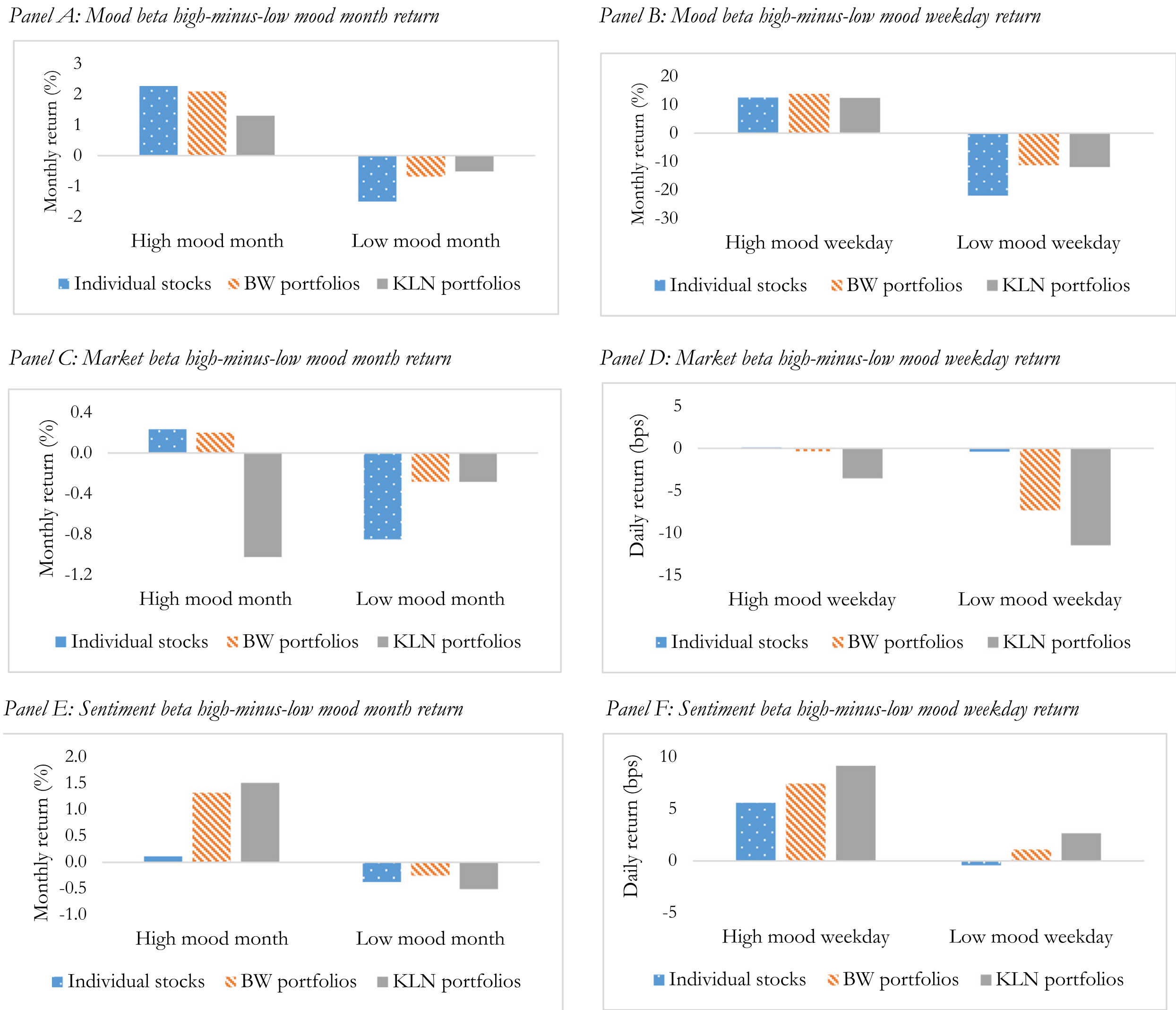


**Fig. 2.** High-minus-low portfolios across high and low mood periods: mood beta versus market beta and sentiment beta.
This figure reports the average high-minus-low portfolio returns sorted based on the composite mood beta ($\beta^{Mood}$) across high and low mood states. The high-minus-low portfolio 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 months include January and March and high mood weekday includes Friday. Low mood months include September and October and low mood weekday includes Monday. The three sets of test assets include the full cross-section of individual stocks, the 94 BW portfolios and the 79 KLN portfolios. The average returns of the long-short portfolios are expressed in percentage points in left-hand-side panels for month-level tests and in basis points in right-hand-side panels for weekday-level tests. The composite mood beta is defined in the Data Appendix.

