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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, and international stock market indices, as well as 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 systematic factors. Our results suggest that seasonalities are not a distinct class of anomalies that requires an explanation of its own, but rather that they are intertwined with other return anomalies through shared systematic factors.

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 rather 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 disappears when the regressions include stock-*calendar*

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[1] See Heston and Sadka (2010).

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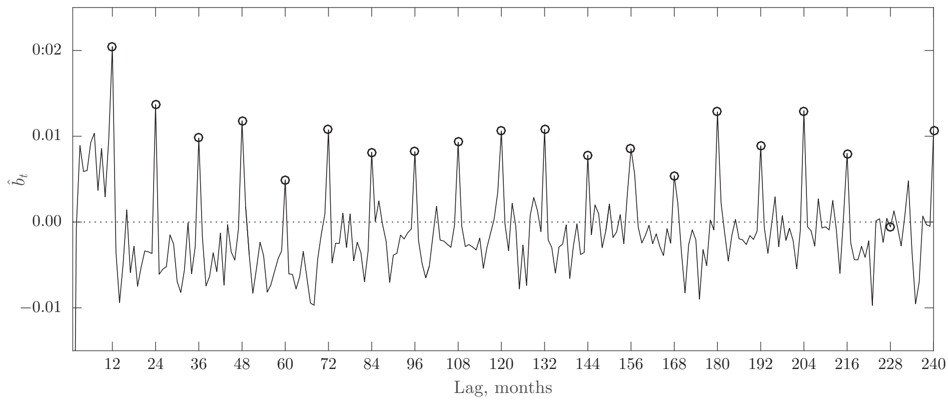

Figure 1. Seasonalities in individual stock returns. This figure plots slope coefficients from univariate Fama and MacBeth (1973) regressions of month t returns against month $t-k$ returns, $r_{i,t} = a_t + b_t\, r_{i,t-k} + e_{i,t}$, with k ranging from 1 to 240 months. The circles denote estimates at annual lags. The regressions use monthly data from January 1963 through December 2011 for NYSE, Amex, and NASDAQ stocks.

month fixed effects. Thus, the estimates in Figure 1 do not mean that stocks "repeat" shocks from the past, but instead suggest that expected returns vary from month to month. A 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 the 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. For instance, a metastrategy 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), while an alternative strategy that selects anomalies based on their *other*-calendar-month premiums earns a slightly negative return! The latter result suggests that knowing how well an anomaly has performed in other calendar months 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.

[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 in the future.

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 separately control for firm size, industry, exposures to the Fama and French (1993) 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.

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 patterns in individual stocks. Individual stocks *aggregate* seasonalities across the various 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 size. 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 factors. A sort on past returns picks up all seasonalities no matter their origin. 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.

Two simple empirical tests suggest that the seasonalities in monthly U.S. stock returns originate in large part from systematic factors. First, the variance of a strategy that trades seasonalities is *five* times higher than what it would be if it took on just idiosyncratic risk. Second, seasonalities are strongly present in returns on well-diversified portfolios. We estimate that at least one-half of the seasonalities in monthly U.S. stock returns derive from systematic factors associated with salient firm characteristics such as size, dividend-to-price, and industry. Moreover, the seasonalities that remain after controlling for these factors continue to be exposed to other systematic risks. The prominence of systematic factors suggests that seasonal strategies have to remain exposed to systematic risk—attempts to hedge those risks would likely reduce (or even eliminate) the seasonalities as well.

The return seasonalities are also 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 approximately 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 strategies trading seasonalities in small stocks and high-dividend-yield stocks is 0.17. The correlations 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 systematic factors, for all the seasonalities.[3] 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 and the premiums on these factors exhibit seasonal variation. Assets that are exposed to one set of risk factors will exhibit seasonalities that "look" the same as the seasonalities found among assets exposed to different risk factors, but the correlations between the return seasonalities across the two groups will be low or negligible. We demonstrate that the low correlations between strategies that trade seasonalities in, say, small stocks and high-dividend-yield stocks are also consistent with a world in which the seasonalities stem from just a few factors. These correlations are low if different groups of stocks load differently on the factors from which the seasonalities emerge.

Our results speak to the striking economic significance of seasonalities. The literature often regards seasonalities as just another anomaly—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 systematic factors, they represent attractive risk-reward trade-offs 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 an HML-style seasonality factor to the investment opportunity set. Even an investor who does not trade seasonalities directly can benefit, for example, by delaying a trade whenever the trading strategy calls for selling a stock with a high expected return next month.

Our key insight is that seasonalities are not an isolated or distinct class of anomalies that requires an explanation of its own. Rather, our theory and decomposition results suggest that seasonalities are intertwined with other return anomalies through many shared systematic factors. This is a promising result because it means that any theory that is able to explain the risks behind the factors is likely able to shed light on both average returns and seasonalities.

Past research extensively studies seasonalities in asset returns. Whereas we study seasonalities in the cross section of asset returns, most extant research focuses on time-series (market-wide) seasonalities. Kamstra, Kramer, and Levi (2003, 2015) and Garrett, Kamstra, and Kramer (2005), for example, ascribe the seasonalities in equity risk premium and Treasury returns to seasonal variation in risk aversion: the price of risk increases during the winter.

[3] 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.

Some seasonalities might stem from mispricing that affects large groups of stocks.[4] Every factor seasonality emerges from seasonalities in the quantity of risk, the price of risk (risk aversion), or mispricing, or some combination thereof. Our results build on this market-wide evidence by demonstrating how the seasonalities in systematic factors carry over to the cross section of asset returns.

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

I. Seasonalities in Risk Premiums and the Cross Section of Expected Returns

A. 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 regressions. To illustrate this idea, suppose returns are generated by the single-factor model[5]

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

where $r_{i,t}$ is the excess return on security i and $\varepsilon_{i,t}$ is the residual. We assume that the factor premium in month 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 i.i.d. and mean zero. The cross-sectional autocovariance of returns is then

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

where we assume that the number of stocks is large. The average autocovariance across many calendar-month $m(t)$ cross sections tends to

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

[4] The turn-of-the-year seasonalities are often attributed to December tax-loss selling and the rebound that follows. See, for example, Kang et al. (2011).

