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COMMON FACTORS IN RETURN SEASONALITIES

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Common Factors in Return Seasonalities
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ABSTRACT

A strategy that selects stocks based on their historical same-calendar-month returns earns an average return of 13% per year. We document similar return seasonalities in anomalies, commodities, international stock market indices, and at the daily frequency. The seasonalities overwhelm unconditional differences in expected returns. The correlations between different seasonality strategies are modest, suggesting that they emanate from different common factors. Our results suggest that seasonalities are not a distinct class of anomalies that requires an explanation of its own---rather, they are intertwined with other return anomalies through shared common factors. A theory that is able to explain the risks behind any common factor is thus likely able to explain a part of the seasonalities.

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1 Introduction

Figure 1 plots the average coefficients from cross-sectional regressions of monthly stock returns against one-month returns of the same stock at different lags. What is remarkable about this plot, which is an updated version of that in Heston and Sadka (2008), is not the momentum up to the one-year mark or the long-term reversals that follow, but the positive peaks that disrupt the long-term reversals at every annual lag. This seasonal pattern, documented for many countries[1], emerges in pooled regressions with stock fixed effects, but it disappears when the regressions include stock-*calendar month* fixed effects. The estimates in Figure 1 thus do not mean that stocks "repeat" shocks from the past but that expected stock returns vary from calendar month to month. A long-short strategy that chooses stocks based on their historical same-calendar month returns earns an average return of 13% per year between 1963 and 2011.

Return seasonalities are not confined to individual stocks or to monthly frequency. We show that seasonality strategies that trade well-diversified portfolios formed by characteristics such as size and industry are about as profitable as those that trade individual stocks. Seasonalities also exist in the returns of commodities and country portfolios[2] and at the daily frequency. Moreover, we show that the returns on most anomalies—accruals, equity issuances, and others—exhibit tremendous seasonal variation. A meta-strategy that takes long and short positions on 15 anomalies based on their historical same-calendar-month premiums earns an average return of 1.88% per month (t-value = 6.43); an alternative strategy that selects anomalies based on their *other*-calendar-month premiums earns a slightly negative return! That is, knowing how well an anomaly has performed in other calendar months

[1] See Heston and Sadka (2010).

[2] Heston and Sadka (2010) document significant seasonalities within 14 international stock markets. Our analysis differs from theirs in that we measure seasonalities in the cross section of country indexes, that is, we test whether a stock market in a country that typically performs well in a particular month relative to the other countries is more likely to do so also in the future.

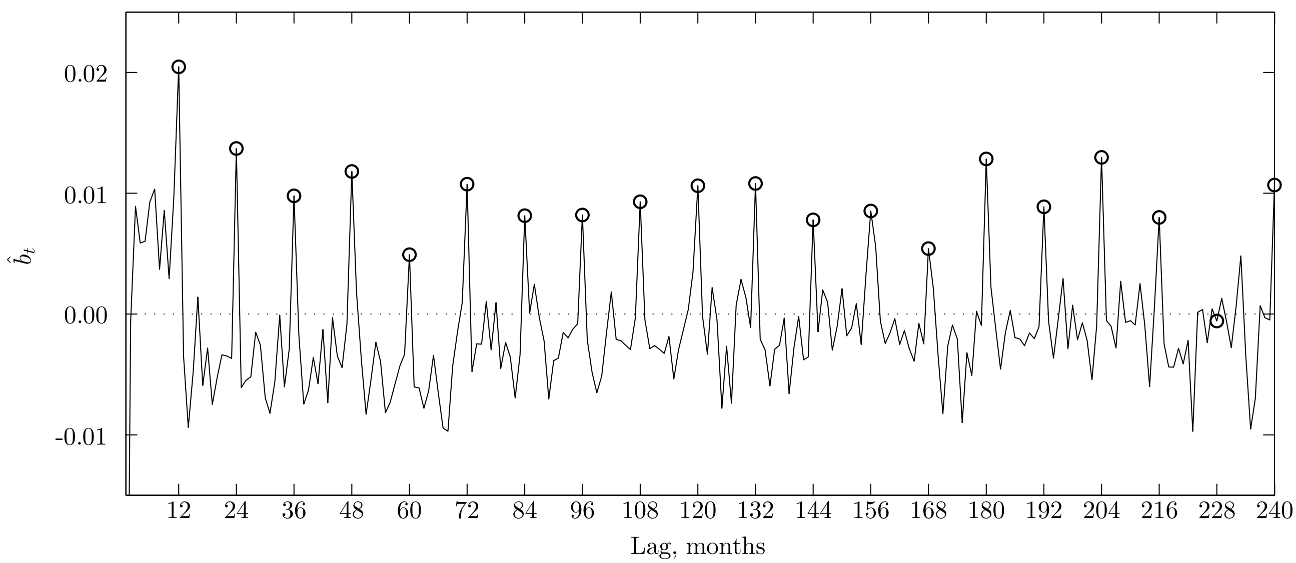

Figure 1: **Seasonalities in individual stock returns.** This figure uses data from January 1963 through December 2011 for NYSE, Amex, and Nasdaq stocks to estimate univariate Fama-MacBeth regressions of month-t returns against month-$t-k$ returns, $r_{i,t} = a_t + b_t\ r_{i,t-k} + e_{i,t}$, with k ranging from one to 240 months. The circles denote estimates at annual lags.

relative to other anomalies is uninformative about how it will perform in the cross section of anomalies this month. Seasonal variation in expected returns for these anomalies thus completely swamps cross-sectional differences in *unconditional* expected returns.

Although both individual stocks and factors exhibit return seasonalities, at first glance the connection between the two realms seems surprisingly weak in the data. Heston and Sadka (2008) consider the possibility that seasonalities reflect systematic risks but find that they survive tests that control, one at the time, for firm size, industry, exposures to common risk factors, and calendar month. At the same time, they find that return seasonalities are not driven by seasonalities in certain firm-specific events such as earnings announcements and dividends.[3]

We show that the seeming disconnect between seasonalities in individual stock returns and those in factor premiums is due to the fact that none of the factors alone is responsible for the seasonal

[3]Frazzini and Lamont (2007) and Barber, De George, Lehavy, and Trueman (2013) show that stocks earn positive abnormal returns around scheduled earnings announcements. Hartzmark and Solomon (2013) find that stocks earn higher returns around ex-dividend days and dividend announcements.

patterns in individual stocks. Individual stocks *aggregate* seasonalities across the factors. To see this, consider the seasonality in stock returns as a function of firm size. Small stocks tend to outperform large stocks in January, so firms' historical January returns are noisy signals of their sizes. A sort of stocks into portfolios by their past January returns thus predicts variation in future January returns because it correlates with firm size. The same intuition applies if the seasonalities originate from many characteristics. A sort on past returns picks up all seasonalities no matter what their origins. A regression of returns on past same-calendar-month returns is equivalent to a regression of returns on a noisy combination of attributes associated with return seasonalities.

A simple empirical test shows that the seasonalities in monthly U.S. stock returns must originate from common factors. The variance of a strategy that trades these seasonalities is *five* times higher than what it would be if it took on just idiosyncratic risk. We estimate that at least two-thirds of the seasonalies in monthly U.S. stock returns derive from common factors associated with firm characteristics such as size, dividend-to-price, and industry. The prominence of common factors means that seasonal strategies *have to* remain exposed to systematic risk, because an attempt to hedge that risk would eliminate the seasonalities as well.

We show that return seasonalities are remarkably pervasive. Whereas many anomalies falter in some corners of the market, seasonalities permeate the entire cross section of U.S. stock returns, varying little from one set of stocks to another. Moreover, unlike every anomaly studied by Stambaugh, Yu, and Yuan (2012), return seasonalities are about equally strong in periods of high and low sentiment. In spite of this, different seasonality strategies are at best weakly correlated with each other. Within U.S. equities, for example, the correlation between the strategies trading seasonalities in small stocks and in high-dividend-yield stocks is 0.17. The correlations become weaker when the assets are less alike and are negligible across asset classes: the seasonalities in country index and commodity returns, for example, are unrelated to those in U.S. equities. Similarly, a strategy that trades daily seasonalities is uncorrelated with a strategy that trades monthly seasonalities.

These low correlations suggest that it is difficult to find one unified explanation, such as a constant set of macroeconomic risk factors, for all the seasonalities.[4] Indeed, we find no measurable link between macroeconomic risks and the seasonalities when we apply the macroeconomic variables and methods used by Chordia and Shivakumar (2002) and Liu and Zhang (2008). Instead, our results are consistent with a world in which there are many risk factors, the premiums on these factors exhibit seasonal variation, and assets in different corners of the market aggregate seasonalities emanating from risks specific to that corner.

Our results speak to the striking economic significance of seasonalities. The literature often regards seasonalities as just another anomaly—and one that is difficult to trade and that may be fading away. We show that return seasonalities exist almost everywhere, are remarkably persistent over time, and are often so large that they completely overwhelm the unconditional differences in expected asset returns. Although seasonality strategies are immensely risky because of their exposures to common factors, they represent attractive risk-reward tradeoffs at least on the margin. The ex-post maximum Sharpe ratio constructed from the market, size, value, and momentum factors increases from 1.04 to 1.67 when we add a HML-style seasonality factor to the investment opportunity set. Even an investor who does not trade seasonalities directly can benefit by screening on them. An investor can, for example, lower turnover and enhance returns by delaying a trade whenever the trading strategy calls for selling a stock whose seasonal pattern predicts a high expected return next month.

Our key insight is that seasonalities are not an isolated or distinct class of anomalies that requires

[4] Asset pricing studies find little support for the view that asset pricing is integrated across different regions and asset classes. Fama and French (1993), for example, create two different models to characterize average returns within U.S. equities and bonds. Studies such as those by Griffin (2002), Hou, Karolyi, and Kho (2011), and Fama and French (2012) find that global versions of asset pricing models typically generate significantly larger pricing errors than models that add factors constructed from local asset returns.

an explanation of its own. Rather, our theory and decomposition results suggest that seasonalities are intertwined with other return anomalies through many shared common factors. This is a promising result, because it means that any theory that is able to explain the risks behind the factors is also likely able to shed light on both average returns and seasonalities.

Past research has extensively studied seasonalities in asset returns. Whereas we study seasonalities in the cross section of asset returns, most of the extant research is about time-series (market-wide) seasonalities. Kamstra, Kramer, and Levi (2003, 2014) and Garrett, Kamstra, and Kramer (2005), for example, ascribe the seasonalities in equity risk premium and Treasury returns to seasonal variation in the price of risk: investors are more risk averse during the winter. Some seasonalities might also stem from mispricing that affects large groups of stocks.[5]

The rest of the paper is organized as follows. Section 2 shows how individual asset returns aggregate seasonalities in factor premiums. Section 3 describes the data. Section 4 examines return seasonalities within U.S. equities. Section 5 documents that return seasonalities can also be found from other asset classes and from different corners of the U.S. stock market, and analyzes the risk exposures and investability of these seasonalities. Section 6 concludes.

2 Seasonalities in risk premiums and the cross section of expected returns

2.1 A stylized model

Seasonal variation in factor risk premiums generates seasonal variation in securities' expected returns which, in turn, induces periodicity into return autocovariances estimated from cross-sectional regres-

[5]The turn-of-the-year seasonalities are often attributed to December tax-loss selling and the rebound that follows. See, for example, Wachtel (1942), Reinganum (1983), and, more recently, Grinblatt and Moskowitz (2004) and Kang, Pekkala, Polk, and Ribeiro (2011).

sions. To illustrate this idea, suppose returns are generated by a single-factor model,[6]

$$r_{i,t} = \beta_i F_t + \varepsilon_{i,t}, \tag{1}$$

where $r_{i,t}$ is the excess return on security i and $\varepsilon_{i,t}$ is the residual. We assume there is seasonal variation in the factor premium such that it in calendar month $m(t)$ equals $\mathrm{E}[F_t] = \lambda_{m(t)}$, where $m(t)$ is the calendar month ($m =$ January, ..., December) corresponding to month t. Factor F_t's return is the sum of its risk premium and a shock, $F_t = \lambda_{m(t)} + \xi_t$. Both $\varepsilon_{i,t}$ and ξ_t are IID and mean zero. The cross-sectional autocovariance of returns is then

$$\begin{aligned} \mathrm{cov}^{\mathrm{cs}}(r_{i,t}, r_{i,t-k}) &= \mathrm{cov}^{\mathrm{cs}}\left(\beta_i(\lambda_{m(t)} + \xi_t), \beta_i(\lambda_{m(t-k)} + \xi_{t-k})\right) \\ &= \mathrm{var}^{\mathrm{cs}}(\beta_i)\left[(\lambda_{m(t)} + \xi_t)(\lambda_{m(t-k)} + \xi_{t-k})\right]. \end{aligned} \tag{2}$$

The average autocovariance across N calendar-month $m(t)$ cross sections is

$$\frac{1}{N}\sum_{m(t)} \mathrm{cov}^{\mathrm{cs}}(r_{i,t}, r_{i,t-k}) = \mathrm{var}^{\mathrm{cs}}(\beta_i)\left[\frac{1}{N}\sum_{m(t)}\left(\lambda_{m(t)}\lambda_{m(t-k)} + \xi_t\lambda_{m(t-k)} + \xi_{t-k}\lambda_{m(t)} + \xi_t\xi_{t-k}\right)\right], \tag{3}$$

which tends to

$$\lim_{N\to\infty}\frac{1}{N}\sum_{m(t)} \mathrm{cov}^{\mathrm{cs}}(r_{i,t}, r_{i,t-k}) = \mathrm{var}^{\mathrm{cs}}(\beta_i)\left[\lambda_{m(t)}\lambda_{m(t-k)}\right]. \tag{4}$$

When we estimate the autocovariances between same-calendar-month returns, $m(t) = m(t-k)$, $\lambda_{m(t)}\lambda_{m(t-k)} = \lambda^2_{m(t)} \geq 0$. In other words, the covariance spikes every 12th lag if there is seasonality in the risk premium. This means that any seasonality in factor premium *always* gets transferred to the cross section of security returns if factor loadings vary across securities, $\mathrm{var}^{\mathrm{cs}}(\beta_i) > 0$.