Across all approaches of identifying future mood periods and for all 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.

Overall, the long-short strategies produce an average return of about 1% per month or above 10 basis points per day, a magnitude that is slightly smaller at the monthly level, but similar at the weekday level, to the baseline strategies based on predesignated mood months or weekdays. Thus, using the alternative definitions of future predictable mood periods leads to qualitatively similar, and quantitatively comparable results. Therefore 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.

### 5.2. Is January atypical?

Heston and Sadka (2008) show that January is associated with a stronger same-month return persistence effect. We extend their analysis by studying the effects of mood recurrence, reversal, and mood beta separately for January and non-January months.

At the monthly level, Table A1 of the Online Appendix reports the FMB regression coefficients. The results show that, indeed, both month-level mood effects are visibly stronger during January months. Although some of the

**Table 9**
Long-short portfolio returns: alternative definition of mood months.

This table reports the mean returns on the long-short portfolios earned in future mood months defined using various alternative methods, and the long-short portfolios are sorted on the average historical congruent ($RET_{High(Low)}$, $RET_{Bhigh(RLow)}$), noncongruent ($RET_{Low(High)}$, $RET_{RLow(Rhigh)}$) mood month returns, and the composite mood betas ($\beta^{Mood}$) during years $t-2$ through $t-5$. The future high (low) mood months are identified using the highest (lowest) mean equal-weighted market excess monthly returns earned (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 (Even years to forecast odd years); and (4) during odd years to forecast only even years from 1963 to 2016 (Odd years to forecast even years). Regression estimates are reported in percentages. The Newey-West $t$-statistics are reported in parentheses. All variables are defined in the Data Appendix.

| | *Dependent variable: month-level $RET_{High(Low)}$* | | | | |
|---|---|---|---|---|---|
| Sorting variable | $RET_{High(Low)}$ (1) | $RET_{RHigh(RLow)}$ (2) | $RET_{Low(High)}$ (3) | $RET_{RLow(RHigh)}$ (4) | $\beta^{Mood}$ (5) |
| *Panel A: Individual stocks* | | | | | |
| *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) |
| *Even years to forecast odd years* | −0.08 | −0.55 | −1.50*** | −1.40*** | 0.77 |
| | (−0.37) | (−1.06) | (−4.66) | (−2.63) | (1.01) |
| *Odd years to forecast even years* | 0.29 | 0.12 | −1.33*** | −1.34*** | 1.84** |
| | (1.54) | (0.28) | (−4.83) | (−2.95) | (2.28) |
| *Panel B: Baker and Wurgler (BW) 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) |
| *Even years to forecast odd years* | 1.11*** | 0.94** | −0.20 | −0.63 | 0.88* |
| | (3.23) | (2.19) | (−0.61) | (−1.56) | (1.82) |
| *Odd years to forecast even years* | 1.21*** | 1.37*** | −0.87*** | −1.32*** | 1.26*** |
| | (3.23) | (3.53) | (−2.64) | (−3.12) | (2.71) |
| *Panel C: Keloharju, Linnainmaa, and Nyberg (KLN) 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) |
| *Even years to forecast odd years* | 1.62*** | 0.84* | −0.05 | −0.73* | 0.78 |
| | (4.40) | (1.76) | (−0.12) | (−1.66) | (1.53) |
| *Odd years to forecast even years* | 1.12*** | 1.31*** | −0.89*** | −1.33*** | 1.17*** |
| | (2.63) | (3.18) | (−2.74) | (−3.13) | (2.72) |

historical seasonal returns lose predictive power in non-January mood months, 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 and 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.

### 5.3. Mood beta in high and low mood periods

Does mood beta predict future returns in the hypothesized high or low mood periods? We find that the predictability comes from both periods. As plotted in Panel A of Fig. 2, the three high-minus-low portfolios based on the composite mood beta yield positive average returns during high mood months (January and March) and weekdays (Friday) and negative average returns during low mood months (September and October) and weekdays (Monday). 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.