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

Let us now assume that the calendar-month-specific risk premiums $\lambda_{m(t)} \sim N(0, \sigma_\lambda^2)$ are drawn once in the beginning by nature independently of each other, $\mathrm{E}(\lambda_m \lambda_{m'}) = 0$ for $m \neq m'$. The *expected* cross-sectional autocovariance is then

$$\mathrm{E}[\mathrm{cov}^{\mathbf{cs}}(r_{i,t}, r_{i,t-k})] = \begin{cases} \mathrm{var}^{\mathbf{cs}}(\beta_i)\sigma_\lambda^2 > 0 & \text{if } m(t) = m(t-k), \\ 0 & \text{otherwise.} \end{cases} \tag{4}$$

Equation (4) shows that any seasonality in factor premium, $\sigma_\lambda^2 > 0$, *always* gets transferred to the cross section of security returns if factor loadings vary across securities, $\mathrm{var}^{\mathbf{cs}}(\beta_i) > 0$.

B. 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,

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

Similar to above, the month t return on factor j is the sum of its risk premium and a shock. We assume that the draws of the risk premiums and all shocks are independent across calendar months and factors. We also assume that both the factors and the firms are symmetric, so that the same parameters characterize all factors and firms.

The expected cross-sectional autocovariance of returns in this multi-factor model equals

$$\mathrm{E}[\mathrm{cov}^{\mathbf{cs}}(r_{i,t}, r_{i,t-k})] = J\mathrm{var}^{\mathbf{cs}}(\beta)\sigma_\lambda^2. \tag{6}$$

Seasonalities in factor risk premiums therefore *aggregate* into larger seasonalities in security returns. 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 multiple factors. Dispersion in loadings determines the amount of seasonalities in the cross section. If $\mathrm{var}^{\mathbf{cs}}(\beta) = 0$, variation in the risk premium leaves no trace in the *cross section* of security returns. 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.

The Fama-MacBeth (1973) regression slopes, such as those displayed in Figure 1, scale cross-sectional autocovariances by the cross-sectional variance of stock returns. These regression slopes therefore measure the fraction of cross-sectional variance that is due to the differences in expected returns.[6]

[6] In an Internet Appendix, we compute the expected Fama-MacBeth (1973) slope coefficient for the multifactor model and show that it satisfies the bound $\mathrm{E}(b_k) > \frac{J\mathrm{var}^{\mathbf{cs}}(\beta)\sigma_\lambda^2}{J\mathrm{var}^{\mathbf{cs}}(\beta)(\sigma_\lambda^2+\sigma_\xi^2)+\sigma_\varepsilon^2}$. The Internet Appendix is available in the online version of the article on the *Journal of Finance* website.

C. Alternative Explanations: Idiosyncratic Seasonalities and Autocorrelated Innovations

An alternative explanation for the return seasonalities is that they are firm specific. We simplify the description of this alternative by assuming that each stock's realized return equals its seasonally varying expected return, $\mu_{i,m(t)}$, plus a residual, $\varepsilon_{i,t}$, $r_{i,t} = \mu_{i,m(t)} + \varepsilon_{i,t}$, with $\mathrm{var}^{\mathrm{cs}}(\mu_{i,m(t)}) = \sigma_\mu^2$. In this case, the cross-sectional autocovariance of returns simplifies to

$$\begin{aligned}\mathrm{cov}^{\mathrm{cs}}(r_{i,t}, r_{i,t-k}) &= \mathrm{cov}^{\mathrm{cs}}(\mu_{i,m(t)} + \varepsilon_{i,t}, \mu_{i,m(t-k)} + \varepsilon_{i,t-k}) \\ &= \begin{cases} \sigma_\mu^2 > 0 \text{ if } m(t) = m(t-k), \\ 0 \qquad\quad \text{otherwise.} \end{cases}\end{aligned} \tag{7}$$

The difference between this model and the "systematic seasonalities" model shows up in the variances. When the seasonalities are idiosyncratic, the cross-sectional autocovariance of returns (at annual lags) always tends to a constant σ_μ^2 as the number of stocks increases. Because all shocks are idiosyncratic, they wash out in each cross section, that is, $\mathrm{var}^{\mathrm{ts}}(\mathrm{cov}^{\mathrm{cs}}(r_{i,t}, r_{i,t-k})) = 0$. In the model in which the seasonalities stem from risk factors, by contrast, the factor shocks, ξ_t^j, always remain. Equation (2) indicates that in this case, $\mathrm{var}^{\mathrm{ts}}(\mathrm{cov}^{\mathrm{cs}}(r_{i,t}, r_{i,t-k})) > 0$. We use this observation in Section C to distinguish between these two models. If the seasonalities are firm specific, then the volatility of a long-short seasonality strategy should be comparable to that of a *random* long-short strategy. In the systematic seasonalities model, by contrast, the shocks hitting the factors raise the volatility of a seasonality strategy.

Autocorrelated innovations could also generate a pattern that is observationally equivalent to seasonalities in expected returns. That is, it could be the case that $\mathrm{cov}^{\mathrm{ts}}(\varepsilon_{i,t}, \varepsilon_{i,t-k})$ is greater than zero at annual lags but is equal to zero (or is negative) at other lags. If expected returns are constant over time and across stocks but the residuals display this pattern, then

$$\begin{aligned}\mathrm{E}[\mathrm{cov}^{\mathrm{cs}}(r_{i,t}, r_{i,t-k})] &= \mathrm{E}[\mathrm{cov}^{\mathrm{cs}}(\mu + \varepsilon_{i,t}, \mu + \varepsilon_{i,t-k})] \\ &= \begin{cases} \mathrm{cov}^{\mathrm{ts}}(\varepsilon_{i,t}, \varepsilon_{i,t-k}) > 0 \text{ if } m(t) = m(t-k), \\ 0 \qquad\qquad\qquad\qquad\quad \text{otherwise.} \end{cases}\end{aligned} \tag{8}$$

Because the seasonalities are again firm specific—the only difference relative to the idiosyncratic seasonalities model is that they now lie in the residuals—we can use the same approach as above to distinguish this model from the systematic seasonalities model. We also use another approach in Section A to distinguish this model from the others. In both the systematic and idiosyncratic seasonalities models, the seasonalities are tied to expected returns. In these models, the seasonalities would therefore disappear if we were to control for differences in (seasonal) expected returns, that is, stock-calendar month fixed effects would drive out the seasonalities. In the autocorrelated innovations model, by contrast, stock-calendar month fixed effects would do nothing because the seasonalities stem from autocorrelated residuals.