[6] We thank a referee for suggesting this stylized model.

2.2 The aggregation mechanism

The periodicity in return autocovariances is not specific to this stylized example, and a model in which securities are exposed to multiple risks illustrates how returns *aggregate* seasonalities stemming from risk premiums. Suppose returns are generated by a J-factor model,

$$r_{i,t} = \beta_i^1 F_t^1 + \beta_i^2 F_t^2 + \cdots + \beta_i^J F_t^J + \varepsilon_{i,t}, \tag{5}$$

where the superscripts index factors $j = 1, \ldots, J$ and $\varepsilon_{i,t}$ is the firm-specific shock with mean zero and variance $\sigma_\varepsilon^2 < \infty$. Similar to above, month-t return on factor j is the sum of its risk premium and a shock,

$$F_t^j = \lambda_{m(t)}^j + \xi_t^j. \tag{6}$$

The risk premiums $\lambda_{m(t)}^j \sim N(0, \sigma_\lambda^2)$ are drawn once in the beginning by nature. We assume that $\sigma_\lambda^2 > 0$, which means that the risk premiums vary over the calendar year. The draws of $\lambda_{m(t)}^j$ are independent across calendar months and factors: $\mathrm{E}(\lambda_m^j \lambda_{m'}^j) = 0$ for $m \neq m'$ and $\mathrm{E}(\lambda_m^j \lambda_{m'}^{j'}) = 0$ for $j \neq j'$. Factor shocks $\xi_t^j \sim N(0, \sigma_\xi^2)$ are similarly independent with $\mathrm{E}(\xi_t^j \xi_{t'}^{j'}) = 0$ for $t \neq t'$ or $j \neq j'$. We assume that both the factors and firms are symmetric so that the same parameters characterize all factors and firms.

We show in the Internet appendix that the expected slope coefficient from a cross-sectional regression of month-t returns on month-$t-k$ returns equals

$$\mathrm{E}(b_k) = \begin{cases} \frac{\sigma_\lambda^2}{\sigma_\lambda^2 + \sigma_\xi^2} \left(1 - \frac{\sigma_\varepsilon^2}{\sigma_\beta^2 \left(\sigma_\lambda^2 + \sigma_\xi^2\right)} \mathrm{E}\left[\frac{1}{Q_J + \frac{\sigma_\varepsilon^2}{\sigma_\beta^2 \left(\sigma_\lambda^2 + \sigma_\xi^2\right)}}\right]\right) & \text{if } m(t) = m(t-k), \\ 0 & \text{if } m(t) \neq m(t-k), \end{cases} \tag{7}$$

where $Q_J \sim \chi^2(J)$. By Jensen's inequality, the lower bound on the expected slope coefficient computed from same-calendar-month regressions is

$$\mathrm{E}(b_k) > \frac{J\sigma_\beta^2\sigma_\lambda^2}{J\sigma_\beta^2(\sigma_\lambda^2+\sigma_\xi^2)+\sigma_\varepsilon^2}. \tag{8}$$

Equation (7) shows how seasonalities in risk premiums *aggregate* into larger seasonalities in security returns. The amount of seasonalities apparent in security returns is strictly increasing in the number of common factors J. This aggregation mechanism is important. Even if each factor carries only modest seasonality in its risk premium, the seasonalities in security returns are large if securities are exposed to a large number of distinct risks.

Equation (7) shows that dispersion in loadings determines the amount of seasonalities in the cross section. The expected slope coefficient in equation (7) is zero for $\sigma_\beta^2 = 0$ and strictly increasing in σ_β^2. That is, even if all securities are exposed to a risk factor whose premium varies seasonally, such a variation leaves no trace in the *cross section* of security returns if every security has the same loading against that factor. Conversely, even modest variation in a factor's risk premium can have a large effect on the cross section of expected returns if stocks have markedly different exposures against that factor.

3 Data

Our tests use monthly and daily return data on stocks listed on NYSE, Amex, and Nasdaq from the Center for Research in Securities Prices (CRSP). We exclude securities other than ordinary common shares. We use CRSP delisting returns; if a delisting return is missing, and the delisting is performance-related, we impute a return of −30%.[7] We use returns from January 1963 through December 2011 to compute portfolio returns and as dependent variables in cross-sectional regressions. However, for

[7]See Shumway (1997) and Shumway and Warther (1999). The coverage of delisting returns on CRSP has improved since these papers. In 2012 CRSP files delisting returns are available for 98.3% of the firms that delist for performance-related reasons, up from 11.7% in Shumway (1997).

right-hand-side returns we use monthly returns going back to January 1943.

All accounting data are from annual Compustat files. We use the Davis, Fama, and French (2000) data to fill in the gaps in the book values of equity in the pre-1963 Compustat data. We follow the usual conventions to time the variables that use accounting information. The book value of equity, for example, is from the fiscal year ending in calendar year $t-1$ and, in computing the book-to-market ratio, this book value is divided by the market value of equity at the end of December of year $t-1$.

4 An analysis of return seasonalities within U.S. equities

4.1 Stocks do not repeat past return shocks

The cross-sectional Fama-MacBeth regressions reported in Figure 1 show that returns in months $t-12$, $t-24$, ..., $t-240$ predict returns in month t. Although in our model these seasonalities spring from calendar-month differences in expected returns, they could also derive from a peculiar autocorrelation structure in the return shocks. If stock returns equal a constant expected return and an innovation, $r_{i,t} = \mu_i + e_{i,t}$, the autocorrelation pattern in $e_{i,t}$ could be such that it "repeats" itself at annual lags.

We can distinguish between these alternative explanations by controlling for each stock's calendar month-$m(t)$ expected return in the cross-sectional regressions:

$$r_{i,t} = a_t + b_t \, r_{i,t-k} + c_t \, \hat{\mu}_{i,t} + e_{i,t}. \tag{9}$$

We estimate $\hat{\mu}_{i,t}$ by computing each stock's average same-calendar-month return from the prior 20-year period. To isolate cross-sectional differences in expected returns, and to take into account the fact that stocks differ in their availability of historical return data, we demean stock returns in the cross section before taking the average. We include stocks that have at least five years of historical data at time t.

We use the same demeaning procedure and sample selection rules throughout the study. Regression (9) is equivalent to a regression with stock-calendar-month fixed effects, except that it estimates the fixed effects from historical data to avoid a downward bias in the estimate of b_t.[8]

If the seasonalities reside with the expected returns, the cross-sectional variation in expected returns will be soaked up by $\hat{\mu}_{i,t}$, making the coefficients of the lagged returns statistically insignificant at annual lags. If, on the other hand, the seasonalities arise because the market "repeats" returns from the past, controlling for differences in the expected-return component will not change the annual-slope pattern.

The thick line in Figure 2 plots the coefficient estimates for lagged returns from the augmented regression (9). The one-year slope coefficient is positive and statistically significant at the 5% level—perhaps because of the stock price momentum—but the statistical significance of the lagged returns fades after this point: only one of the remaining 19 same-month return coefficients is significantly positive at the 5% level. The slope coefficient on the estimated expected return component, $\hat{\mu}_{i,t}$, is statistically highly significant. In the $k = 240$ regression, for example, the average slope coefficient estimate has a t-value of 10.28. The average same-calendar-month return is thus a powerful signal of a stock's expected return in that month.

The absence of seasonality in the augmented regressions stands in stark contrast with the coefficients from the baseline Fama-MacBeth regressions (the thin line in Figure 2). In these regressions 18 of the 20 same-month coefficients are significant at the 5% level. Importantly, our results are specific to controlling for stock-*calendar month* variation in expected returns. We show in the Internet appendix that if we instead control for *unconditional* differences in expected returns using stock fixed effects, 19 of the 20 same-month coefficients are significant at the 5% level.

[8]Nickell (1981), So and Shin (1999), and Choi, Mark, and Sul (2010) study the downward bias that results from the use of fixed effects in dynamic panel data models.

4.2 Return seasonalities in well-diversified portfolios

If return seasonalities stem from seasonal variation in risk premiums, they should appear not only in returns on individual stocks but also in those earned by well-diversified portfolios.[9] Table 1 examines the profitability of long-short strategies that trade on seasonalities in value-weighted portfolios formed by sorts on different firm characteristics. We construct all portfolios except momentum in June of year t and then compute value-weighted returns on these portfolios from year-t July to year-$t+1$ June. The momentum portfolios are rebalanced monthly.

The first row of Table 1 sets the stage by sorting individual stocks into winner-loser deciles by the 20-year average same-calendar-month or other-calendar-month return. In March 1964, for example, we sort on either the average March ("Same-month return") or non-March ("Other-month return") returns in 1944–63. The seasonality strategies are long the winner and short the loser decile. The same-month strategy earns an average return of 1.19% per month (t-value = 6.27) while the strategy based on *other* months earns a return of -0.96% (t-value = -4.12). These estimates are consistent with Figure 1's regression estimates. The three-factor model does not explain these seasonalities: the alpha for the difference between the same- and other-month strategies has a t-value of 7.42. This result is consistent with Heston and Sadka's (2008) finding that the seasonality strategy's unconditional covariances against the market, size, and value factors are small.

The other rows construct the long-short strategies by buying and selling portfolios of stocks. Seasonalities abound in most portfolio sorts: a seasonality strategy based on 10 size portfolios earns an average return of 1.35% (t-value = 6.64); that based on dividend-to-price earns 0.48% (t-value = 3.12); and the industry strategy earns 0.70% (t-value = 3.79). The last row, "Composite," collects size, value, mo-

[9]Lewellen (2002) makes a related argument about stock price momentum. He notes that momentum cannot be attributed to firm-specific returns because well-diversified size and book-to-market ratio portfolios exhibit as strong momentum as individual stocks.

mentum, dividend-to-price, and industry portfolios—58 portfolios in all—and constructs the long-short strategy from the top six and bottom six portfolios. (We exclude earnings-to-price and profitability portfolios because their data start later.) This strategy earns an alpha of 1.3% per month with a t-value of 8.65, that is, it earns a higher Sharpe ratio than the strategy that trades seasonalities through individual stocks. In each of these cases the abnormal returns are specific to the same-month sort; the average returns on strategies based on *other*-month sorts are either negative or statistically insignificant, and the three-factor model alphas for the same-minus-other differences are significantly positive.[10]

Seasonalities are, however, wholly absent from certain portfolios. Both the same- and other-month strategies based on momentum portfolios, for example, earn high returns, and the difference between the two is modestly negative. Similarly, no seasonalities are apparent in the returns on the portfolios formed by sorts on gross profitability. These counterexamples are important. They show that some characteristics (such as size and industry) are associated with seasonalities in expected returns while others (such as profitability) are not.

The right-hand side of Table 1 shows that when seasonalities are present, they are typically not limited to January. The composite strategy, for example, earns an average return of 0.90% (t-value = 6.95) in non-January months. These results confirm and extend the result documented by Heston and Sadka (2008) that individual-stock seasonalities are stronger in the month of January, but by no means limited to it.

[10]An important difference between the results in Table 1 and those in Heston and Sadka (2008) is that whereas we find significant industry seasonalities—the long-short same-calendar-month strategy earns 0.70% per month (t-value = 3.79)—Heston and Sadka (Figure 5 and Table 6) show that return seasonalities are largely independent of industry effects. The reason for this seeming discrepancy is that Heston and Sadka study a different question. They sort stocks into portfolios based on individual stock returns, and then examine the extent to which the industry component of returns explains seasonalities in individual stock returns. Their Table 6, for example, shows that a long-short strategy that sorts stocks into portfolios based on month-$t-12$ returns earns an average return of 1.15% per month, and that this total return breaks down to an average industry component of 0.12% and a non-industry component of 1.03%. Our analysis, by contrast, measures the prevalence of seasonalities in industry returns; it is equivalent to sorting stocks into portfolios by stocks' industry components. In Section 4.4 we measure the extent to which characteristics such as industry membership explain seasonalities in individual stock returns. Our estimate of 9.7% is remarkably close to that in Heston and Sadka (Table 6) even though the two papers use different methodologies.