As a comparison, we plot in Panels B and C of Fig. 2 the high-minus-low portfolio returns based on the market beta and sentiment beta, again, separately for the hypothesized high and low mood months and weekdays. Panel B shows that high market beta assets tend to underperform during low mood periods but do not consistently overperform during high mood periods. Panel C, however, shows that while high sentiment beta assets do overperform during high mood periods, they do not consistently underperform during low mood periods. Thus, the effects of mood beta are far from fully captured by either market beta or the sentiment beta. Mood beta captures the distinctive opposite-sign relation with average returns across high and low mood periods.

### 5.4. Mood beta effect across time periods

Is the mood beta effect persistent across time? If there is mood-induced mispricing, mood-insensitive investors have an incentive to arbitrage it away, which implies that the effect should have weakened over time with the rising assets under management of hedge funds and active institutional investors in general.

In Fig. A1 of the Online Appendix, we plot the annual return of the mood beta strategies (that flips the long

**Table 10**
Long-short portfolio returns: alternative definition of mood weekdays.

This table reports the mean returns on the long-short portfolios earned in future mood weekdays defined using various alternative methods, and the long-short portfolios are sorted on the average historical congruent ($RET_{High(Low)}$, $RET_{Bhigh(RLow)}$), noncongruent ($RET_{Low(High)}$, $RET_{RLow(Rhigh)}$) mood weekday returns, and the composite mood betas ($\beta^{Mood}$) during weeks $t-2$ through $t-10$. The high (low) mood weekdays 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 ten years (Rolling window), (3) during even years to forecast only odd years from 1963 to 2016 (Even years to forecast odd years); and (4) during odd years to forecast only even years from 1963 to 2016 (Odd years to forecast even years). Regression estimates are reported in percentages. . The Newey-West t-statistics are reported in parentheses. All variables are defined in the Data Appendix.

| | *Dependent variable: weekday-level $RET_{High(Low)}$* | | | | |
|---|---|---|---|---|---|
| Sorting variable | $RET_{High(Low)}$ (1) | $RET_{RHigh(RLow)}$ (2) | $RET_{Low(High)}$ (3) | $RET_{RLow(RHigh)}$ (4) | $\beta^{Mood}$ (5) |
| *Panel A: Individual stocks* | | | | | |
| *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) |
| *Even years to forecast odd years* | 0.08*** | 0.01 | −0.06*** | −0.13*** | 0.16*** |
| | (7.11) | (0.51) | (−5.94) | (−6.41) | (6.33) |
| *Odd years to forecast even years* | 0.06*** | 0.00 | −0.12*** | −0.17*** | 0.20*** |
| | (4.46) | (0.04) | (−8.92) | (−7.72) | (6.99) |
| *Panel B: Baker and Wurgler (BW) 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) |
| *Even years to forecast odd years* | 0.10*** | 0.08*** | −0.00 | −0.02** | 0.12*** |
| | (13.19) | (8.50) | (−0.18) | (−2.54) | (12.35) |
| *Odd years to forecast even years* | 0.09*** | 0.08*** | −0.02** | 0.08*** | 0.13*** |
| | (8.81) | (7.59) | (−2.36) | (7.59) | (11.61) |
| *Panel C: Keloharju, Linnainmaa, and Nyberg (KLN) 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) |
| *Even years to forecast odd years* | 0.13*** | 0.09*** | 0.02** | 0.00 | 0.10*** |
| | (13.50) | (6.81) | (2.14) | (0.35) | (8.88) |
| *Odd years to forecast even years* | 0.11*** | 0.11*** | −0.01 | −0.02 | 0.14*** |
| | (8.73) | (6.92) | (−1.00) | (−1.25) | (10.12) |

and short legs across high versus low mood periods) from 1967 to 2016, separately for the three sets of test assets in three panels. The plots show strong performance of these strategies since the early 1970s through early 2000s, which peaked in 2000 and became less positive and more volatile since then.

We also separately report the mean long-short portfolio returns across three time periods (before 1980, from 1981 to 2000, and after 2000) in Fig. A1. The evidence suggests a diminishing profitability associated with the strategies since 2001. This is not surprising given the corresponding rise of sophisticated, active investors, who may have eliminated much mispricing related to calendar time seasonality effects. These strategies continue to yield an average positive return in recent years, though the small magnitude may be unattractive after accounting for transaction costs.

It is worth noting that these strategies are implemented only in four months a year or two days a week, so they effectively achieve zero gains during other periods. Thus in a full year of trading, performance is heavily diluted by the inactive periods. By the same token, the strategy has a hidden virtue: during inactive periods, the strategy does not exhaust the investor's capital constraints/risk-bearing capacity, so the investor can potentially redeploy capital to earn alpha on other strategies. This hidden benefit should be kept in mind in considering the strategy's annual return performance.