II. 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 right-hand-side returns we use monthly returns going back to January 1943. Unless otherwise mentioned, our portfolio sorts use unconditional break points, that is, break points computed using all stocks.

All accounting data are from annual Compustat files. We use 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 $t-1$.

III. An Analysis of Return Seasonalities within U.S. Equities

A. Stocks Do Not Repeat Past Return Shocks

The cross-sectional Fama-MacBeth (1973) regressions reported in Figure 1 show that returns in months $t-12$, $t-24$, ..., $t-240$ predict returns in month t. Although in the systematic seasonalities model, these seasonalities spring from calendar-month differences in expected returns, in Section C's alternative model, they emerge from autocorrelated return innovations.

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. We demean stock returns in each historical cross section before taking the average because stocks differ in their availability of historical data. We include stocks that have existed for at least five years as of month t. We use the same demeaning procedure and sample selection rules throughout the study. Regression (9) is equivalent to a regression with

[7] See Shumway (1997). The coverage of delisting returns on CRSP has improved over time. 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).

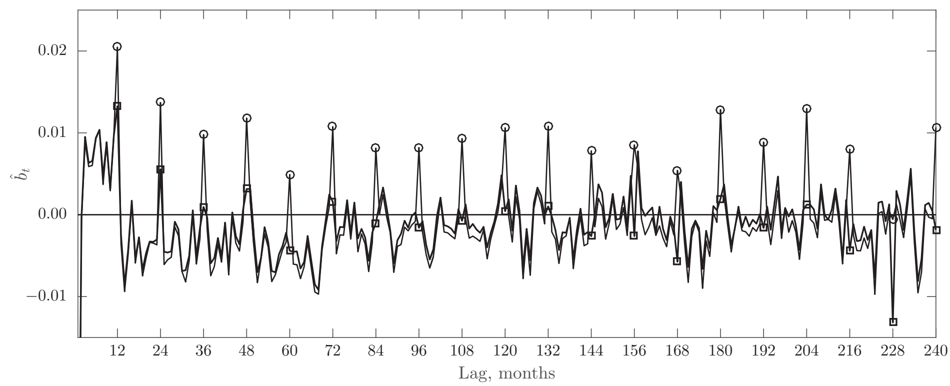

Figure 2. Seasonalities in individual stock returns when controlling for stocks' historical average same-calendar-month returns. The thin line plots slope coefficients from univariate Fama and MacBeth (1973) regressions of month t returns against month $t-k$ returns, $r_{i,t} = a_t + b_t\, r_{i,t-k} + e_{i,t}$, with k ranging from 1 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. The regressions use monthly data from January 1963 through December 2011 for NYSE, Amex, and NASDAQ stocks.

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 emerge from autocorrelated innovations, controlling for differences in seasonal expected returns 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 highly statistically significant. In the $k = 240$ regression, for example, the average slope coefficient estimate has a t-value of 10.3. 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 to the coefficients from the baseline Fama-MacBeth (1973) 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

[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.

to controlling for stock-calendar month variation in expected returns. In the Internet Appendix, we show 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.

B. 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 of well-diversified portfolios.[9] Table I examines the profitability of long-short strategies that trade 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 I 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 over the period 1944 to 1963. The seasonality strategies are long the winner decile 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 seasonality strategy is 1.22% per month (t-value = 6.45). 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, momentum, 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 case, 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.[10]

[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.

[10] An important difference between the results in Table I and those in Heston and Sadka (2008) is that, whereas we find significant industry seasonalities—the long-short same-calendar-month

Table I

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 and gross profitability is the ratio of revenue minus cost of goods sold to total assets. Except for momentum, we rebalance the portfolios every June and compute value-weighted returns from July of year t to June of year $t+1$; momentum portfolios are rebalanced monthly. The row "Composite" combines the 58 size, value, momentum, dividend-to-price, and industry portfolios. Same-month sorts are based on average same-calendar-month returns over the prior 20 years. Other-month sorts are based on average other-calendar-month returns over the same period, skipping months $t-11$ through $t-1$. The individual stock strategy trades the top and bottom deciles. Strategies based on size, value, momentum, profitability, dividend-to-price, and earnings-to-price trade the top and bottom portfolios. The industry strategy trades the top two and bottom two portfolios. The composite strategy trades the top six and bottom six portfolios. FF3 α is the Fama and French (1993) three-factor model alpha. 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.