Table 1 shows that the seasonalities in expected returns are economically large. The results for momentum portfolios—which serve as a counterexample—best illustrate this point. Both the same- and other-month strategies based on momentum portfolios earn significantly positive returns; the reason is that the *unconditional* expected returns vary so much across momentum portfolios. Suppose that we are given return data on ten momentum portfolios but no information on which one is the "winner" and which one the "loser" portfolio. Because of the magnitude of the momentum effect, we would nevertheless be able to infer these portfolios almost perfectly from historical data. A long-short strategy based on historical same- or other-month returns is thus close to a standard momentum strategy: it buys the "winner" and sells the "loser" portfolio. The surprising result in Table 1 is that this argument does not hold for *any* of the other portfolios.[11] The amount of seasonal variation in expected returns is so large that it completely swamps the unconditional differences.

To formalize this insight, suppose that each portfolio's return equals a constant plus noise,

$$r_{p,t} = \mu_p + e_{p,t}. \tag{10}$$

In that case each portfolio's average historical return equals $\mu_p + \frac{1}{T}\sum_{k=1}^{T} e_{p,t-k}$ and is therefore a good signal of its expected return. If, on the other hand, portfolio returns vary seasonally, the return process equals

$$\begin{aligned} r_{p,t} &= \mu_{p,m(t)} + e_{p,t} \\ &= \mu_p^* + (\mu_{p,m(t)} - \mu_p^*) + e_{p,t}, \end{aligned} \tag{11}$$

[11]Momentum is the only sorting variable for which the strategies based on both the same- and other-month returns generate statistically significant return spreads and, at the same time, the difference between the two is not statistically significantly different from zero. The gross-profitability strategies are similar to the momentum strategies in that the same-versus-other-month difference is not statistically significant, so it could be viewed as another exception. At the same time, the average returns on the gross-profitability strategies are also low. That is, although there is little evidence of seasonalities in expected returns in the cross section of gross-profitability portfolios—at least before regressing the returns against the three-factor model—the cross-sectional differences in average returns are also modest.

where the second equality decomposes expected returns into the unconditional and seasonal components. The results in Table 1 imply that, in terms of extracting information about expected returns from historical returns, the seasonal component $\mu_{p,m(t)} - \mu_p^*$ completely overwhelms the unconditional component μ_p^*!

Figure 3 illustrates the seasonalities found in portfolio returns by replicating Figure 1 using portfolio return data. The data are the returns on the 58 portfolios of the composite strategy in Table 1. The coefficient patterns in Figures 1 and 3 are strikingly similar: the seasonalities in portfolio returns are as impressive as those in individual stock returns. The average coefficient is positive in the portfolio regressions at all annual lags up to 20 years, and 19 of the 20 coefficients are associated with a t-value of at least 2.[12]

4.3 Seasonality strategies are risky

If the seasonalities in stock returns stem from seasonal variation in risk premiums, then a sort of stocks into portfolios by their historical same-month returns groups together stocks with similar factor loadings. Such a similarity should come at a cost: the extreme portfolios should be exposed to common factor shocks. That is, although portfolios formed by sorting on historical returns diversify away much of the idiosyncratic risk, they are left exposed precisely to those sources of systematic risk that generate the seasonalities in the first place. Forming a long-short portfolio does not wash away this risk, because the stocks in the long and short legs are systematically different.

We compare the risk of the seasonality strategy to that of a *randomized* seasonality strategy. Every month when stocks are assigned into portfolios by their average same-month returns, we also assign them separately into ten random portfolios, and use these portfolios to generate one long-short strategy. We

[12]See the Internet appendix for details.

then repeat this process 10,000 times. The average annualized volatility of this randomized strategy—which uses the same universe of stocks and the same time period as the true seasonality strategy—is 7.35%. The volatility of the true seasonality strategy is much larger, 16.64%. That is, the variance of the true seasonality strategy exceeds that of its randomized counterpart by a factor of five! This simple comparison confirms that return seasonalities are intertwined with systematic risk without necessitating a stance on the identities of those risks.

4.4 Explaining seasonalities with firm characteristics

4.4.1 Time-series regressions

Table 2 measures the extent to which seasonalities in well-diversified portfolios explain the seasonalities in individual stock returns. The dependent variable is the return on the long-short strategy that buys the top and sells the bottom decile based on the average same-calendar-month return over the prior 20 years. Columns (2) through (8) regress this strategy against long-short strategies that trade seasonalities in different portfolios. These explanatory strategies are the same as those examined in Table 1.

The individual-stock seasonality strategy correlates significantly with the seasonalities present in these well-diversified portfolios and its alpha decreases. The intercept is 0.74% per month ($t = 4.49$) in column (7) that regresses the returns against all seasonality strategies. The R^2 is 17% in this regression, suggesting that seasonality-mimicking factors capture a meaningful amount of the return variation of the individual-stock seasonality strategy. The last column shows that the intercept is 0.60% ($t = 3.66$) when the seasonality-mimicking factor is derived from the 58 size, value, momentum, dividend-to-price, and industry portfolios. Thus, even though the seasonalities in stock returns emanate from multiple risk factors, in time-series regressions a seasonality strategy constructed from a relatively small set of portfolios already explains half of the profits of the individual-stock seasonality strategy.[13]

4.4.2 Cross-sectional regressions

We can also use cross-sectional regressions to quantify the importance of firm characteristics in explaining seasonalities in individual stock returns. We take the cyclical pattern in Figure 1 as the starting point. Ignoring the momentum and long-term reversals, all the coefficients in that figure would be equal if returns exhibited no seasonality. In Table 3 we measure how much the observed seasonality pattern "flattens" as we control for different firm characteristics. We measure this decrease in seasonality by comparing the sum of squared deviations of the annual-lag coefficients in regressions with and without controls for firm characteristics.

We augment the baseline regression with dummy variables for five groups of firm characteristics: 10 dummy variables each for market beta, firm size, book-to-market ratio, and dividend yield, and 17 dummy variables for industry,[14]

$$r_{i,t} = a_t + b_t \, r_{i,t-k} + \text{firm characteristics} + e_{i,t}. \tag{12}$$

By adding these controls the interpretation of b_t changes to that of a marginal effect: how informative is the lagged same-calendar-month return about month-t returns when holding, for example, industry constant? The slope estimates from these augmented regressions yield a plot similar to that in Figure 1 except that the peaks are less pronounced *if* firm characteristics explain some of the seasonal variation in expected returns.

[13] Industries do not necessarily induce return seasonalities because they themselves are "common factors." An alternative interpretation for these results is that different industries are exposed to different risks. Industry portfolios then represent combinations of common factors.

[14] We again drop gross profitability and earnings-to-price from this analysis because the data are not available for the entire sample period.

Because additional regressors can decrease the covariance between month-t and -$t-k$ returns just by reducing the variation in the dependent variable, we estimate the augmented regressions twice. The first regression uses actual stock characteristics, while the second regression randomly reorders the rows of the data matrix. We measure the explanatory power of characteristics by comparing the sum of squared deviations (SSQ) of the actual model to that of the randomized model:

$$\text{Explanatory power of characteristics} = 1 - \frac{\text{SSQ}_{\text{actual characteristics}}}{\text{SSQ}_{\text{randomized characteristics}}}, \tag{13}$$

in which the sums of squared deviations of the estimated regression coefficients from zero are computed at lags $k = 12, 24, \ldots, 240$. We bootstrap the Fama-MacBeth coefficient estimates to obtain standard errors for the model's overall explanatory power and the change in the explanatory power when adding more characteristics. In each simulation we enter the characteristics into the model in random order and record the incremental change in the sum of squared deviations.

Table 3 reports the estimates separately for the full sample period and for two subperiods. The full-sample estimate for industry, for example, is 9.7%, which indicates that the industry controls account for approximately one-tenth of the seasonalities in individual stock returns. This estimate is marginally significant; it is associated with a (bootstrapped) standard error of 5.8%.

Size, value, dividend-to-price, market beta, and industry explain a total of 68% (S.E. = 13%) of the seasonalities in individual stock returns in the full sample. Firm size and dividend-to-price stand out for their statistical significance, although the remaining characteristics are jointly significant as well. Given that our regressions control only for *salient* variables correlated with common seasonalities, 68% is a conservative estimate of the fraction of seasonalities explained by common factors.

Our estimates also suggest that the sources of seasonalities may change over time. A comparison of the first- and second-half estimates shows that the roles of size and dividend-to-price ratio have decreased, that of industries has increased, and the overall explanatory power of the five variables has decreased from 69% to 59%. That is, although seasonalities are strong in both halves of the data, the factors from which they emanate may have changed. This analysis, however, is only suggestive as the estimated contributions are measured with considerable noise.

Figure 4 plots the average Fama-MacBeth coefficients from regressions of month-t returns against month-$t-k$ returns from regressions that include (thick line) or do not include (thin line) the characteristics controls. The estimates show that observable characteristics explain the majority of the seasonal pattern: the residual coefficients are much smaller than the baseline coefficients at annual lags. The figure also shows that the characteristics explain the seasonal patterns better at long lags than at short lags. This suggests that the characteristics used in our decomposition analysis are more stable than any seasonality-generating characteristics omitted from our regressions.

The estimates in Tables 2 and 3 suggest that most of the common seasonalities in individual stock returns can be traced to characteristics such as size and industry. A simple modification to the test in Section 4.3 suggests that the combined effect of other common factors to returns is nevertheless substantial. We first run cross-sectional regressions against industry, book-to-market, size, dividend-to-price, and market beta dummies and collect the residuals. We then construct the seasonality strategy by sorting stocks into portfolios based on average same-month residuals. This strategy is profitable, earning an average monthly return of 0.86% (t-value = 5.49). It also continues to be exposed to systematic risk: its variance is 2.96 times that of the randomized strategy. Comparing this number to the five-fold estimate in Section 4.3 suggests that controlling for industry and size eliminates about one half of the systematic risk associated with the seasonality strategy—leaving the remaining half to all other sources of systematic risk.

4.5 Seasonalities in the cross section of anomaly returns

Return seasonalities are not only confined to individual stocks and well-diversified portfolios but are also strongly present in anomaly strategies. We establish the playing field in Table 4 Panel A by reporting the average returns for the market and 15 anomaly strategies. These anomalies are among those analyzed in Stambaugh, Yu, and Yuan (2012), Novy-Marx (2013), and Lewellen (2014). Except for momentum, we form deciles at the end of June and hold the value-weighted portfolios for the following year; we rebalance momentum monthly. Similar to Stambaugh, Yu, and Yuan (2012), we change the sort order from ascending to descending as needed so that the "high" portfolio is always the better-performing extreme decile as reported by previous studies. The anomaly strategies are long the top and short the bottom decile.

The first two columns in Panel A report the average monthly returns for the market and the anomalies and the t-values associated with these averages. The momentum strategy, for example, is the most profitable anomaly (before either CAPM or multifactor-model adjustments), earning 1.92% per month (t-value = 5.38). The p-value in the next column is from the test that the average returns are the same in every calendar month. In the case of the market portfolio, for example, the seasonalities are not strong enough to stand out in month-by-month comparisons; the p-value from the test of equality of monthly returns is 0.41.

Many anomalies show considerable seasonal variation in their profitability. The results for asset growth illustrate the nature of these seasonalities. We reject the null of constant expected returns with a p-value < 0.001 when we use all months of the year. At the same time, asset growth performs particularly well in January. Indeed, the "Excluding January" estimates in Table 4 show that the average return on asset growth is lower, and the evidence of seasonalities less compelling (p-value = 0.05), in the non-January data. Return seasonalities are highly significant in joint tests of the 14 anomalies of

Table 4. These tests reject the no-seasonality null hypothesis in both the full and non-January data with p-values < 0.001.[15]

Some anomaly strategies display significant seasonalities even though their unconditional average returns are not statistically different from zero. A strategy that trades on Ohlson's O-score, for example, earns a statistically insignificant return of 0.21% per month, yet we reject the null hypothesis of constant average returns with a p-value < 0.001. The size anomaly is the most prominent example in this class of anomalies. Anomalies such as these earn relatively high returns in some months and low returns in other months, so that over the calendar year the abnormal returns almost perfectly offset each other.