### *5.5. Mood beta effect after portfolio formation*

How much mispricing does mood generate, and how long does it take to correct the mispricing? We consider either a monthly or daily frequency. To answer this question, we track the total seasonal mood-induced mispricing by calculating the cumulative returns on a long-short portfolio formed based upon mood beta deciles during the mood month over the next 12 months or the weekday over the next 5 trading days, during which we do not rebalance the long-short portfolios. Thus a cumulative return of zero at some point indicates a complete correction of mispricing generated starting at portfolio formation during the pre-specified high or low mood periods.

Fig. A2 of the Online Appendix plots these cumulative long-short returns for the three sets of test assets (individual stocks, the BW portfolios, and the KLN portfolios) and separately for the high versus low mood conditioning periods. We focus on the magnitude of the initial mispricing and the number of months or days it takes the mispricing to correct to zero during a 12-month or 5-trading-day period.

We cannot be sure that pricing is correct at any given point in the season, so our focus is on the cumulative increment mispricing after a given starting point. In the left figure of Panel A (plotting the month-level patterns for individual stocks), we find that the average initial long-short return in the high mood months (January and March) is 4.83%. If we interpret the starting point as correct pricing, this suggests that during January and March, high mood beta stocks, on average, become incrementally overpriced by nearly 5% relative to low mood beta stocks. This overpricing takes about nine months to correct. (The long-short return next turns slightly negative when low mood months ensue and then gradually rises until the end of the 12-month period.) As for the low mood months (September and October), the long-short portfolio earns an average of $-1.06\%$ initially. If we interpret the starting point as correct pricing, this indicates that the low-mood months induce incremental underpricing of about 1%. This takes about three months to correct to zero. (The long-short return then moves up to a positive level about 5% after high mood months arrive).

The right figure of Panel A plots the cumulative long-short returns across the five-trading-day cycle for individual stocks. Here the initial average positive long-short return (5.67 basis points) earned on Fridays quickly turns to negative during the next trading day (usually Monday) and stays negative for four days before the next cycle starts. The initial average negative return earned on Mondays ($-21.34$ basis points) worsens the next day before reversing gradually in the next three days. Neither long-short return recovers back to zero during the five trading days. Our untabulated tests show that these cumulative negative returns do not recover for an extended period of a few weeks, suggesting a negative premium attached to high mood beta, at least at the weekday level for individual stocks.

We observe somewhat similar patterns when moving to the two sets of portfolios in Panels B and C. The 12-month or 5-trading-day period may end in positive or negative zones, depending on the frequency or assets we examine. The overall picture is that mood-induced mispricing created during the high or low mood period is corrected over the subsequent several months or days, and correction to the initial mispricing is concentrated in the periods when noncongruent moods arrive. Although the effects for January and Monday are large, several of the effects that we show would be hard for investors to exploit at a large scale given transaction costs and the required rebalancing frequency, which may help explain why they have persisted.

## 6. Conclusion

We propose and test a mood seasonality hypothesis, which asserts that seasonal variations in investor mood are in part responsible for both aggregate and cross-sectional return seasonalities. Consistent with this hypothesis, we find a variety of strong, novel cross-sectional mood recurrence and reversal effects across calendar months and weekdays. Assets that outperform in the past periods when investors are in ascending moods tend to outperform in future periods when an ascending mood is expected and to underperform in future periods when a descending mood is expected.

Our empirical results also highlight the role of mood beta, which measures a security's return sensitivity to market-wide mood-induced mispricing, in integrating various mood recurrence and reversal effects. Across the board, we observe that high mood beta stocks outperform during future ascending mood periods and underperform during future descending mood period. The predictive power of mood beta 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. The evidence in KLN provides the insight that both aggregate and cross-sectional return seasonalities are manifestations of seasonal shifts in factor premia—though not necessarily rational risk premia. Our evidence points to one source of such seasonal factor return predictability: that seasonal factor mispricing is induced by seasonal variations in mood.