	Monthly Returns and Alphas (%)				t-Values			
	Sort by				Sort by			
	Same-Month Return		Other-Month Return	Same − Other	Same-Month Return		Other-Month Return	Same− Other
Set of Assets	Avg	FF3 α			Avg	FF3 α		
All Months								
Individual stocks	1.19	1.22	−0.96	2.16	6.27	6.45	−4.12	7.94
Portfolios								
Size	1.35	1.27	−0.94	2.29	6.64	6.33	−3.94	6.53
Value	0.47	0.24	0.23	0.24	2.76	1.66	1.27	1.05
Momentum	1.83	1.97	1.89	−0.07	5.77	6.15	5.39	−0.20
Profitability	0.20	0.32	0.33	−0.13	1.21	1.91	1.91	−0.64
Dividend-to-price	0.48	0.59	−0.50	0.99	3.12	3.76	−3.08	3.97
Earnings-to-price	0.57	0.39	0.12	0.45	2.93	2.06	0.50	1.35
Industry	0.70	0.80	−0.81	1.51	3.79	4.22	−4.32	5.40
Composite	1.30	1.30	0.01	1.29	8.65	8.77	0.06	6.31
Excluding January								
Individual stocks	0.99	1.07	−0.56	1.56	5.45	6.14	−2.51	6.28
Portfolios								
Size	0.73	0.77	−0.55	1.28	3.88	4.07	−2.15	3.61
Value	0.23	0.17	0.16	0.07	1.55	1.17	0.85	0.33
Momentum	1.82	2.01	2.30	−0.48	6.08	6.61	5.81	−1.77
Profitability	0.21	0.34	0.36	−0.15	1.31	2.14	2.03	−0.74
Dividend-to-price	0.34	0.47	−0.31	0.65	2.09	2.98	−1.88	2.60
Earnings-to-price	0.30	0.27	0.18	0.12	1.73	1.51	0.68	0.33
Industry	0.59	0.72	−0.69	1.28	3.11	3.76	−3.66	4.74
Composite	0.90	1.02	0.28	0.62	6.95	7.72	1.81	3.68

Seasonalities are absent, however, 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 negative. Similarly, no seasonalities are apparent in the returns on the gross profitability portfolios. 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.

Table I 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 are by no means limited to it.

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 10 momentum portfolios but no information on which one is the "winner" and which one is the "loser." 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" portfolio and sells the "loser" portfolio. The surprising result in Table I 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.

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 nonindustry component of 1.03%. Our analysis, by contrast, measures the prevalence of seasonalities in industry returns, which is equivalent to sorting stocks into portfolios by stocks' industry components.

[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, the cross-sectional differences in average returns are also modest.

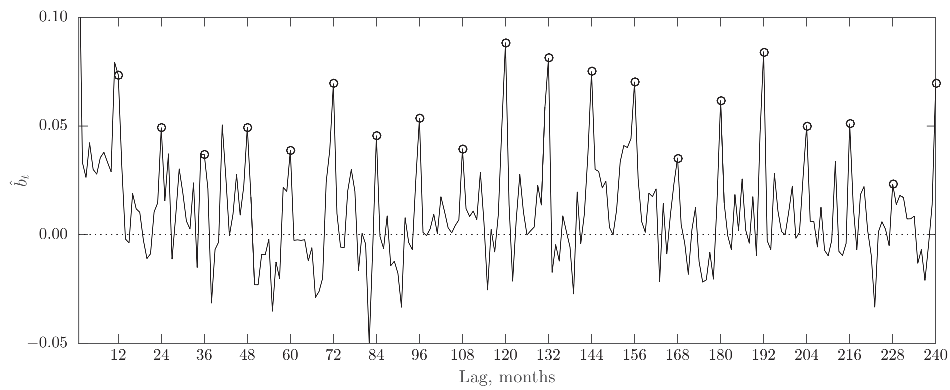

Figure 3. Seasonalities in portfolio returns. This figure plots slope coefficients from univariate Fama and MacBeth (1973) regressions of month t returns against month $t-k$ returns, $r_{p,t} = a_t + b_t\, r_{p,t-k} + e_{p,t}$, with k ranging from 1 to 240 months. The data are returns on 58 size, value, momentum, dividend-to-price, and industry portfolios. The circles denote estimates at annual lags. The regressions use monthly data from January 1963 through December 2011 for NYSE, Amex, and NASDAQ stocks.

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

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

Each portfolio's average historical return then 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

$$r_{p,t} = \mu_{p,m(t)} + e_{p,t} = \mu_p^* + \left(\mu_{p,m(t)} - \mu_p^*\right) + e_{p,t}, \tag{11}$$

where the second equality decomposes expected returns into their unconditional and seasonal components. The results in Table I 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^*!

If some assets have higher unconditional means than others, and there are no return seasonalities, both same- and other-month sorts yield profitable trading strategies. Therefore, we use same-versus-other-month comparisons throughout this paper to confirm that the same-calendar-month sorts pick up return *seasonalities* rather than unconditional differences in expected returns. The same-calendar-month sorts, however, are always our main object of interest because they are the ones that capture return seasonalities when they exist.

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 I. 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 two.[12]

C. 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. Although these portfolios diversify away much of the idiosyncratic risk, they are left exposed 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 to portfolios by their average same-month returns, we also assign them to 10 random portfolios and use these portfolios to generate one long-short strategy. We 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%. Thus, the variance of the true seasonality strategy exceeds that of its randomized counterpart by a factor of 5! This simple comparison suggests that return seasonalities are intertwined with systematic risk.

While persuasive, this test cannot rule out the possibility that the volatilities and seasonalities align but the seasonalities do not compensate for risk. To see why, consider the results of Cohen and Polk (1996) and Cohen, Polk, and Vuolteenaho (2003) on the intraindustry component of the value effect. These studies find that the *interindustry* component of book-to-market does not predict the cross section of returns. At the same time, stocks within the same industry covary with each other, exposing an interindustry value strategy to systematic risk. An analysis of the value effect might therefore suggest at first glance that the value premium helps compensate for industry risk. In reality, however, an investor can capture the value premium even after hedging the underlying industry risk (Novy-Marx (2013)). Similarly, in our application, it could be the case that investors hedge some of the risks that our randomization analysis attributes to the seasonality strategy. We revisit this point in Section D in which we show that hedging industry, size, and value risks does not eliminate the link between return seasonalities and systematic risk.

D. Explaining Seasonalities with Firm Characteristics

D1. Time-Series Regressions

Table II measures the extent to which portfolio seasonalities explain the seasonalities in individual stock returns. The dependent variable is the return on the long-short strategy that buys the top decile and sells the bottom decile of

[12] See the Internet Appendix for details.