Panel A's evidence on *time-series* variation in anomaly returns does not imply that there must be *cross-sectional* seasonalities in expected anomaly returns. If all anomalies perform well or poorly at the same time, the cross section of expected returns will be devoid of seasonalities—this case corresponds to having $\sigma_\beta = 0$ in Section 2's model. If, by contrast, some anomalies do well in some months while others do well in other months, an investor can profit by buying each month the ones with the highest expected returns and selling the ones with the lowest expected returns. Panel B of Table 4 examines the profitability of such meta-strategies. We compute average same-month returns for each anomaly over the prior 20-year period and form a strategy that is long the top-three and short the bottom-three anomalies. If, for example, in month t the momentum anomaly ranks the highest and the accruals anomaly the lowest based on the prior 20 years of data, the meta-strategy would in part be long the momentum strategy and short the accruals strategy.

The return estimates in Panel B reveal significant cross-sectional seasonalities in anomaly returns. A strategy that buys the three best- and sells the three worst-performing same-month anomalies based

[15] We do not include Distress anomaly into this test because its returns start in 1974. We estimate seemingly unrelated regressions of returns on 11 calendar-month dummy variables for each of the 14 anomalies and then test the restriction that the slope estimates on the 14×11 dummy variables are jointly zero. The test statistics for the full and non-January data are $F(154, 7980) = 2.38$ and $F(140, 7322) = 1.63$.

on historical data earns a monthly return of 1.88% (t-value = 6.43). Remarkably, a strategy based on historical *other*-month returns earns a slightly negative average return. That is, rotating through anomalies based on their historical returns is profitable in the domain of same-calendar-month returns; but knowing how well a given anomaly has done in *other* months is uninformative about how well it will perform in this month in the cross section of anomalies. Our estimates thus do not emerge because historical same-calendar-month returns rank anomalies from the best to worst, and because the meta-strategy then buys the best anomalies (that remain the best) and sells the worst anomalies (that remain the worst).

The seasonalities in anomaly returns are not limited to the month of January. The meta-strategy based on same-calendar-month returns earns an average return of 1.26% (t-value of 4.73) in the non-January data. Our results are also not specific to small stocks. Columns labeled "All-but-microcaps" reconstruct the anomalies without including stocks that lie below the 20th percentile of the NYSE market capitalization distribution (Fama and French 2008a). Because NYSE stocks are typically larger than Nasdaq and Amex stocks, this data restriction excludes over 50% of the stocks in the average month but only 3% of the total market capitalization. The estimates are quite similar for all-but-microcaps and for the market as a whole. For example, the meta-strategy based on same-calendar-month returns for all-but-microcaps earns an average return of 1.03% (t-value of 5.74) in the non-January data.

5 Seasonalities everywhere: risk exposures, prevalence, and investability

5.1 Macroeconomic risks and time-varying expected returns

Chordia and Shivakumar (2002) find that a set of lagged macroeconomic variables explain profits to momentum strategies and that these profits disappear after adjusting returns for this predictability. Columns labeled "Momentum" in Table 5 replicate three key results of the Chordia and Shivakumar paper using our 1963 through 2011 sample.

The first analysis shows that momentum profits are statistically significantly different from zero only when the economy is expanding. The second analysis decomposes total holding-period returns into predicted and unexplained components in two steps. The first step estimates stock-by-stock regressions of month-t returns on month-$t-1$ market dividend yield, default spread, term spread, and yield on three-month T-bills using the prior 60 months of returns. The second step obtains month-$t+1$ predicted return by combining the first-stage estimates with the realizations of month-t macroeconomic variables. Similar to Chordia and Shivakumar (Table III), we find that the average return on the momentum strategy is statistically insignificant after adjusting momentum payoffs for the predicted-return components. The third analysis uses the Chordia and Shivakumar methodology to examine the payoffs earned by a momentum strategy that trades industry momentum (Moskowitz and Grinblatt 1999). Consistent with Chordia and Shivakumar (Table VIII), the "unpredicted" payoff on the industry momentum strategy is statistically insignificant.

Table 5 indicates that the macroeconomic variables used by Chordia and Shivakumar are unable to explain the returns on the seasonality strategy. First, the seasonality strategy, unlike the momentum strategy, earns higher returns during recessions, and the data cannot reject the null hypothesis that the average payoffs are the same under different macroeconomic conditions. Second, this strategy's average unexplained payoff greatly exceeds its predicted payoff. When the seasonality strategy is based on the returns on individual stocks (17 industries), the average unexplained payoff is 1.15% (2.33%) per month. The average predicted payoffs, by contrast, are 0.04% and −1.62% per month. As in the analysis of momentum payoffs, the decomposition induces so much noise into the two payoff components that we cannot reject the null hypothesis that the averages are the same or that each component is zero. Table 5 thus reveals no evidence of a connection between this set of macroeconomic variables and return seasonalities.

5.2 Momentum and seasonality profits and macroeconomic risk

Liu and Zhang (2008) examine the relation between momentum and the five macroeconomic variables of Chen, Roll, and Ross (CRR, 1986): industrial production growth, unexpected inflation, change in expected inflation, term premium, and default premium. Like Chordia and Shivakumar (2002), Liu and Zhang compare realized momentum profits with predicted profits. They first estimate risk premiums on the CRR variables using the two-stage Fama and MacBeth (1973) regressions with 10 size, value, and momentum portfolios as the test assets. They then calculate momentum strategy's loadings against the CRR variables and, by combining the risk premium estimates with the estimated factor loadings, find predicted momentum profits to be close to the realized momentum profits.

Table 6 Panel A replicates the key findings of the Liu and Zhang study. The risk premium estimates and the loadings of the winner-minus-loser momentum strategy against the CRR variables are comparable to those reported in Liu and Zhang. The realized momentum profits are 1.38%, the predicted profits are 0.86%, and their difference of 0.52% is statistically insignificant with a t-value of 1.72. The CRR variables thus seem to explain 63% of the momentum profits in our sample. The seasonality strategy does not fare as well in this test. The difference between the realized (1.19%) and predicted (0.35%) seasonality profits is associated with a t-value of 4.45. At the same time, the CRR variables appear to account for just 29% of the seasonalities in stock returns.

One of the innovations in Liu and Zhang (2008, p. 2432) is to augment the set of test assets with ten momentum portfolios: "[o]ur economic question is what drives momentum profits, so it is only natural to include momentum portfolios as a part of the testing assets!" We apply this argument in Panel B, where we estimate the risk premiums and predicted momentum and seasonality profits by augmenting the set of test assets with *seasonality* portfolios instead of momentum portfolios. While the model's ability to explain momentum evaporates as a result of this change, its ability to explain seasonality profits increases to 69%. The difference between the realized and predicted profits has a t-value of just 1.92.

The above analysis, however, is problematic. Columns labeled "Randomized" show that the Liu-Zhang specification has limited power to reject the null hypothesis that realized profits equal expected profits. We repeat their procedure 10,000 times with the following exception: instead of using the actual realizations of the CRR macroeconomic variables, we randomize these data by drawing months without replacement. The bootstrapped 95% confidence interval for the fraction of seasonality explained is [41%, 82%] when the testing assets contain the ten seasonality portfolios. The estimated fraction of 69% is thus well within an interval obtained from data in which macroeconomic variables are replaced with "noise." Momentum behaves the same way. The observed-minus-predicted difference of 0.52 lies close to median of the bootstrapped difference, 0.55, and well inside the 90% confidence interval. The bootstrapping results imply that almost half of the randomly generated sets of macroeconomic variables explain the momentum profits better than the CRR variables!

The Liu-Zhang specification suffers from a variant of the problem examined in detail in Lewellen, Nagel, and Shanken (2010), worsened by the fact that the test assets contain the same return information that the methodology seeks to explain. A set of test assets consisting of ten size, value, and momentum portfolios has a rigid factor structure—its covariance matrix could be reconstructed from just four statistical factors. This makes it relatively easy to find a five-factor model (in this case, the CRR model) in which linear combinations of the estimated betas span the average returns of the underlying portfolios. It suffices that the CRR variables correlate even weakly with the statistical factors (Lewellen, Nagel, and Shanken 2010, Proposition 1); moreover, in finite samples even the sampling noise alone typically induces sufficient correlations between random variables and these factors. The bootstrapped distributions in Table 6 show that the Liu-Zhang methodology can indeed "easily" match the data, that is, it can recover such factor loadings for the test assets that the estimated risk premiums align with the average returns on the test assets.[16]

Table 6 shows that when the momentum strategy is evaluated without the momentum portfolios in the set of test assets, or when the seasonality strategy is evaluated without the seasonality portfolios, the evidence on the connection between momentum and macroeconomic risks—and that between seasonality and these risks—is very weak.[17] For example, Panel A's result that the difference between observed and predicted seasonality profits is 0.85% lies well within the bootstrapped 90% confidence interval for this difference. Table 6 thus reveals no evidence of a connection between the CRR macroeconomic variables and return seasonalities.

[16] As Lewellen, Nagel, and Shanken (2010) point out, their critique is not specific to any one paper. Kramer (1994) and Priestley (1997) are two papers that relate to ours in that they investigate seasonal patterns in the cross section. Kramer (1994) explains the size effect in January using a model with January-specific prices of macroeconomic risks and Priestley (1997) finds that the estimated prices of risks on their macroeconomic variables vary over the calendar year. These studies follow methodologies that are subject to the Lewellen-Nagel-Shanken criticism.

[17] The inability of the CRR variables to explain momentum is consistent with Griffin, Ji, and Martin (2003), whose analysis of momentum otherwise follows a path very similar to that in Liu and Zhang. The main difference is that Griffin et al. estimate the risk premiums using the 25 size and book-to-market sorted portfolios as the test assets.

5.3 Investor sentiment and anomalies

Stambaugh, Yu, and Yuan (2012) study differences in payoffs to 11 anomaly strategies following periods of high and low investor sentiment. They find each anomaly to be more profitable following periods of high sentiment, a result driven by the increased profitability of each anomaly's short leg. The authors interpret this result as supporting a behavioral (mispricing) story where short-sales constraints induce asymmetric misvaluation. Under this story, short-sales constraints make it difficult for rational investors to counteract overpricing induced by irrational investors during high-sentiment periods. These constraints are not binding during low-sentiment periods, when irrational investors try to push the prices too low.

Table 7 replicates Stambaugh et al.'s analysis for their combination anomaly, five representative anomalies, and for strategies that trade seasonalities in individual stocks and portfolios. We follow the original study and classify as high-sentiment months those in which the value of the Baker and Wurgler (2006) market-wide sentiment index for the previous month is above the index's median value for the sample period. The low-sentiment months are those that follow below-median index values. Our estimates for the Stambaugh et al. anomalies support their findings: each anomaly is more profitable following periods of high sentiment, and the payoffs are higher in each anomaly's short leg. Only the size effect, which Stambaugh et al. exclude because it is not an anomaly with respect to the three-factor model, breaks this pattern.

None of the seasonality strategies in Panel B follow this pattern. The seasonality in individual stock returns is stronger following periods of low sentiment, and the average difference between high and low sentiment is statistically indistinguishable from zero for all portfolio-seasonality strategies. The seasonality strategies differ from Panel A's anomalies also in that their payoffs originate predominantly from each strategy's long leg. Panel B's result on seasonality are inconsistent with the asymmetric mispricing mechanism posited by Stambaugh et al. To be clear, our results do not prove that the seasonalities in stock returns are unrelated to mispricing. Rather, they show that seasonalities stand out as rare exceptions in a sea of anomalies.

5.4 Pervasiveness of anomalies

Fama and French (2008b) study how pervasive various anomalies are among stocks of different size. Whereas accruals, momentum, and net-issuance anomalies exist among all size groups, asset growth and profitability anomalies are less robust. Understanding how pervasive an anomaly is can be important for three reasons. First, if the anomaly is found only among small and illiquid stocks, it affects only a small portion of the market wealth (Fama and French 2008b, p. 1655). Second, the more pervasive an anomaly is, the less likely it is merely an outcome of data snooping. Third, if an anomaly exists in many corners of the market or in different asset classes, cross-correlations can be used to measure the extent to which it emanates from the same source, be it risk or mispricing.

5.4.1 Seasonalities in different partitions of the U.S. stock market

Table 8 Panel A examines the pervasiveness of return seasonalities in different corners of the U.S. equity market. We sort stocks into groups based on firm size, book-to-market, dividend-to-price, and credit rating[18] and then, within each group, compute returns on quintile portfolios formed by historical same-calendar-month returns. For reference we also report returns for three prominent anomalies—momentum, net issuances, and asset growth—studied in Fama and French (2008b).

Seasonalities permeate the entire cross section of U.S. stock returns. They can be found among both microcaps and large-cap stocks; value and growth stocks; stocks that do not pay dividends or pay

[18] We use the Avramov, Chordia, Jostova, and Philipov (2007) methodology that assigns firms into 30/40/30 categories based on S&P Long-Term Domestic Issuer Credit Ratings. The credit-rating sample starts in January 1986 and is restricted to firms with credit ratings.

high dividends; and companies with high and low credit ratings. The patterns for the other anomalies are less robust. Momentum, for example, is weaker among value stocks and stocks that pay dividends, and it is wholly absent for firms with medium or high credit ratings (Avramov, Chordia, Jostova, and Philipov 2007). Likewise, net issuances are weaker among both value and growth stocks relative to "neutral" stocks. Finally, the asset-growth anomaly is absent among large stocks, growth stocks, and high-dividend-yield stocks.

