When low beats high: Riding the sales seasonality premium

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Abstract

This paper examines whether predictable seasonal patterns in firm fundamentals generate time variation in stock returns. And they find that stock return is counter seasonal, which means that low(high)-sales season firm has high(low) stock return. This seasonality premium cannot be captured by existing asset pricing model and is independent with other anomalies.

1. Data and methodology

2. Main findings

3. Economic mechanisms

Data and methodology

Stock data – Main sample consists of all nonfinancial US stocks on the CRSP(Center for Research in Security Prices) files listed on the NYSE, Amex and Nasdaq exchange.

Accounting data – Annual and quarterly fundamental files in Compustat.

Final sample consist 1,509,794 firm month observations and 14,008 firms over 1970 to 2017.

Data and methodology

SEA is used to measure seasonality in quarter q and year t.

$$SEAqt = SALESqt/ANNUALSALESt$$

Negative quarter and annul sales are excluded.

If sum of 4 quarters sales are not equal to annul sales, they include only firm-year observations in which the sum of quarterly sales is between 95% and 105% of total annual sales.

They also examine the persistence of SEAqt over time. The result is that the seasonality is persistent over time.

Advantages of using sales: obviating negative values, less likely to be affected by seasonal changes in capital structure or by the presence of unusual and nonrecurring items

Main findings

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1. Seasonal patterns can generate an α-8.4% with t-test of 4.56, when in five-factor model, by longing low-season stocks and shorting high-season stocks.

2. This seasonal effect is stronger in large size firm.

3. Sales seasonality factor is uncorrelated with the range of important asset pricing factors in the literature.

4. This seasonal effect is independent with other previously documented seasonal anomalies.

1. Positive α

They divided all the firms into 10 groups according to sales season (SEA).

Equal-weighted and value-weighted excess returns of 10 different groups are calculated by three assets pricing model: CAPM, Fama and French three-factor model, Fama and French five-factor model.

The α of long-short strategy is the difference between lowest decile and highest decile.

1. Positive α (cont.)

Equal-weighted			
	Lowest	Highest	L-H
CAPM	0.60%(0.3)	-2.52%(-1.21)	3.12%(2.88)
Three-factor	-0.72%(-0.5)	-3.96%(-2.79)	3.24%(2.95)
Five-factor	1.92%(1.49)	-1.56%(-1.11)	3.48%(3.09)
value-weighted			
	Lowest	Highest	L-H
CAPM	2.76%(1.75)	-5.04%(-3.37)	7.8%(4.32)
Three-factor	4.68%(3.43)	-4.2%(-2.94)	8.88%(4.98)
Five-factor	6.72%(4.86)	-1.68%(-1.21)	8.4%(4.56)

The value-weighted α of five-factor model is 8.4% and it is significant.

2. Stronger in large firm

According to the results above, obviously, the value-weighted α is larger than equal-weighted α under same pricing model, which indicates that stronger sales seasonality effect among large firms.

To test this finding, they divided data into five groups according to firm size. The five-factor α of long-short strategy is calculated.

For the smallest group the α is 2.04%, than 8.28% for the middle groups, 5.04% for the largest group. The results shows that the sales seasonality premium is larger in large firm.

3. Uncorrelated with other factors

It is important to test the correlation between sales seasonality effect and existing asset pricing factors.

They estimate Pearson's correlation coefficients between existing asset pricing factors and a factor based on the sales seasonality strategy (SEAF).

SEAF is equal to the returns of a low-sales season portfolio minus the returns of a high-sales season portfolio.

Existing factors are (i) market excess return (MKTrf),
(ii) size's small minus big (SMB),
(iii) book to market's high minus low (HML),
(iv) investment's conservative minus aggressive (CMA),
(v) profitability's robust minus weak(RMW),
(vi) momentum's up minus down (UMD).

3. Uncorrelated with other factors(cont.)

Variable	MKTRF	SMB	HML	UMD	CMA	RMW	SEAF
Mrktf		0.238	−0.273	−0.148	−0.384	−0.250	0.001
SMB			−0.056	−0.037	−0.035	−0.377	0.025
HML				−0.186	0.692	0.121	−0.121
UMD					0.003	0.104	0.122
CMA						0.038	−0.068
RMW							−0.023
SEAF							1.000

This results confirm that sales seasonality is uncorrelated with existing asset pricing factors.