Table II

Regressions of Individual Stock Return Seasonalities on Portfolio Return Seasonalities

This table reports estimates from regressions in which the dependent variable is the monthly return on a long-short strategy that trades seasonalities in individual stock returns and the explanatory variables are returns on long-short strategies that trade seasonalities in portfolio returns. Table I reports average returns for these strategies. The intercept measures the extent to which the seasonalities in individual stock returns are explained by seasonalities in portfolio returns. t-values are reported in parentheses.

	Regression							
Explanatory 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%

individual stocks 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 I.

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), which regresses 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]

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

Table III

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 indicator variables for industry; 10 indicator variables each for book-to-market, firm size, and market beta; and 11 indicator variables for dividend-to-price with zero-dividend firms kept separate. We measure explanatory power by comparing the average annual regression coefficient in the model that uses actual characteristics to one that randomly resamples firm characteristics without replacement. 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.

	Firm Characteristic					
	Industry	Book-to-Market	Firm Size	Dividend-to-Price	Market Beta	Total
Full sample, 1963 to 2011						
Contribution	0.052	0.014	0.276	0.107	0.030	0.479
S.E.	0.042	0.043	0.045	0.045	0.043	0.096
First half, 1963 to 1986						
Contribution	0.033	0.016	0.320	0.121	0.026	0.515
S.E.	0.061	0.062	0.063	0.063	0.061	0.136
Second half, 1987 to 2011						
Contribution	0.077	0.011	0.218	0.086	0.034	0.424
S.E.	0.057	0.057	0.059	0.058	0.057	0.126

D2. 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 III, we measure the extent to which the observed seasonality pattern "flattens" as we control for different firm characteristics.

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

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

By adding the above controls, the interpretation of b_t changes to that of a marginal effect, shedding light on how informative the lagged same-calendar-month return is about month t returns when holding, for example, industry constant. The slope estimates from these augmented regressions yield a plot

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

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.

Because additional regressors can decrease the covariance between month t and month $t-k$ 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 change in the average regression slope of the actual model to that of the randomized model:

$$\text{Explanatory power of characteristics} = 1 - \frac{\frac{1}{20}\sum_{k=1}^{20}\hat{b}_{k,\text{actual characteristics}}}{\frac{1}{20}\sum_{k=1}^{20}\hat{b}_{k,\text{randomized characteristics}}}, \tag{13}$$

in which the ks index annual lags. We bootstrap the Fama-MacBeth (1973) 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 average regression slope.

Table III reports the estimates for the full sample period and for two subperiods. The full-sample estimate for industry, for example, shows that industry controls account for 5.2% of the seasonalities in individual stock returns. This estimate is associated with a (bootstrapped) standard error of 4.2%.

Size, value, dividend-to-price, market beta, and industry explain a total of 48% (S.E. = 10%) 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 seasonalities, 48% is a conservative estimate of the fraction of seasonalities explained by systematic factors. This estimate is close to the reduction in the intercept in Section III.D.1's time-series regressions.

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 the dividend-to-price ratio have decreased, the role of industries has increased, and the overall explanatory power of the five variables has decreased from 52% to 42%. Thus, although seasonalities are strong in both halves of the data, the factors from which they emanate may have changed. This analysis is only suggestive, however, as the estimated contributions are measured with considerable noise.

Figure 4 plots the average Fama-MacBeth (1973) 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 residual coefficients are far 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. Whereas the characteristics reduce

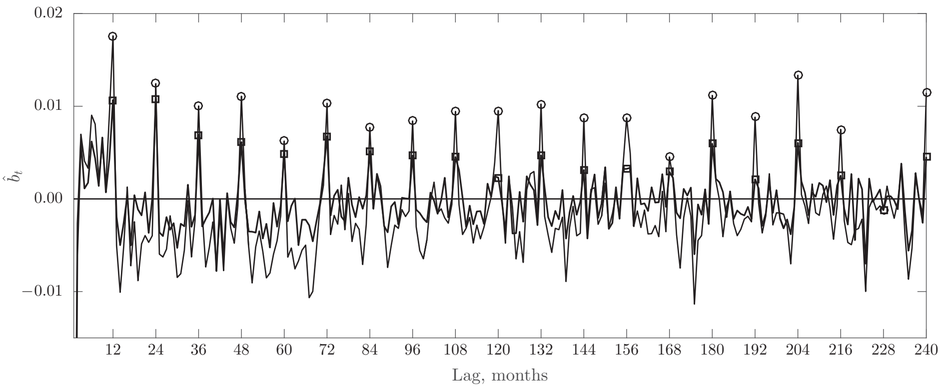

Figure 4. Seasonality in monthly returns with controls for stock characteristics. The thin line plots slope coefficients from univariate Fama and MacBeth (1973) regressions of month t returns on month $t-k$ returns, with k ranging from 1 to 240 months. The thick line plots the same coefficients from regressions that also include decile indicator variables for book-to-market, firm size, dividend-to-price, and market beta as well as indicator variables for the 17 Fama-French industries. The circles and squares denote annual coefficient estimates. The regressions use monthly data from January 1963 through December 2011 for NYSE, Amex, and NASDAQ stocks.

annual slopes 1 through 10 by 39%—we use equation (13) in this computation—the reduction in slopes 11 through 20 is 59%. This difference 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 II and III suggest that most of the seasonalities in individual stock returns can be traced to characteristics such as size and industry. A simple modification to the test in Section C suggests that the combined effect of *other* systematic 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 the 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 fivefold estimate in Section III.C 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. However, the same disclaimer as in Section III.C applies: this analysis does not conclusively prove that the residual seasonalities *originate* from these additional systematic risks, that is, that an investor could not hedge some of these risks while retaining the return spread. Rather, this modification to Section III.C's test suggests that these additional systematic risks must be unrelated to, among other factors, industry, size, and value.