5.4.2 Seasonalities over time

Table 8 Panel B reports average returns for various anomalies and seasonality strategies for different subperiods. Most anomalies flicker in and out of existence. In post-1963 returns the size effect is marginally significant for only the 1973–1982 subperiod; the value premium is significant only in that same subperiod but not before or since; and although momentum is in the data from the beginning, it disappears in the most recent period.

Seasonality strategies resemble momentum in their perseverance. Most of the seasonality strategies earn positive and statistically significant returns in all subperiods except the most recent one. The t-values associated with the composite strategy are above 3.5 in each pre-2003 subperiod. In the 2003–11 subperiod the composite strategy is marginally significant with a t-value of 1.75, which is a respectable result given that the best-performing non-seasonal anomaly (net issuances) has a t-value of 1.31.

5.4.3 Seasonalities in other asset classes

Seasonalities are not confined to U.S. equities. Table 8 Panel C adds to the evidence on the pervasiveness of seasonalities by examining seasonalities in commodity returns and country indexes. Our commodity-return data consist of 24 commodity futures assembled from a variety of sources and markets and cover the period January 1970 through July 2011.[19] We use MSCI return data for the following 15 country indexes: Austria, Belgium, Canada, Denmark, France, Germany, Italy, Japan, Netherlands, Norway, Spain, Sweden, Switzerland, UK, and the USA. These data run from January 1970 through December 2011. We form the high and low portfolios for commodities and country indexes based on historical same- or other-month returns. Each month we include assets that have at least five years of historical return data.

Table 8 Panel C shows that the average return on a long-short strategy that trades on seasonalities in commodity returns is 0.93% per month (t-value = 1.93). The average return is −0.22% (t-value = −0.58) when the long-short strategy instead chooses commodities based on their historical other-calendar-month returns. The difference between the two strategies is economically large (1.15%) and marginally significant (t-value = 1.97). Seasonalities in country indexes are economically smaller but statistically stronger. The same-calendar-month strategy earns 0.48% per month (t-value = 2.20), the other-calendar-month strategy earns −0.36% per month (t-value = −1.66), and the difference between the returns on the two strategies has a t-value of 2.76. Panel C shows that seasonalities in both commodity returns and country indexes exist also in non-January data.

5.4.4 Seasonalities at different frequencies

Regressions and portfolio sorts can uncover seasonalities in average returns at any frequency. Figure 5 plots the average coefficients from daily Fama-MacBeth regressions of day-t returns against day-$t-k$ returns. We study daily returns because of the evidence of significant cross-sectional differences in average returns for different weekdays. Keim and Stambaugh (1983) show that Friday returns are

[19] These futures contracts are on Aluminium, Copper, Nickel, Lead, Zinc, Brent, Gas Oil, Crude Oil, Gasoline, Heating Oil, Natural Gas, Cotton, Coffee, Cocoa, Sugar, Soybean, Kansas Wheat, Corn, Wheat, Lean Hogs, Feeder Cattle, Live Cattle, Gold, and Silver. We thank Ralph Koijen, Toby Moskowitz, Lasse Pedersen, and Evert Vrugt for providing these data. See Koijen, Moskowitz, Pedersen, and Vrugt (2013) for a description of these data.

particularly high for small stocks. Chan, Leung, and Wang (2004) find that stock portfolios with high institutional holdings tend to have higher returns on Mondays than those with low institutional holdings.

The coefficient pattern in Figure 5 is strikingly similar to that in monthly regressions, except that the coefficients spike at weekly instead of annual lags: the regressions pick up seasonal variation in day-of-the-week returns. The estimates are negative for the first four weeks (except for the same-weekday spikes at lags 15 and 20) because of short-term reversals in stock returns.[20] The statistical significance of the coefficients is comparable to that in the monthly regressions. The coefficients for all 48 lags are positive from three weeks ($k = 15$) up to the one-year mark, and 31 of these 48 coefficients have t-values greater than 2. Historical same-weekday returns generate significant differences in average returns also in portfolio sorts. A value-weighted long-short strategy based on historical same-weekday returns over the past 20 years generates an average daily return of 0.11% (t-value = 13.30), while a corresponding other-weekday strategy—for example, sort stocks on Monday based on their historical Tuesday-through-Friday returns—generates an average return of −0.05% (t-value = −4.42).[21]

5.5 Return correlations between seasonality strategies

Even though return seasonalities are pervasive, they appear to stem from different sources. Table 9 reports return correlations for strategies that trade seasonalities within different subsets of U.S. equities, commodities, and country portfolios. Panel A shows that return correlations are low even for strategies that trade seasonalities within U.S. equity markets.[22] Consider, for example, the strategies that trade seasonalities within small-cap stocks and high-dividend-yield stocks. The estimates in Table 8 indicate that both strategies are highly profitable: their average monthly returns are 0.73% ($t = 6.88$) and 1.23%

[20] See, for example, Lehmann (1990), Jegadeesh (1990), and Gutierrez and Kelley (2008).

[21] The Internet Appendix reports the t-values associated with Figure 5's regression coefficients, along with average returns for various strategies that trade day-of-the-week seasonalities.

[22] We do not include the credit-rating subsamples in this analysis because these data do not start until 1986.

($t = 6.42$). Yet the correlation between these two strategies is just 0.17. To gain perspective on these correlations, Panel B reports corresponding correlations for momentum strategies. The momentum strategies in these same corners are profitable as well—their average returns are 1.35% ($t = 5.19$) and 0.83% ($t = 2.39$)—but their correlation is much higher, 0.65. In fact, the lowest correlation between *any* two momentum strategies is as high as 0.56.

The low correlations between the seasonality strategies within U.S. equities imply that even though each strategy is exposed to systematic risks, in each case the seasonalities appear to spring from somewhat different risk factors. An investor can thus obtain diversification benefits by viewing seasonalities within different subsets of assets as distinct trading strategies. A 50-50 combination of the small-cap and high-dividend-yield seasonality strategies, for example, generates a Sharpe ratio of 1.24, which is substantially higher than the Sharpe ratios of 0.9 and 1.0 earned by these strategies on their own. The total amount of diversification benefits within U.S. equities is substantial because seasonality strategies are so profitable in every corner of the market and because their correlations are so low. The best-performing standalone strategy is the one that trades seasonalities within value stocks; its Sharpe ratio is 0.95. The maximum ex-post Sharpe ratio for a strategy that combines all nine seasonality strategies in Table 9 Panel A is 1.52.

Panel C shows that return correlations drop close to zero for strategies that trade seasonalities in different asset classes or that capture seasonalities at different frequencies. The correlation between the U.S.-stock and country-index strategies, for example, is 0.02, and that between the country-index strategy and the commodity strategy is −0.09. The correlation between the monthly and daily seasonalities (cumulated to monthly returns) in U.S. equities is just 0.05. These low estimates, along with those reported in Panel A, suggest that the risks from which the seasonalities stem must vary considerably not only from one asset class to another, but even between different corners of an asset class.

5.6 Investment perspective

Table 9 Panel D reports how the maximum ex-post Sharpe ratio changes if an investor adds different seasonality strategies to the investment opportunity set. We construct the monthly and daily seasonality strategies in this table using the same rules that Fama and French (1993) use for constructing the HML factor. The Sharpe ratio on the market is 0.46, and an investor who also trades the size, value, and momentum factors attains a Sharpe ratio of 1.04. This Sharpe ratio increases to 1.67 after adding the U.S. monthly equity seasonality factor, and further to 1.69 after adding the commodity and country-index strategies. The optimal weight on the monthly-seasonality factor is as high as 46%, and it cuts the weight on momentum from 23% to 12% and that on the market to just 8%. The last row shows that daily seasonality crowds out not only other seasonality strategies—the optimal weight on monthly seasonalities decreases from 41% to 21%—but also further weakens momentum: an investor would now invest only 4% in the momentum strategy. Although the daily seasonality strategy is infeasible from an investment perspective due to its high trading costs, these estimates suggest that seasonalities play a remarkably large role in the cross section of returns.

The monthly seasonality strategies are potentially feasible investment strategies, and it is instructive to compare them to short-term reversals as both strategies require almost 100% monthly turnover (Heston and Sadka 2008). Frazzini, Israel, and Moskowitz (2012) use trading data from a large hedge fund to suggest that the total amount of money that could be invested at a given point of time in short-term reversals in U.S. equities while retaining some alpha is $9 billion. The total capacity of monthly seasonalities is probably substantially higher than this figure because the seasonality strategy is more profitable and because it also applies to large stocks. Moreover, even if investors do not trade seasonalities as separate strategies, they are substantial enough to influence investors' decisions to enter and exit positions. An investor can, for example, lower turnover and enhance returns by delaying a trade whenever the trading strategy calls for selling a stock whose seasonal pattern predicts a high expected return next month.[23]

6 Discussion and Conclusions

Return seasonalities are remarkably pervasive. They permeate all partitions of the U.S. equity markets, reside at different frequencies, and are also present in the cross sections of commodity and country index returns. At the same time, different return seasonalities are only weakly correlated with each other. These low correlations suggest that the return seasonalities in various corners of the asset markets stem from different sources. Our results are consistent with security returns *aggregating* seasonalities stemming from multiple risks. If U.S. equities, for example, are exposed to different risks than commodities, it comes as no surprise that the seasonalities found within these two asset classes are unrelated to each other. We also find that the factors generating seasonalities are largely the same as those generating differences in average returns. This suggests that seasonalities are not an isolated or distinct class of anomalies and that there may not be a need for a separate explanation for the risks associated with them.

Return seasonalities are economically significant. A strategy that takes long and short positions in 15 anomalies based on historical *same*-calendar month returns earns an average monthly return of 1.88% (t-value = 6.43). For all anomalies but momentum, the amount of seasonal variation is so large that it completely masks any unconditional differences in average returns. We show that historical *other*-calendar month returns are uninformative about how well a particular anomaly will do in the cross section of anomalies in the future.

The economic significance of seasonalities can be characterized by studying how much they matter

[23] Novy-Marx and Velikov (2014) analyze cost-mitigation techniques that trade one strategy "on the margin" of another strategy, and find that such techniques lower turnover and enhance net returns.

in asset allocation. Adding a seasonality factor to an investment opportunity set that includes the market, size, value, and momentum, increases the Sharpe ratio from 1.04 to 1.67. This is a substantial increase—about as large as the one obtained from adding size, value, and momentum to an investment opportunity set consisting of the market factor alone. Adding the seasonality factor also significantly tilts the composition of the optimal portfolio away from the traditional factors. For example, a mean-variance optimizing investor would invest under 10% of the assets in the market portfolio—and almost 50% in the seasonality factor. These computations buttress the conclusion that seasonal variation in expected returns is strikingly large relative to unconditional differences in expected returns.

Our results have implications for research in asset pricing. First, our results suggest that one can identify additional factors by searching not only for variables that explain variation in average returns, but also for those associated with return seasonalities. Both methods can be just as powerful if risk premiums exhibit seasonal variation. Second, our results inform theory. A theory that aims to model variation in expected returns should also be able to account for the seasonalities in risk premiums.