## Data Appendix: Variable definition

### A.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. |
| ${\beta^{Mood}}_{Month}$ | Monthly-return-estimated mood beta, or monthly 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 ten-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, or weekday 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 six-month rolling window ending in the prior month, updated monthly. A minimum of 50 observations are required. |
| $\beta^{Mood}$ | Composite mood beta, defined as the principal component of ${\beta^{Mood}}_{Month}$ and ${\beta^{Mood}}_{Weekday}$, extracted monthly. It is normalized to have zero mean and unit standard deviation. |
| ${\beta^{MKT}}_{Month}$ | Monthly-return-estimated market beta, estimated from a market model using monthly returns over a ten-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 six-month rolling window ending in the prior month, updated monthly. The market portfolio is proxied by the value-weighted CRSP index. |
| $\beta^{SENT}$ | 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. |

### A.2. Firm characteristics

#### A.2.1. Baker and Wurgler (BW) 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 $t+1$. |

(*continued on next page*)

(*continued*)

| Variables | Definitions |
|---|---|
| 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 $t+1$. |

### *A.2.2. Keloharju, Linnainmaa, and Nyberg (KLN) Portfolios*

| Variables | Definitions |
|---|---|
| ME | As defined in Appendix 2.1. |
| B/M | As defined in Appendix 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 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 (mining and minerals), oil (oil and petroleum products), clothes (textiles, apparel and footware), consumer durables, chemicals, consumer goods (drugs, soap, perfumes, and tobacco), construction (construction and construction materials), steel (steel works etc.), fabricated products, machine (machinery and business equipment), cars (automobiles), transportation, utilities, retail stores, financial (banks, insurance companies, and other financials), and other. |

## References


Baker, M., Bradley, B., Wurgler, J., 2011. Benchmarks as limits to arbitrage: understanding the low-volatility anomaly. Financial Anal. J. 67, 1–15.

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

Baker, M., Wurgler, J., 2007. Investor sentiment in the stock market. J. Econ. Perspect. 21, 129–152.

Barberis, N., Greenwood, R., Jin, L., Shleifer, A., 2015. X-CAPM: an extrapolative capital asset pricing model. J. Financ. Econ. 115, 1–24.

Barberis, N., Greenwood, R., Jin, L., Shleifer, A., 2018. Extrapolation and bubbles. J financ econ 129, 203–227.

Bassi, A., Colacito, R., Fulghieri, P., 2013. 'O sole mio: an experimental analysis of weather and risk attitudes in financial decisions. Rev. Financ. Stud. 26, 1824–1852.

Bergsma, K., Jiang, D., 2016. Cultural new year holidays and stock returns around the world. Financ. Manage 45, 3–35.

Birru, J., 2018. Day of the week and the cross-section of returns. J. Financ. Econ. 130, 182–214.

Bouman, S., Jacobsen, B., 2002. The halloween indicator, "sell in may and go away"; another puzzle. Am. Econ. Rev. 92, 1618–1635.

Breaban, A., Noussair, C., 2017. Emotional state and market behavior. Rev. Financ. 22, 279–309.

Carhart, M.M., 1997. On persistence in mutual fund performance. J. Finance 52, 57–82.

Chhaochharia, V., Kim, D., Korniotis, G., Kumar, A., 2019. Mood, firm behavior, and aggregate economic outcomes. J. Financ. Econ. 132, 427–450.

Daniel, K.D., Hirshleifer, D., Subrahmanyam, A., 1998. Investor psychology and security market under and over-reactions. J. Finance 53, 1839–1886.

Daniel, K.D., Hirshleifer, D., Subrahmanyam, A., 2001. Overconfidence, arbitrage, and equilibrium asset pricing. J. Finance 56, 921–965.

deHaan, E., Madsen, J., Piotroski, J., 2017. Do weather-induced moods affect the processing of earnings news? Journal of Accounting Research 55, 509–550.

DellaVigna, S., Pollet, J., 2009. Investor inattention and Friday earnings announcements. J. Finance 64, 709–749.

Doran, J.S., Jiang, D., Peterson, D.R., 2012. Gambling preference and the new year effect of assets with lottery features. Rev. Financ. 16, 685–731.

Edmans, A., García, D., Norli, Ø, 2007. Sports sentiment and stock returns. J. Finance 62, 1967–1998.

Fama, E.F., French, K.R., 2015. A five-factor asset pricing model. J. Financ. Econ. 116, 1–22.

Frazzini, A., Pedersen, L.H., 2014. Betting against beta. J. Financ. Econ. 111, 1–25.

French, K., 1980. Stock returns and the weekend effect. J. Financ. Econ. 8, 55–69.

Goetzmann, W.N., Kim, D., Kumar, A., Wang, Q., 2015. Weather-induced mood, institutional investors, and stock returns. Rev. Financ. Stud. 28, 73–111.