E. Seasonalities in the Cross Section of Anomaly Returns

Return seasonalities are also present in anomalies. We establish the playing field in Table IV, Panel A by reporting the average returns for the market and 15 anomaly strategies. These anomalies are among those analyzed by Stambaugh, Yu, and Yuan (2012), Novy-Marx (2013), and Lewellen (2015). 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 decile 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, earning 1.92% per month (t-value = 5.38).[15] 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 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 IV show that the average return on asset growth is lower, and the evidence for seasonalities less compelling (p-value = 0.05), in non-January data. Return seasonalities are highly significant in joint tests of the 14 anomalies of Table IV. These tests reject the no-seasonality null hypothesis in both the full and the non-January data with p-value < 0.001.[16]

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 p-value < 0.001. The size anomaly is the most prominent example in this class of anomalies. These anomalies 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.

[15] Recall that our analysis uses unconditional break points. With a return of 1.39% per month (t-value = 4.56), the momentum strategy would remain the most profitable strategy if we were to use NYSE break points.

[16] We do not include the Distress anomaly in this test because its returns start in 1974. We estimate seemingly unrelated regressions of returns on 11 calendar month indicator variables for each of the 14 anomalies, and then test the restriction that the slope estimates on the 14×11 indicator variables are jointly zero. The test statistics for the full data and the non-January data are $F(154, 7{,}980) = 2.38$ and $F(140, 7{,}322) = 1.63$.

Table IV

Seasonalities in the Cross Section of Anomaly Returns

Panel A reports average monthly returns for the market portfolio 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 "top" decile is the higher performing extreme decile as reported by previous studies. Anomaly strategies are long the top decile and short the bottom decile. Column "$\bar{r}_{\mathrm{Jan}} = \cdots = \bar{r}_{\mathrm{Dec}}$, 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 in 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. t-values are reported in parentheses. We form these strategies by sorting on either the same- or other-calendar-month returns over the prior 20-year period. The all-but-microcaps sample in Panel B excludes stocks with a market value of equity below the 20th percentile of the NYSE market capitalization distribution. 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	$\bar{r}_{\mathrm{Jan}} = \bar{r}_{\mathrm{Feb}} \cdots = \bar{r}_{\mathrm{Dec}}$, p-Value	Mean	t-Value	$\bar{r}_{\mathrm{Feb}} = \bar{r}_{\mathrm{Mar}} \cdots = \bar{r}_{\mathrm{Dec}}$, 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	
Metastrategy	All Months	Excluding January	All Months	Excluding January
Sort strategies by estimated	1.88	1.26	1.38	1.03
same-calendar-month premiums	(6.43)	(4.73)	(6.78)	(5.74)
Sort strategies by estimated	−0.36	0.10	−0.05	0.22
other-calendar-month premiums	(−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)

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 $\text{var}^{\text{cs}}(\beta) = 0$ in Section I's model. If, on the other hand, some anomalies do well in some months while others do well in other months, then each month an investor can profit by buying the ones with the highest expected returns and selling the ones with the lowest expected returns. Panel B of Table IV examines the profitability of such metastrategies. 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 metastrategy 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-performing anomalies and sells the three worst-performing anomalies based on historical same-month returns earns a monthly return of 1.88% (t-value = 6.43). Remarkably, a strategy based on historical *other*-month returns earns a slightly negative return. That is, rotating through anomalies based on their historical same-calendar-month returns is profitable, but knowing how well an anomaly has done in *other* months is uninformative about how well it will perform this month relative to the others. Our estimates thus do not emerge because historical same-calendar-month returns yield an *unconditional* ranking of anomalies from the best to worst, with the metastrategy then buying the best anomalies (that remain the best) and selling the worst anomalies (that remain the worst).

The seasonalities in anomaly returns are not limited to the month of January. The metastrategy 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 20^{th} percentile of the NYSE market capitalization distribution (Fama and French (2008b)). 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 metastrategy 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.

IV. Seasonalities Everywhere: Risks, Prevalence, and Investability

A. Return Seasonalities and Macroeconomic Risk

Return seasonalities could be linked to salient macroeconomic risks. If, for example, the risk premiums on the Chen, Roll, and Ross (CRR (1986)) variables—industrial production growth, unexpected inflation, change in expected inflation, term premium, and default premium—accrue unevenly over the calendar year, then these macroeconomic seasonalities could get carried over to the cross section of security returns. We examine this possibility in detail in the Internet Appendix using the tests proposed by Chordia and Shivakumar (2002) and Liu and Zhang (2008). We summarize the key findings of those tests here.

The tests in Chordia and Shivakumar (2002) reveal no evidence of a connection between their set of macroeconomic variables—market dividend yield, default spread, term spread, yield on three-month T-bills, and business cycle—and return seasonalities. First, we cannot reject the null hypothesis that the average seasonality payoffs are the same during recessionary and expansionary periods. Second, unlike with the momentum strategy, a seasonality strategy's unexplained payoff—that is, the component unrelated to the macroeconomic variables—greatly exceeds the predicted payoff.

The tests in Liu and Zhang (2008) similarly yield no evidence of a connection between return seasonalities and macroeconomic risk. To be clear, at first glance, the Liu and Zhang (2008) tests suggest that macroeconomic risks explain more than half of the seasonality profits. However, we use a bootstrapping procedure to show that this test suffers from a variant of the problem detailed in Lewellen, Nagel, and Shanken (2010), worsened by the use of the same return information in the left- and right-hand-side portfolios. An adjusted version of the Liu-Zhang test reveals no evidence of a connection between the CRR macroeconomic variables, momentum, or return seasonalities.

B. 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 story whereby short-sales constraints induce asymmetric mispricing. 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.

In the Internet Appendix, we replicate Stambaugh, Yu, and Yuan's (2012) analysis for several of their anomalies as well as for strategies that trade seasonalities in individual stocks and portfolios. The seasonality strategies do not obey the same pattern as the Stambaugh, Yu, and Yuan (2012) anomalies. 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' abnormal profits also originate predominantly from each strategy's long leg. These seasonality results are thus inconsistent with the asymmetric mispricing mechanism posited by Stambaugh, Yu, and Yuan (2012). 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.