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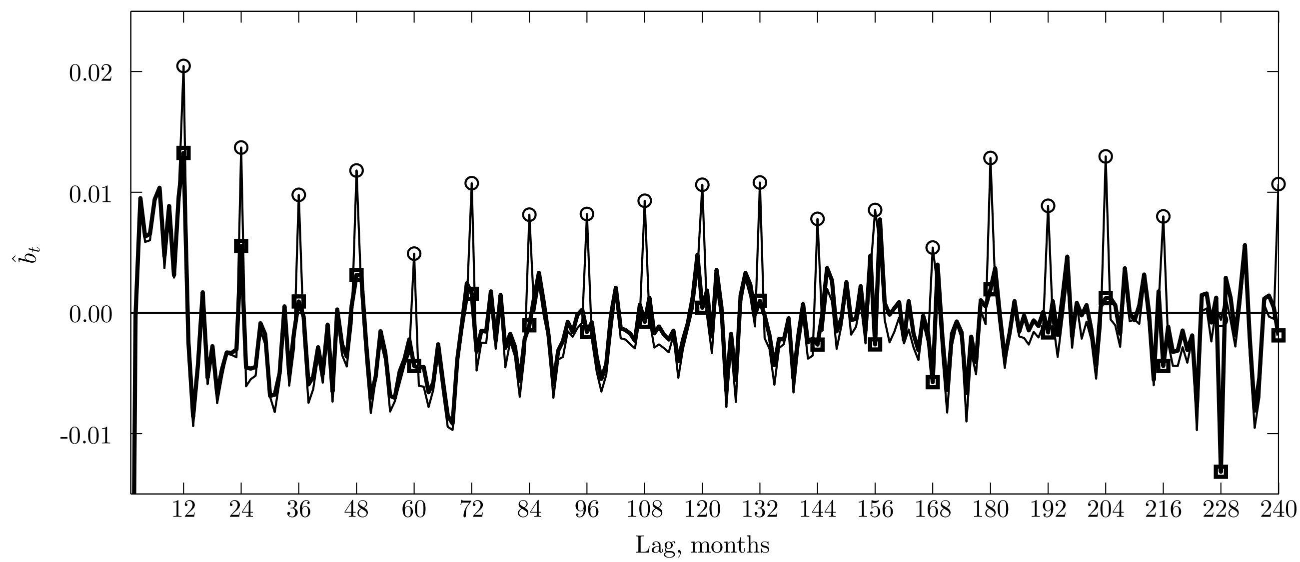

Figure 2: **Seasonalities in individual stock returns when controlling for stocks' historical average same-calendar-month returns.** The thin line uses data from January 1963 through December 2011 for NYSE, Amex, and Nasdaq stocks to estimate univariate Fama-MacBeth regressions of month-t returns against month-$t-k$ returns, $r_{i,t} = a_t + b_t\ r_{i,t-k} + e_{i,t}$, with k ranging from one to 240 months. The thick line adds to this regression each stock's average same-calendar-month return from the prior 20-year period, $r_{i,t} = a_t + b_t\ r_{i,t-k} + c_t\ \hat{\mu}_{i,t} + e_{i,t}$. The circles and squares denote annual coefficient estimates.

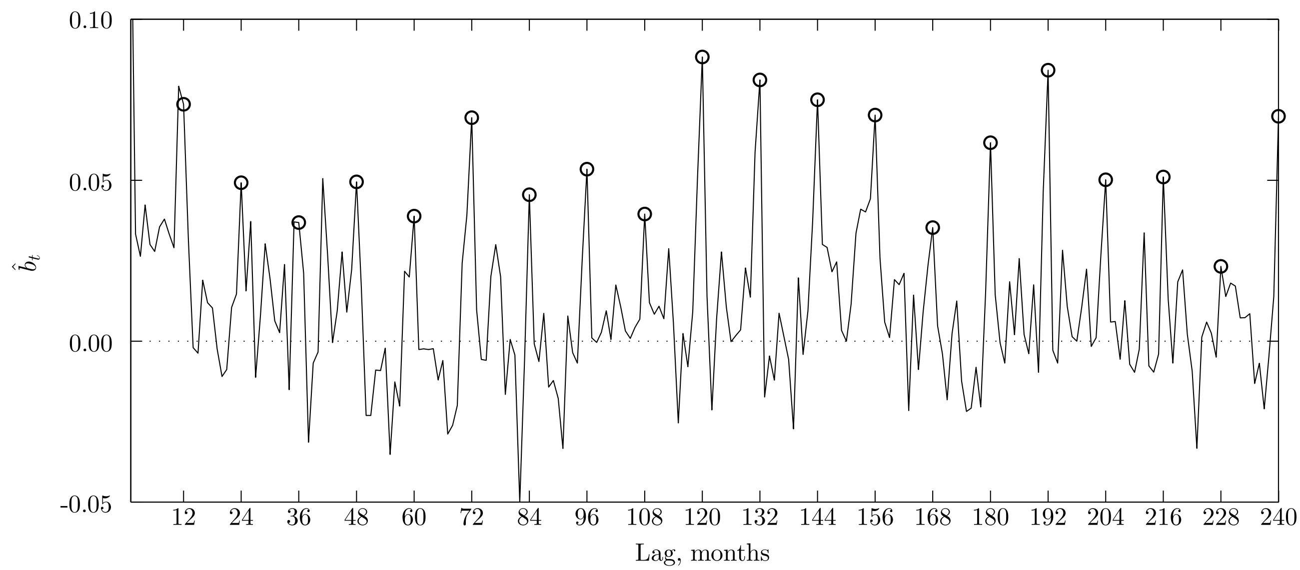

Figure 3: **Seasonalities in portfolio returns.** This figure uses data from January 1963 through December 2011 for NYSE, Amex, and Nasdaq stocks to estimate univariate Fama-MacBeth regressions of month-t returns against month-$t-k$ returns, $r_{p,t} = a_t + b_t\, r_{p,t-k} + e_{p,t}$, with k ranging from one to 240 months. The data are returns on 58 size, value, momentum, dividend-to-price, and industry portfolios. The circles denote estimates at annual lags.

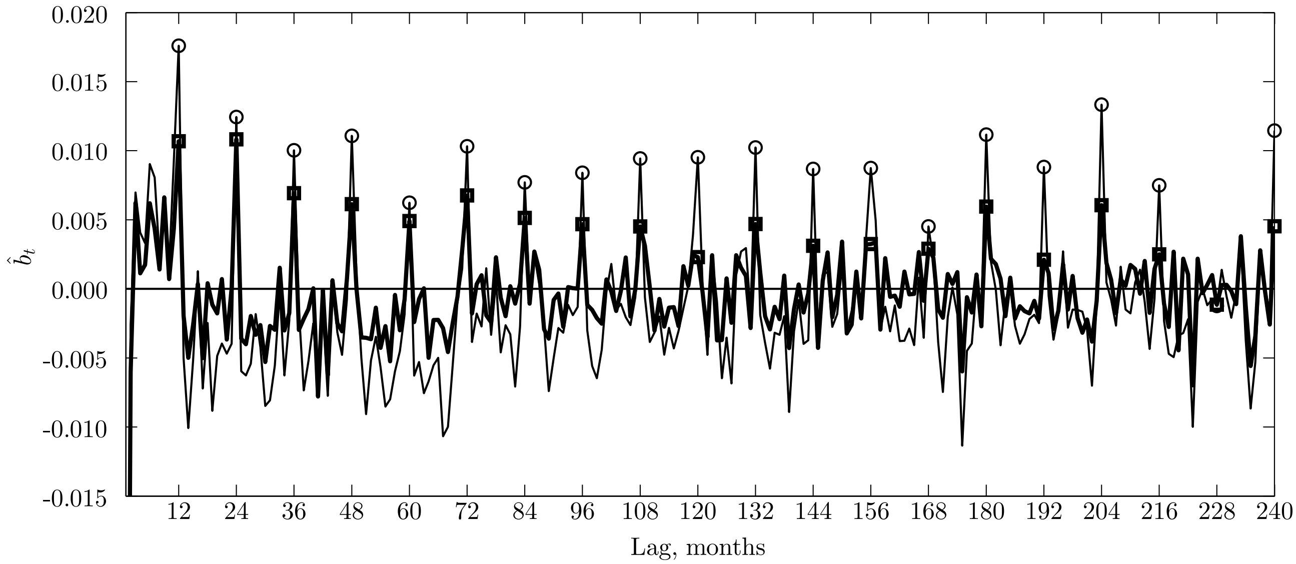

Figure 4: **Seasonality in monthly returns with controls for stock characteristics.** The thin line shows the average Fama-MacBeth coefficients from regressions of month-t returns on month-$t-k$ returns, where k ranges from 1 to 240. The thick line plots coefficients from returns-on-returns regressions that include decile dummy variables for book-to-market, firm size, dividend-to-price, and market beta as well as dummy variables for the 17 Fama-French industries. The circles and squares denote annual coefficient estimates.

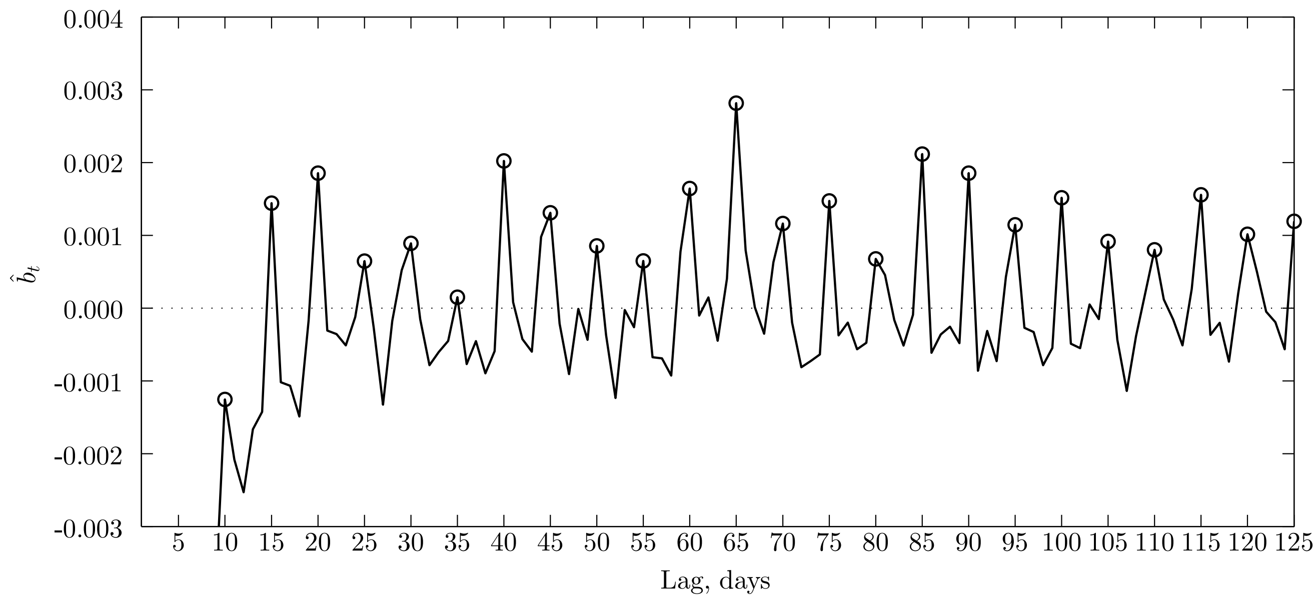

Figure 5: **Day-of-the-week seasonalities in stock returns.** This figure uses data on NYSE, Amex, and Nasdaq stocks from January 1963 through December 2011 to estimate Fama-MacBeth regressions of day-t returns against day-$t-k$ returns, where k ranges from 1 to 125. These regressions also include the average daily stock return from month $t-12$ to $t-2$ to control for one-year return momentum. The circles denote weekly lags.

Table 1: Seasonalities in individual-stock and portfolio returns

We form 10 portfolios by sorting on size, book-to-market, momentum, and gross profitability; 11 portfolios by sorting on dividend-to-price and earnings-to-price with zero-dividend and negative-earnings stocks in their own portfolios; and 17 portfolios for Fama-French industries. Momentum is the prior one-year return skipping a month ($r_{t-12,t-2}$) and gross profitability is revenue minus cost of goods sold to total assets. Except for momentum, we rebalance the portfolios every June and then compute value-weighted returns from July of year t to June of year $t+1$; momentum portfolios are rebalanced monthly. Row "Composite" combines the 58 size, value, momentum, dividend-to-price, and industry portfolios. The same-month portfolio sorts rank individual stocks and portfolios by their average return in the same calendar month over the prior 20 years. The other-month portfolio sorts rank stocks or portfolios based on the average return in all other months over the same period, skipping months $t-11$ through $t-1$. The long-short strategy based on individual stocks trade the top and bottom deciles; those based on size, value, momentum, profitability, dividend-to-price, and earnings-to-price trade the top and bottom portfolios; that based on the industry portfolios trade the top two and bottom two portfolios; and the composite strategy trades the top six and bottom six portfolios. FF3 α is the Fama and French (1993) three-factor model alpha for the difference between the same- and other-month strategies. We use monthly data from January 1963 through December 2011 except for the gross profitability and earnings-to-price portfolios for which the data begin in January 1973.