4. Independence

Compared with earning seasonality shown in Chang et al.(2017), despite an apparent resemblance, their sales seasonality measure is different.

First, Chang et al. focus on the month of earning announcements following high or low earning seasons. They focus on the quarters in which firms' sales are low or high.

Second, investment strategies are totally different. Chang et al. long high-season stocks and short low-season stocks. They long low-season stocks and short high-season stocks.

Thus, they remove all earning announcement firm-month observations to remove effects from Chang et al. The result still shows that their long-short strategy make a significant α.

4. Independence (cont.)

Another anomaly is reported by Heston and Sadka (2008) who find that firms have abnormal returns every year in the same month. The main difference is that Heston and Sadka use a return-based measure of seasonality, whereas they use sales a measure which only decided by the market. This difference is vital because Keloharju et al. (2016) show that return seasonality is driven by seasonality in the market.

For robustness, authors copy the Heston and Sadka measure of seasonality and drop their highest and lowest deciles from authors' sample. The result is that regardless of return seasonality, sales seasonality still make α.

Economic mechanisms

1. Investment and financing decisions and sales seasonality

2. Investor attention and sales seasonality

3. Stock price efficiency

1. Investment and financing decisions

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They examine the changes in corporate investment and financing decisions on sales seasons. In these examination, they controlling for size, book-to-market, profitability, firm fixed effects.

Hypothesis: In high-season, firms should have high investment and low leverage. In low-season, firms should have low investment and high leverage.

1. Investment and financing decisions (cont.)

Investment decisions: SEA is the measure of seasonality. Investment changes in quarter q (IAQ) measures the investment decision. The change also be divided into three parts: i) the change in current assets at quarter q relative to total assets at q − 1 (IACQ), (ii) the change in net property plant and equipment at quarter q relative to total assets at q − 1 (PPEQ), and (iii) the change in inventories at quarter q relative to total assets at q − 1 (INVQ).

Consistent with hypothesis, the result is that coefficients between SEA and three proxies for corporate investment is significant positive. This means that in high sale season firms tend to have more investment, which will lead to low return in stocks in high-season.

1. Investment and financing decisions (cont.)

Financing decisions: SEA is still the measure of seasonality.
Change in bool leverage (BLChange) and market leverage (MLChange) from quarter q-1 to q are proxies for changes in leverage ratios.

The result is consistent with the hypothesis, both measures of leverage are negatively correlated with SEA. Namely, in high-season, firms will be in low leverage which means less risk and low return in stocks.

Additionally, CDs spreads also can explore the risk of firms. They also examine the relationship with seasonality and CDs spreads. A negative correlation is shown in the results. Thus, in high-season, firm with low CDs spreads will have low return.

2. Investor attention

According to Merton (1987), sales seasonality premium may serve as compensation for holding neglected stock. Thus, the hypothesis is that proxy for level of investor attention should be high in high-season.

Advertising expense and breadth of ownership is the proxies for investor attention. Advertising expense can be a proxy for investor attention, because Grullon et al. (2004) find that spend more on advertising could attract more shareholders.

The results of the regression, which control for size, book-to-market, profitability, firm fixed effect, two proxies have positive relationship with SEA. This support the previous hypothesis.

2. Investor attention(cont.)

According to Merton model, investors tend to make their portfolio by the securities they knows. Thus less attention stock attract less investor, which result in overweighting the stocks neglected in some investors' portfolio. This can increase idiosyncratic risk, which lead to more required return of investors. In behavior finance, investors will be too optimistic to high-sale season stocks and too pessimistic to low-sale season stock.

3. Stock price efficiency

This another way to explain why low attention stock means high return. Investors pay less attention to stocks. Thus, in low-sales season, stock price including less new information. This will lead to high marginal costs in getting information. Investors require more returns for this.

Post-earning announcement drift as a proxy for stock price efficiency.
Hypothesis: if high levels of investor attention make stock prices more efficient, the post-earning drift should be stronger during low-sales season.

The result is that marginal benefit of acquiring information during low season is lower , which means that high attention could make stock price efficient.