C. Pervasiveness of Anomalies

Fama and French (2008b) study the pervasiveness of various anomalies 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, if an anomaly is more pervasive, it is less likely to be 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.

C1. Seasonalities in Different Partitions of the U.S. Stock Market

Table V, 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,[17] 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 and stocks that pay 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 is absent for firms with medium or high credit ratings (Avramov et al. (2007)). Likewise, net issuances are weaker among both value and growth stocks relative to "neutral" stocks. The asset growth anomaly, in turn, is absent among large stocks, growth stocks, and high-dividend-yield stocks.

C2. Seasonalities over Time

Table V, Panel B, reports average returns for the seasonality strategies for different subperiods. In the Internet Appendix, we show that most nonseasonal

[17] We use the Avramov et al. (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.

Table V

Pervasiveness of Anomalies

Panel A measures the performance of value-weighted seasonality, momentum, net issuance, and asset growth strategies within different subgroups of U.S. equities. Microcaps are stocks with a market value of equity 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 use the 30- and 70-percentile break points. The dividend-to-price subsamples separate stocks that do not pay dividends and assign 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 break points 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 in January 1986 and is restricted to firms with credit ratings. We form the 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 the seasonality strategies 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 and end the sample in December 2011. t-values are reported in parentheses.

Panel A: Seasonality and Other Return Anomalies within U.S. Equity Subsamples

	Firm Size			Book-to-Market		
Anomaly	Micro	Small	Large	Growth	Neutral	Value
Seasonality						
Q_1	0.86	0.78	0.34	0.30	0.52	0.87
Q_5	1.48	1.51	1.30	1.35	1.52	1.74
$Q_5 - Q_1$	0.62	0.73	0.96	1.05	1.00	0.87
	(6.44)	(6.88)	(5.66)	(6.07)	(6.00)	(4.51)
Momentum						
$Q_5 - Q_1$	1.69	1.35	0.94	1.34	0.85	0.71
	(6.81)	(5.19)	(3.10)	(5.10)	(2.66)	(2.36)
Net issuances						
$Q_5 - Q_1$	0.76	0.52	0.52	0.47	0.59	0.40
	(4.82)	(3.83)	(3.95)	(2.97)	(5.23)	(2.45)
Asset growth						
$Q_5 - Q_1$	0.62	0.44	0.25	0.11	0.25	0.32
	(4.20)	(3.54)	(1.66)	(0.68)	(1.81)	(2.22)

	Dividend-to-Price			Credit Rating		
Anomaly	= 0	Low	High	Low	Medium	High
Seasonality						
Q_1	0.45	0.31	0.48	0.56	0.52	−0.02
Q_5	1.57	1.45	1.71	1.26	1.37	1.73
$Q_5 - Q_1$	1.11	1.14	1.23	0.70	0.85	1.74
	(6.61)	(5.21)	(6.42)	(2.76)	(4.63)	(4.23)

(*Continued*)

Table V—*Continued*

Panel A: Seasonality and Other Return Anomalies within U.S. Equity Subsamples

	Dividend-to-Price			Credit Rating		
Anomaly	= 0	Low	High	Low	Medium	High
Momentum						
$Q_5 - Q_1$	1.60	1.05	0.83	1.69	0.65	0.24
	(6.13)	(3.34)	(2.39)	(3.19)	(1.45)	(0.54)
Net issuances						
$Q_5 - Q_1$	0.88	0.48	0.37	1.01	0.56	0.54
	(4.64)	(3.66)	(3.47)	(2.60)	(2.44)	(2.88)
Asset growth						
$Q_5 - Q_1$	0.37	0.39	0.10	1.03	0.34	0.26
	(2.06)	(2.79)	(0.76)	(2.33)	(1.81)	(1.33)

Panel B: Returns on Seasonality Strategies by Subperiod

	Period				
Strategy	1963 –1972	1973 –1982	1983 –1992	1993 –2002	2003 –2011
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)

anomalies flicker in and out of existence across the same subperiods. Momentum is the strongest, disappearing only in the most recent period. Seasonality strategies resemble momentum in their perseverance. Most 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 to 2011 subperiod, the composite strategy is marginally significant with a t-value of 1.75, which is a respectable result given that the best-performing nonseasonal anomaly (net issuances) has a t-value of 1.3 during this period.[18]

C3. Seasonalities in Other Asset Classes

Seasonalities are not confined to U.S. equities. Table V, 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 December 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 United States. These data run from January 1970 through December 2011. We form 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 V, Panel C, shows that the average return on a long-short strategy that trades 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. Seasonalities in both commodities and country indexes also exist in non-January data.

C4. 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 (1973) regressions of day t returns against day $t - k$ returns. We

[18] See the Internet Appendix for details.

[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 et al. (2013) for a description of these data.

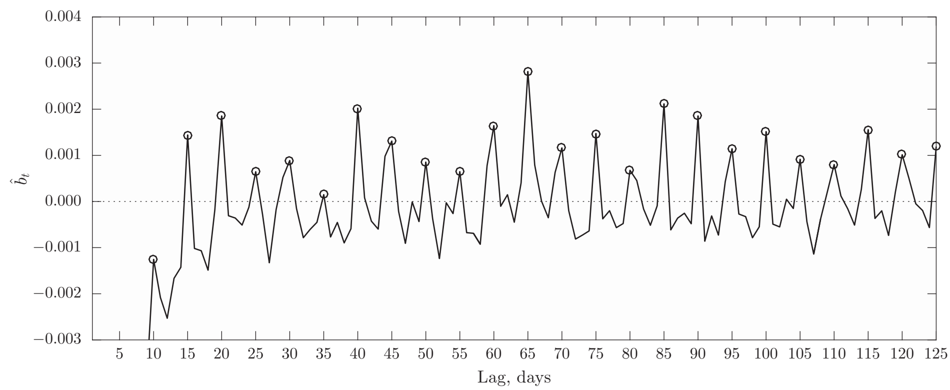

Figure 5. Day-of-the-week seasonalities in stock returns. This figure plots slope coefficients from univariate Fama and MacBeth (1973) regressions of day t returns on day $t-k$ returns, where k ranges from 1 to 125. Lags are measured in trading days and adjusted for market closures. These regressions 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. The regressions use daily data from January 1963 through December 2011 for NYSE, Amex, and NASDAQ stocks.

measure lags in trading days so that lags that are multiples of five correspond to the same weekday even when there are market closures. 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 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 now 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 (Jegadeesh (1990)). 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 also generate significant differences in average returns 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).[20]

[20] The Internet Appendix reports the t-values associated with Figure 5's regression coefficients, along with average returns for various portfolio sorts based on day-of-the-week seasonalities.