	Sample							
	All months				Excluding January			
	Sort by:				Sort by:			
Set of assets	Same-month return	Other-month return	Difference Avg	Difference FF3 α	Same-month return	Other-month return	Difference Avg	Difference FF3 α
Individual stocks	1.19	−0.96	2.16	1.63	0.99	−0.56	1.56	1.35
	(6.27)	(−4.12)	(7.94)	(7.42)	(5.45)	(−2.51)	(6.28)	(6.54)
Portfolios sorted by:								
Size	1.35	−0.94	2.29	2.29	0.73	−0.55	1.28	1.45
	(6.64)	(−3.94)	(6.53)	(6.78)	(3.88)	(−2.15)	(3.61)	(4.48)
Value	0.47	0.23	0.24	0.44	0.23	0.16	0.07	0.36
	(2.76)	(1.27)	(1.05)	(2.31)	(1.55)	(0.85)	(0.33)	(1.84)
Momentum	1.83	1.89	−0.07	−0.34	1.82	2.30	−0.48	−0.63
	(5.77)	(5.39)	(−0.20)	(−1.21)	(6.08)	(5.81)	(−1.77)	(−3.07)
Gross profitability	0.20	0.33	−0.13	−0.33	0.21	0.36	−0.15	−0.30
	(1.21)	(1.91)	(−0.64)	(−1.53)	(1.31)	(2.03)	(−0.74)	(−1.37)
Dividend-to-price	0.48	−0.50	0.99	1.07	0.34	−0.31	0.65	0.86
	(3.12)	(−3.08)	(3.97)	(4.41)	(2.09)	(−1.88)	(2.60)	(3.62)
Earnings-to-price	0.57	0.12	0.45	0.55	0.30	0.18	0.12	0.32
	(2.93)	(0.50)	(1.35)	(1.98)	(1.73)	(0.68)	(0.33)	(1.13)
Industry	0.70	−0.81	1.51	1.35	0.59	−0.69	1.28	1.27
	(3.79)	(−4.32)	(5.40)	(4.71)	(3.11)	(−3.66)	(4.74)	(4.49)
Composite	1.30	0.01	1.29	1.18	0.90	0.28	0.62	0.69
	(8.65)	(0.06)	(6.31)	(5.92)	(6.95)	(1.81)	(3.68)	(4.30)

Table 2: Regressions of individual stock return seasonalities on portfolio return seasonalities

This table reports estimates from regressions in which the dependent variable is the return on the long-short strategy that trades on seasonalities in individual stock returns and the explanatory variables are returns on long-short strategies that buy and sell portfolios based on portfolios' average same-calendar-month returns. The average returns for the individual-stock and portfolio strategies are reported in Table 1. The intercept measures the extent to which the seasonalities in individual-stock returns are explained by the seasonality-mimicking factors.

Explanatory	Regression							
variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Intercept	1.19	0.97	1.11	1.12	1.04	0.94	0.74	0.60
	(6.27)	(5.37)	(5.57)	(6.03)	(5.85)	(5.52)	(4.49)	(3.66)
Seasonality strategy								
Size		0.17					0.11	
		(2.11)					1.57	
Value			0.18				0.07	
			(2.22)				(1.07)	
Momentum				0.04			−0.03	
				(0.58)			−0.45	
Dividend-to-price					0.32		0.22	
					5.03		(3.21)	
Industry						0.36	0.30	
						6.56	(6.14)	
Composite								0.46
								(6.27)
Adjusted R^2		3.0%	1.8%	0.0%	8.0%	11.4%	17.3%	12.6%

Table 3: Decomposing monthly seasonalities by stock characteristics

This table reports estimates of the extent to which various firm characteristics explain seasonalities in monthly stock returns. We estimate regressions of month-t returns on month-$t-k$ returns for the first 20 annual lags. These regressions include as controls 17 dummy variables for industry; 10 dummy variables each for book-to-market and market beta; and 11 dummy variables for dividend-to-price with zero-dividend firms kept separate. We compute the average coefficient on the lagged return from the Fama-Macbeth regressions and record the sum of their squared deviations from zero. We measure a model's explanatory power by comparing the sum of squared deviations between the model that uses actual characteristics to one that randomly reorders firm characteristics. We randomize the order in which the characteristics enter the model and repeat these computations 100,000 times to obtain bootstrapped standard errors. This table reports the average change in the explanatory power for each firm characteristic.

	Characteristic					
	Industry	Book-to-market	Firm size	Dividend-to-price	Market beta	Total
			Full sample, 1963–2011			
Contribution	0.097	0.028	0.346	0.162	0.044	0.678
S.E.	0.058	0.059	0.061	0.062	0.058	0.131
			First half, 1963–1986			
Contribution	0.088	0.043	0.347	0.176	0.036	0.689
S.E.	0.075	0.076	0.075	0.077	0.075	0.166
			Second half, 1987–2011			
Contribution	0.126	0.011	0.269	0.135	0.053	0.592
S.E.	0.079	0.082	0.082	0.080	0.080	0.177

Table 4: Seasonalities in the cross section of anomaly returns

Panel A reports average monthly returns for the market over the one-month T-bill and 15 anomalies. Except for momentum, we sort stocks into deciles at the end of June and hold the value-weighted portfolios for the following year; momentum is rebalanced monthly. The "high" portfolio is the higher-performing extreme decile as reported by previous studies. Anomaly strategies are long the high decile and short the bottom decile. Column "$\bar{r}_{\text{Jan}} = \cdots = \bar{r}_{\text{Dec}}$, p-value" reports the p-value from the test that the average return is the same in every calendar month; the last row reports p-values from joint tests that the anomalies on rows 2 through 15 show no seasonalities in their average returns. Panel B forms meta-long-short strategies that take long and short positions in 3+3 anomaly strategies. We form these strategies by sorting on either the same- or other-calendar-month returns over the prior 20-year period. The sample period is from July 1963 through December 2011 for all anomalies except Distress, for which the data begin in July 1974.

Panel A: Seasonal variation in expected anomaly returns

		All months			Excluding January		
#	Strategy	Mean	t-value	$\bar{r}_{\text{Jan}} = \bar{r}_{\text{Feb}}$ $\cdots = \bar{r}_{\text{Dec}}$, p-value	Mean	t-value	$\bar{r}_{\text{Feb}} = \bar{r}_{\text{Mar}}$ $\cdots = \bar{r}_{\text{Dec}}$, p-value
1	Market	0.439	2.19	0.411	0.384	1.91	0.381
2	Size	0.354	1.17	0.000	−0.363	−1.24	0.000
3	Value	0.508	2.17	0.000	0.224	0.95	0.007
4	Momentum	1.916	5.38	0.003	2.327	5.79	0.186
5	Gross profitability	0.451	2.69	0.080	0.567	3.31	0.266
6	Dividend to price	0.026	0.11	0.077	−0.023	−0.10	0.034
7	Earnings to price	0.559	2.61	0.003	0.370	1.59	0.043
8	Investment to assets	0.462	3.25	0.032	0.353	2.42	0.152
9	Return on assets	0.396	1.27	0.000	0.798	2.50	0.576
10	Asset growth	0.454	2.62	0.000	0.236	1.23	0.050
11	Net operating assets	0.672	4.85	0.566	0.695	5.09	0.496
12	Accruals	0.498	2.78	0.974	0.479	2.73	0.954
13	Composite equity issuance	0.628	3.53	0.524	0.679	3.78	0.519
14	Net issuances	0.845	5.70	0.547	0.874	5.63	0.474
15	Ohlson's O-score	0.205	0.66	0.000	0.655	2.05	0.062
16	Distress	0.663	1.58	0.000	1.599	3.86	0.058
2–15	Joint seasonality test			0.000			0.000

Panel B: Profitability of long-short meta-strategies that rotate anomalies

	Sample			
	All stocks		All-but-microcaps	
Meta-strategy	All months	Excluding January	All months	Excluding January
Sort strategies by estimated same-calendar-month premiums	1.88	1.26	1.38	1.03
	(6.43)	(4.73)	(6.78)	(5.74)
Sort strategies by estimated other-calendar-month premiums	−0.36	0.10	−0.05	0.22
	(−1.49)	(0.38)	(−0.23)	(0.89)
Difference	2.24	1.16	1.43	0.81
	(6.06)	(3.76)	(5.24)	(3.18)

Table 5: Macroeconomic risks and time-varying expected returns

This table uses the methods of Chordia and Shivakumar (2002, Tables II, III, and VIII) to study the connection between macroeconomic risks and the returns on the seasonality strategy. Panel A partitions the 588-month sample period from 1963 through 2011 into recessions and expansionary periods using the NBER classification and reports the average returns on momentum and seasonality strategies. Panel B decomposes each stock's return into predicted and unexpected components (see text). We report the average returns and the averages of the predicted and unexpected return components for the momentum and seasonality strategies. The momentum strategy is the 6/0/6 strategy of Chordia and Shivakumar, which sorts stocks into portfolios by month-$t-6$ to $t-1$ returns and holds the portfolios for six months. The seasonality strategy sorts stocks by their average same-calendar-month returns over the prior 20 years. We construct the momentum and seasonality strategies using both individual stocks and 17 Fama-French industries. The industry strategies buy the top-two and sell the bottom-two industries. The sample contains all stocks traded on NYSE, Amex, and Nasdaq. All portfolios are value-weighted.

Panel A: Returns conditional on business cycle

	Individual stocks		17 Industries	
Period	Momentum	Seasonality	Momentum	Seasonality
Expansions	1.17	1.14	0.44	0.76
($N = 498$)	(4.70)	(6.26)	(2.54)	(4.14)
Recessions	0.34	1.47	−0.17	0.41
($N = 90$)	(0.31)	(2.09)	(−0.31)	(0.54)
Difference	0.83	−0.33	0.62	0.34
	(0.74)	(−0.46)	(1.08)	(0.43)

Panel B: Return decomposition based on macroeconomic variables

Return	Individual stocks		17 Industries	
component	Momentum	Seasonality	Momentum	Seasonality
Total	1.06	1.19	0.36	0.71
	(3.81)	(6.39)	(2.05)	(3.84)
Predicted	1.14	0.04	1.49	−1.62
	(0.41)	(0.04)	(1.20)	(−2.34)
Unexpected	−0.08	1.15	−1.14	2.33
	(−0.03)	(1.32)	(−0.90)	(3.24)

Table 6: Momentum and seasonality profits and macroeconomic risk

This table explains returns to momentum and seasonality strategies by combining these strategies' estimated loadings against macroeconomic risks with estimates of risk premiums associated with these risks. The macroeconomic variables are industrial production growth (MP), unexpected inflation (UI), change of expected inflation (DEI), term premium (UTS), and default premium (UPR). Panel A follows the Liu and Zhang (2008) methodology and uses ten value-weighted size, value, and momentum portfolios as testing assets for computing the risk premiums using Fama and MacBeth's (1973) two-stage procedure. All portfolios are value-weighted. Panel B replaces momentum portfolios with seasonality portfolios in the set of test assets. t-values associated with the risk premium estimates are Shanken (1992)-corrected. Factor loadings are estimated using full-sample time-series regressions. "Observed vs. predicted returns" reports the realized and predicted returns, the difference between the two, and the t-value associated with this difference. The "fraction explained" is 1 − Predicted/Observed. "Bootstrapped observed − predicted distributions" repeats the estimation procedure 10,000 times using randomized CRR data matrixes and reports the percentiles of the observed-minus-predicted difference.

Panel A: Size, value, and momentum portfolios as test assets

Risk premium estimates	Intercept	MP	UI	DEI	UTS	UPR
	0.23	0.73	−0.09	−0.01	0.76	−0.57
	(0.53)	(1.97)	(−1.03)	(−0.28)	(0.61)	(−2.37)

Factor loadings	Strategy	MP	UI	DEI	UTS	UPR
	Momentum	0.34	−1.39	6.78	−0.29	−1.37
		(0.90)	(−0.67)	(1.59)	(−1.41)	(−1.14)
	Seasonality	−0.12	0.65	−3.49	0.12	−0.63
		(−0.36)	(0.66)	(−1.14)	(1.00)	(−1.75)

Observed − predicted returns	Strategy	Observed	Predicted	diff	t(diff)	Fraction explained
	Momentum	1.38	0.86	0.52	1.72	62.6%
	Seasonality	1.19	0.35	0.85	4.45	29.0%

Bootstrapped observed − predicted distributions		Percentile				
	Strategy	5th	25th	50th	75th	95th
	Momentum	0.24	0.41	0.55	0.73	1.01
	Seasonality	0.67	1.05	1.31	1.56	1.95

Panel B: Size, value, and seasonality portfolios as test assets

Risk premium estimates	Intercept	MP	UI	DEI	UTS	UPR
	0.34	−0.22	0.12	−0.08	2.42	−0.24
	(0.57)	(−0.32)	(0.78)	(−1.20)	(1.84)	(−0.62)

Factor loadings	Strategy	MP	UI	DEI	UTS	UPR
	Momentum	0.34	−1.39	6.78	−0.29	−1.37
		(0.90)	(−0.67)	(1.59)	(−1.41)	(−1.14)
	Seasonality	−0.12	0.65	−3.49	0.12	−0.63
		(−0.36)	(0.66)	(−1.14)	(1.00)	(−1.75)

Observed − predicted returns	Strategy	Observed	Predicted	diff	t(diff)	Fraction explained
	Momentum	1.38	−1.19	2.57	8.54	.
	Seasonality	1.19	0.83	0.37	1.92	69.4%

Bootstrapped observed − predicted distributions		Percentile				
	Strategy	5th	25th	50th	75th	95th
	Momentum	0.43	1.11	1.55	1.99	2.71
	Seasonality	0.15	0.38	0.58	0.79	1.07

Table 7: Investor sentiment, seasonality, and anomalies

This table measures the profitability of various anomalies conditional on investor sentiment. The high-sentiment (low-sentiment) months are those in which the value of the Baker and Wurgler (2006) market-wide sentiment index for the previous month is above (below) the index's median value in the sample period. Panel A reports average returns for the five anomalies studied in Table 2 of Stambaugh et al. (2012, SYY), as well as for the 11-anomaly "combination" strategy of that study. Panel B reports average returns for strategies that trade seasonalities in individual stocks as well as in portfolios constructed by sorts on size, value, momentum, gross profitability, dividend-to-price, earnings-to-price, and industry; "Composite" is a seasonality strategy based on 58 portfolios (see Table 1). The average returns for the long and short legs are in excess of the one-month Treasury bill rate. The sample period is from August 1965 through January 2011 except for gross profitability and earnings-to-price, for which the data start in January 1973.