Hartzmark, S.M., Solomon, D.H., 2018. Recurring firm events and predictable returns: the within-firm time series. Ann. Rev. Financ. Econ. 10, 499–517.

Helliwell, J.F., Wang, S., 2014. Weekends and subjective well-being. Soc. Indic Res. 116, 389–407.

Heston, S.L., Sadka, R., 2008. Seasonality in the cross-section of stock returns. J. Financ. Econ. 87, 418–445.

Heston, S.L., Sadka, R., 2010. Seasonality in the cross-section of stock returns: the international evidence. J. Financ. Quant. Anal. 45, 1133–1160.

Hirshleifer, D., Jiang, D., Meng, Y., Peterson, D.R., 2016. 'Tis the season! Pre-holiday cross-Sectional Return Seasonalities. University of California, Irvine Unpublished working paper.
Hirshleifer, D., Shumway, T., 2003. Good day sunshine: stock returns and the weather. J. Finance 58, 1009–1032.
Hirshleifer, D., Teoh, S., 2003. Limited attention, information disclosure, and financial reporting. J. Account. Econ. 36, 337–386.
Jegadeesh, N., 1990. Evidence of predictable behavior of security returns. J. Finance 45, 881–898.
Jegadeesh, N., Titman, S., 1993. Returns to buying winners and selling losers: implications for stock market efficiency. J. Finance 48, 65–91.
Jiang, D., Norris, D., Sun, L., 2019. Weather, Institutional Investors, and Earnings News. Stony Brook University Unpublished working paper.
Kamstra, M.J., Kramer, L.A., Levi, M.D., 2003. Winter blues: a sad stock market cycle. Am. Econ. Rev. 93, 324–343.
Kamstra, M.J., Kramer, L.A., Levi, M.D., Wermers, R., 2017. Seasonal asset allocation: evidence from mutual fund flows. J. Financ. Quant. Anal. 52, 71–109.
Kaplanski, G., Levy, H., 2010. Sentiment and stock prices: the case of aviation disasters. J. Financ. Econ. 95, 174–201.
Kaplanski, G., Levy, H., Veld, C., Veld-Merkoulova, Y., 2015. Do happy people make optimistic investors? J. Financ. Quant. Anal. 50, 145–168.
Kaustia, M., Rantapuska, E., 2016. Does mood affect trading behavior? J. Financ. Markets 29, 1–26.
Keim, D.B., 1983. Size-related anomalies and stock return seasonality: further empirical evidence. J. Financ. Econ. 12, 13–32.
Keloharju, M., Linnainmaa, J.T., Nyberg, P., 2016. Return seasonalities. J. Finance 71, 1557–1590.
Lakonishok, J., Smidt, S., 1988. Are seasonal anomalies real? a ninety-year perspective. Rev. Financ. Stud. 1, 403–425.
Lerner, J.S., Li, Y., Valdesolo, P., Kassam, K.S., 2015. Emotion and decision making. Annu. Rev. Psychol. 66, 799–823.
Makridis, C., 2018. Can You Feel the heat? Extreme temperatures, Stock returns, and Economic Sentiment. MIT Unpublished working paper.
McFarlane, J., Martin, C.L., Williams, T.M., 1988. Mood fluctuations: women vesus men and menstrual versus other cycles. Psychol. Women Q 12, 201–223.
Newey, W.K., West, K.D., 1987. Hypothesis testing with efficient method of moments estimation. Int. Econ. Rev. (Philadelphia) 28, 777–787.
Peng, L., Xiong, W., 2006. Investor attention, overconfidence and category learning. J. Financ. Econ. 80, 563–602.
Ritter, J.R., 1988. The buying and selling behavior of individual investors at the turn of the year. J. Finance 43, 701–717.
Rossi, A.S., Rossi, P.E., 1977. Body time and social time: mood patterns by menstrual cycle phase and day of the week. Soc. Sci. Res. 6, 273–308.
Saunders, E.M., 1993. Stock prices and wall street weather. Am. Econ. Rev. 83, 1337–1345.
Stone, A.A., Schneider, S., Harter, J.K., 2012. Day-of-week mood patterns in the united states: on the existence of 'Blue monday', 'Thank god it's friday' and weekend effects. J. Pos. Psychol. 7, 306–314.
Thaler, R.H., 1987. Anomalies: the January effect. J. Econ. Perspect. 1, 107–201.