D. Return Correlations between Seasonality Strategies

Table VI 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.[21] Consider, for example, the strategies that trade seasonalities within small-cap stocks and high-dividend-yield stocks. The estimates in Table V indicate that both strategies are highly profitable: their average monthly returns are 0.73% ($t = 6.88$) and 1.23% ($t = 6.42$). Yet, the correlation between these two strategies is just 0.17. To gain perspective on these correlations, in the Internet Appendix, we report the same correlation matrix 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. In Table VI, the lowest correlation is 0.13.

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 combining different seasonality 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 Sharpe ratio of the ex-post mean-variance efficient portfolio of all nine seasonality strategies is 1.52.

Panel B shows that return correlations drop nearly 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 strategy and the country index strategy, 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.

The low correlations reported in Table VI are consistent with a world in which seasonalities originate from multiple risk factors. If different factors drive the returns on U.S. equities and commodities, the seasonalities are independent of each other even though they "look" the same on the surface. They are related to different risks. The within-asset-class correlations can also be low if different groups of stocks load differently on the same systematic factors.

Let us use the portfolio seasonality strategies for size and industry from Table I to illustrate the magnitude of the correlations. Because these

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

Table VI

Correlations between Seasonality Strategies

Panel A reports correlations between seasonality strategies that trade stocks within different subgroups of U.S. equities. These strategies select stocks based on the average same-calendar-month return over the prior 20 years. The sample period in Panel A is from July 1963 through December 2011. Panel B 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 C reports weights and ex-post maximum Sharpe ratios for strategies formed from market, value, size, momentum, and seasonality factors. The U.S. equity seasonality factors in Panel C are HML-like factors that are constructed by sorting stocks into six portfolios using NYSE break points based on the size and historical same-month (or same-day) returns. Panels B and C use data from January 1975 through December 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 Seasonalities in Different Asset Classes and Frequencies

	Monthly Stocks	Daily Stocks	Countries	Commodities
Monthly U.S. stocks	1			
Daily U.S. stocks	0.05	1		
Countries	0.02	0.00	1	
Commodities	0.11	0.01	−0.09	1

Panel C: Portfolio Weights and Maximum Ex-Post Sharpe Ratios

					Seasonalities				
#	Market	Size	Value	Momentum	Monthly U.S. Equity	Commodities	Countries	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

strategies trade well-diversified portfolios, we can view them as trading seasonalities in size and industry *factors*. Although each strategy is profitable—the *t*-values are 6.6 and 3.8—their correlation is just 0.09. Now consider two seasonality strategies, r_a and r_b, that derive their profits from these "base" seasonalities:

$$r_a = \beta_{a,1} S_{\text{size}} + \beta_{a,2} S_{\text{industry}},$$
$$r_b = \beta_{b,1} S_{\text{size}} + \beta_{b,2} S_{\text{industry}},$$

where we assume that the strategies are well diversified so that the residual risks are negligible. The two strategies will be perfectly positively correlated only if the factor loadings are proportional to each other, that is, $\beta_a = k\beta_b$ for some constant $k > 0$. The correlation ranges from -1 to 1 depending on the factor loadings (Roll (2013)). If, for example, the loadings are $\beta_{a,1} = 0.96$ and $\beta_{a,2} = 0.04$ for strategy a and $\beta_{b,1} = 0.04$ and $\beta_{b,2} = 0.96$ for strategy b, then the correlation between r_a and r_b is 0.17—which is the same as the correlation between the seasonalities in small-cap stocks and high-dividend-yield stocks in Table VI. Alternatively, if the loadings are $\beta_{a,1} = 0.68$ and $\beta_{a,2} = 0.32$ for a and $\beta_{b,1} = 0.37$ and $\beta_{b,2} = 0.63$ for b, then the correlation between a and b matches the highest correlation of 0.85 found in Table VI. The low correlations in Table VI do not imply that the seasonalities are firm-specific. Seasonality strategies constructed from the universe of U.S. equities can have fairly low correlations even if the seasonalities stem from just a few factors.

E. Investment Perspective

Table VI, Panel C, 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 to 1.69 after also 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 not only crowds out 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 are remarkably important in explaining the cross section of returns.

The monthly seasonality strategies are potentially feasible investment strategies, and hence it is instructive to compare them to short-term reversals as both strategies require almost 100% monthly turnover. Frazzini, Israel, and Moskowitz (2012) use trading data from a large hedge fund and estimate 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 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 (Novy-Marx and Velikov (2015)). 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.

V. Discussion and Conclusions

Return seasonalities are remarkably pervasive. They permeate all partitions of the U.S. equity markets, arise at different frequencies, and are 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 market emerge 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 from commodities, it should come as no surprise that the seasonalities found within these two asset classes are unrelated to each other. Some of the factors generating seasonalities are the same as those generating differences in average returns—seasonalities in the size factor represent the single largest source of seasonalities in individual stock returns—but others are associated with only small differences in average returns. Industry and dividend-to-price factors, for example, are important for seasonalities but less so for average returns (e.g., Fama and French (1992, 1997)).

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 the extent to which they matter for 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 that 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, mean-variance optimizing investors would invest less than 10% of their assets in the market portfolio—and almost 50% in the seasonality factor. These computations support 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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Supporting Information

Additional Supporting Information may be found in the online version of this article at the publisher's website:

Appendix S1: Internet Appendix.