Panel A: Average anomaly returns conditional on sentiment

	Sentiment								Diff. in long − short	
	High				Low					
	Leg				Leg					
Anomaly	Long	Short	Diff.	t	Long	Short	Diff.	t	Avg	t
Net issuances	0.78	−0.39	1.17	4.72	0.92	0.42	0.50	2.69	0.67	2.13
Ohlson's O-score	0.27	−0.69	0.96	1.86	0.60	1.10	−0.50	−1.21	1.46	2.18
Momentum	0.73	−1.75	2.48	5.83	1.62	0.21	1.41	2.31	1.07	1.40
Gross profitability	0.54	−0.16	0.70	2.99	0.77	0.67	0.09	0.39	0.61	1.85
Asset growth	0.36	−0.38	0.74	2.98	1.05	0.71	0.34	1.42	0.39	1.11
SYY combination	0.44	−0.62	1.06	6.00	0.94	0.68	0.27	1.44	0.79	3.06
Size	0.07	0.27	−0.21	−0.51	1.57	0.52	1.05	2.35	−1.26	−2.04
Value	0.65	−0.03	0.68	1.98	1.12	0.66	0.46	1.41	0.21	0.47

Panel B: Average returns on seasonality strategies conditional on sentiment

	Sentiment								Diff. in long − short	
	High				Low					
	Leg				Leg					
Assets	Long	Short	Diff.	t	Long	Short	Diff.	t	Avg	t
Individual stocks	0.61	−0.23	0.84	2.81	1.70	0.06	1.64	5.84	−0.80	−2.11
Portfolios										
Size	0.91	−0.41	1.32	4.29	1.73	0.34	1.39	4.58	−0.06	−0.14
Value	0.73	0.17	0.56	2.45	1.10	0.57	0.52	2.01	0.03	0.09
Momentum	0.84	−1.30	2.15	3.99	1.64	−0.08	1.72	4.24	0.42	0.63
Gross profitability	0.28	0.24	0.05	0.19	0.86	0.52	0.35	1.77	−0.30	−0.95
Dividend-to-price	0.60	0.05	0.54	2.41	1.16	0.72	0.44	1.76	0.11	0.30
Earnings-to-price	0.47	0.08	0.39	1.37	1.11	0.39	0.72	2.65	−0.33	−0.83
Industry	0.60	−0.02	0.63	2.07	1.02	0.16	0.86	3.44	−0.23	−0.61
Composite	0.86	−0.40	1.26	5.35	1.58	0.15	1.42	6.59	−0.17	−0.50

Table 8: Pervasiveness of anomalies

Panel A measures the performance of value-weighted seasonality, momentum, net issuance, and asset growth strategies by partitioning the universe of U.S. equities based on firm size, book-to-market, dividend-to-price, and credit rating. Microcaps are stocks with market capitalizations below the 20th percentile of the NYSE distribution; small firms are firms above this percentile and below the median; and large firms are firms above the median. The book-to-market subsamples assign stocks using the 30- and 70-percentile breakpoints. The dividend-to-price subsamples separate stocks that do not pay dividends and breaks dividend-paying stocks using the median. The credit-rating subsamples use the Avramov et al. (2007) methodology and assign firms into categories using the 30- and 70-percentile breakpoints of S&P Long-Term Domestic Issuer Credit Ratings. The sample period in Panel A is from July 1963 through December 2011 except for the credit-rating sample which starts January 1986 and is restricted to firms with credit ratings. We assign stocks into subsamples at the end of June except for credit rating for which we use the Avramov et al. (2007) procedure. Seasonality and momentum strategies are rebalanced monthly; net-issuance and asset-growth strategies are rebalanced at the end of June. Panel B reports average returns for anomalies examined in Table 7 by subperiod. Panel C reports average returns for strategies that trade seasonalities in commodities and country indexes. Portfolios are constructed each month based on average same- or other-calendar-month returns. The number of commodities in the high and low portfolios is two until December 1993 and three after this point as the number of commodities with sufficient historical return data increases to 15. The country-index strategy has three countries in the long and short legs throughout the sample. We begin forming commodity and country-index portfolios at the end of December 1974. The sample period ends in January 2011. t-values are reported in parentheses.

Panel A: Seasonality and other return anomalies within U.S. equity subsamples

	Firm size			Book-to-market			Dividend-to-price			Credit rating		
Anomaly	Micro	Small	Large	Growth	Neutral	Value	$= 0$	Low	High	Low	Medium	High
Seasonality												
Q_1	0.86	0.78	0.34	0.30	0.52	0.87	0.45	0.31	0.48	0.56	0.52	−0.02
Q_5	1.48	1.51	1.30	1.35	1.52	1.74	1.57	1.45	1.71	1.26	1.37	1.73
$Q_5 - Q_1$	0.62	0.73	0.96	1.05	1.00	0.87	1.11	1.14	1.23	0.70	0.85	1.74
	(6.44)	(6.88)	(5.66)	(6.07)	(6.00)	(4.51)	(6.61)	(5.21)	(6.42)	(2.76)	(4.63)	(4.23)
Momentum												
$Q_5 - Q_1$	1.69	1.35	0.94	1.34	0.85	0.71	1.60	1.05	0.83	1.69	0.65	0.24
	(6.81)	(5.19)	(3.10)	(5.10)	(2.66)	(2.36)	(6.13)	(3.34)	(2.39)	(3.19)	(1.45)	(0.54)
Net issuances												
$Q_5 - Q_1$	0.76	0.52	0.52	0.47	0.59	0.40	0.88	0.48	0.37	1.01	0.56	0.54
	(4.82)	(3.83)	(3.95)	(2.97)	(5.23)	(2.45)	(4.64)	(3.66)	(3.47)	(2.60)	(2.44)	(2.88)
Asset growth												
$Q_5 - Q_1$	0.62	0.44	0.25	0.11	0.25	0.32	0.37	0.39	0.10	1.03	0.34	0.26
	(4.20)	(3.54)	(1.66)	(0.68)	(1.81)	(2.22)	(2.06)	(2.79)	(0.76)	(2.33)	(1.81)	(1.33)

Panel B: Seasonality and other return anomalies by subperiod

	Period				
Strategy	1963 –1972	1973 –1982	1983 –1992	1993 –2002	2003 –2011
Net issuances	0.90	0.66	0.84	1.30	0.50
	(2.58)	(2.36)	(3.01)	(4.20)	(1.31)
Ohlson's O-score	−0.07	−0.44	1.48	0.09	0.04
	(−0.12)	(−0.77)	(2.74)	(0.09)	(0.06)
Momentum	2.08	2.05	2.35	2.98	0.10
	(4.38)	(3.37)	(4.09)	(3.03)	(0.09)
Gross profitability	0.63	−0.28	0.52	0.86	0.62
	(2.19)	(−0.83)	(1.50)	(2.22)	(1.30)
Asset growth	−0.05	1.10	−0.06	1.34	−0.14
	(−0.15)	(3.78)	(−0.18)	(3.15)	(−0.38)
SYY combination	0.55	0.36	0.98	1.10	0.29
	(2.80)	(1.55)	(4.15)	(3.47)	(0.90)
Size	1.08	0.95	−0.54	0.16	0.15
	(1.34)	(1.88)	(−0.89)	(0.25)	(0.25)
Value	0.13	1.35	0.52	0.27	0.23
	(0.33)	(2.67)	(0.89)	(0.48)	(0.57)
		Seasonality strategies			
Individual stocks	1.13	0.83	1.89	1.65	0.40
	(3.32)	(1.93)	(5.29)	(2.87)	(1.35)
Portfolios					
Size	0.94	1.33	1.83	1.78	0.77
	(1.78)	(2.49)	(4.30)	(3.08)	(1.84)
Value	0.13	1.45	0.60	0.17	−0.16
	(0.40)	(3.85)	(1.42)	(0.50)	(−0.53)
Momentum	1.54	1.62	2.60	2.98	0.30
	(4.06)	(3.02)	(5.53)	(2.83)	(0.42)
Gross profitability		0.14	0.16	0.28	0.23
		(0.41)	(0.73)	(0.93)	(0.51)
Dividend-to-price	0.29	0.23	0.72	0.66	0.52
	(0.75)	(0.63)	(2.90)	(1.59)	(1.29)
Earnings-to-price		1.53	0.96	−0.09	−0.18
		(3.72)	(3.67)	(−0.19)	(−0.67)
Industry	0.68	0.69	0.95	1.57	−0.49
	(2.66)	(1.88)	(2.36)	(3.77)	(−1.00)
Composite	0.98	1.40	1.68	1.77	0.58
	(3.76)	(3.79)	(4.90)	(4.53)	(1.75)

Panel C: Seasonalities in returns on commodities and country indexes

	All months		Excluding January	
	Commodities	Country indexes	Commodities	Country indexes
Sort by same-month return	0.93	0.48	0.96	0.50
	(1.93)	(2.20)	(2.03)	(2.20)
Sort by other-month return	−0.22	−0.36	−0.19	−0.23
	(−0.58)	(−1.66)	(−0.47)	(−1.06)
Same − Other	1.15	0.84	1.15	0.73
	(1.97)	(2.76)	(2.02)	(2.28)

Table 9: Correlations between seasonality strategies

Panels A and B reports correlations between seasonality and momentum strategies that trade stocks within different subsamples of U.S. equities (see Table 8). Seasonality strategies select stocks based on the average same-calendar-month return over the prior 20 years; momentum selects stocks based on the prior one-year returns skipping a month. The time periods in Panels A and B are the same as those in Table 8. Panel C reports correlations between strategies that trade monthly seasonalities in U.S. equities, daily seasonalities in U.S. equities, and seasonalities in country indexes and commodities. Panel D reports weights and ex-post maximum Sharpe ratios for optimal portfolios formed from market, value, size, and momentum factors and different seasonality strategies. The U.S. equity seasonality strategies in Panel D are HML-like factors that are constructed by sorting stocks into six portfolios based on size and historical same-month (or same-day) return. Panels C and D use data from 1975 through 2011.

Panel A: Correlations between seasonality strategies within subsets of U.S. equities

		Size			Book-to-market			Dividend-to-price		
		Micro	Small	Large	Growth	Neutral	Value	= 0	Low	High
Size	Micro	1								
	Small	0.50	1							
	Large	0.28	0.41	1						
B/M	Growth	0.28	0.42	0.85	1					
	Neutral	0.34	0.46	0.69	0.48	1				
	Value	0.23	0.36	0.41	0.26	0.39	1			
D/P	= 0	0.35	0.42	0.59	0.63	0.41	0.26	1		
	Low	0.20	0.31	0.66	0.65	0.53	0.25	0.33	1	
	High	0.13	0.17	0.47	0.31	0.50	0.48	0.17	0.27	1

Panel B: Correlations between momentum strategies within subsets of U.S. equities

		Size			Book-to-market			Dividend-to-price		
		Micro	Small	Large	Growth	Neutral	Value	= 0	Low	High
Size	Micro	1								
	Small	0.86	1							
	Large	0.72	0.82	1						
B/M	Growth	0.72	0.81	0.92	1					
	Neutral	0.76	0.83	0.88	0.79	1				
	Value	0.68	0.72	0.72	0.61	0.70	1			
D/P	= 0	0.82	0.86	0.79	0.81	0.78	0.67	1		
	Low	0.64	0.74	0.86	0.84	0.80	0.62	0.69	1	
	High	0.56	0.65	0.76	0.65	0.76	0.65	0.58	0.64	1

Panel C: Correlations between seasonalities in different asset classes and frequencies

	Monthly stocks	Daily stocks	Countries	Commodities
Monthly stocks	1			
Daily stocks	0.05	1		
Countries	0.02	0.00	1	
Commodities	0.11	0.01	−0.09	1

Panel D: Portfolio weights and maximum ex-post Sharpe ratios

#	Market	Size	Value	Momentum	Seasonalities: Monthly U.S. equity	Seasonalities: Commodities	Seasonalities: Countries	Seasonalities: Daily U.S. equity	Sharpe ratio
1	100%								0.46
2	22%	15%	40%	23%					1.04
3	8%	10%	24%	12%	46%				1.67
4	8%	10%	24%	12%	44%	2%			1.69
5	7%	9%	23%	11%	41%	2%	7%		1.74
6	3%	2%	23%	4%	21%	1%	4%	41%	2.75