When low beats high: Riding the sales seasonality premium

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Contents

- Introduction
  - Background
  - Literature
  - Motivation
  - Contribution
  - Design
- Data
- Method
- Results
- Conclusion

1.Backgound

- Seasonal patterns in fundamentals can generate time variation in stock returns.
- People study this issue from different perspectives in the time dimension. Many of them focus on short-term, but few people study the impact of long-term regular seasonal changes on returns. For example: the variability in firms’ sales.
- Seasonal fluctuations in supply and demand can account for a significant fraction of the variability in firms’ sales.
- Sales are always nonnegative and should not be affected either by seasonal changes in capital structure or by the presence of unusual and nonrecurring items.

1.Backgound

restaurant chain Denny's

25%-25%-25%-25%

tax service provider H&R Block

68% tax season
7% low season

Different performance in stock market

1.Literature

- Hartzmark and Solomon (2018): Many common firm events tend to be associated with large positive returns in the period when the events are predicted to occur——there is seasonal effects in stock returns
- Chang et al. (2017): (a seasonality measure based on earnings announcements) high-earnings seasonality stocks outperform low-earnings seasonality stocks during the earnings announcement month.
- Berk et al. (1999):as firms convert most of their growth opportunities into assets in place during their high seasons, their average systematic risk declines, thereby reducing firms’ expected returns

1.Literature

- Da et al., 2011 ; Lou, 2014: the relation between investor attention and stock returns is positive and temporary in the short run
- Fang and Peress (2009): this relation is negative over comparatively longer horizons.
- Merton (1987): returns should be higher during periods when stocks become comparatively more neglected

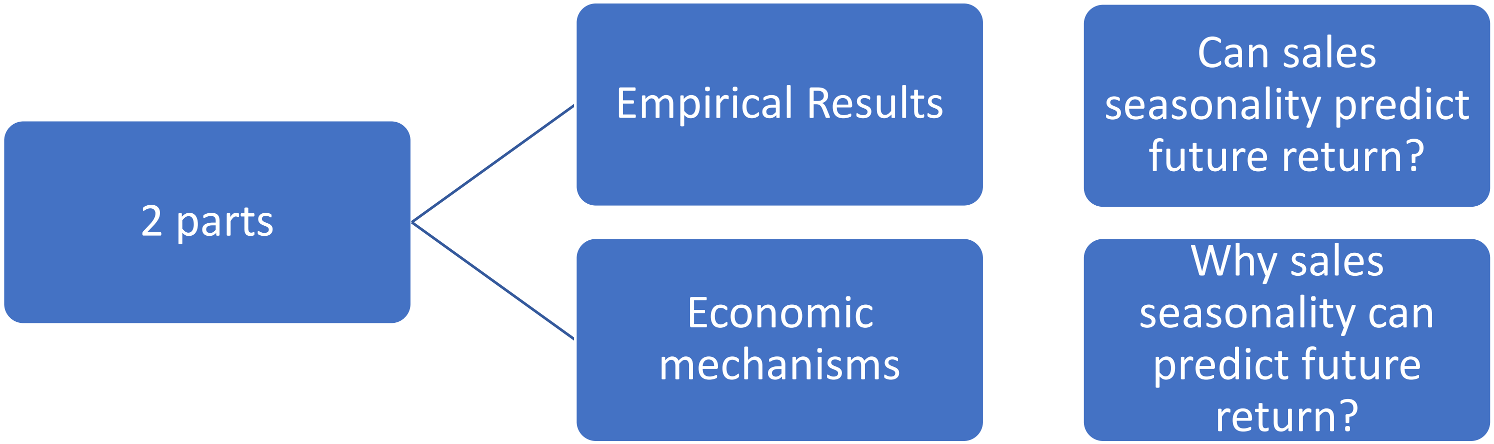
1.Motivation

- Most of these studies focus on the short-term price behavior around corporate events such as earning announcements and corporate distributions.
- What about the longer quarterly seasonal pattern that captures other dynamics of the firms’ product markets?

1.Contribution

- This article studies the relationship between the company’s seasonality and future earnings from a novel "market sales" perspective.
- Prove that seasonal patterns in investment and financing decisions, as well as patterns in the level of investor attention, can potentially explain certain seasonal effects in stock returns.
- This paper contributes to the literature examining the relation between measures of investor attention and stock returns

1.Design


2 parts
Empirical Results
Economic mechanisms
Can sales seasonality predict future return?
Why sales seasonality can predict future return?

2.Data

- all nonfinancial US stocks of NYSE, Amex, and Nasdaq exchanges
- All yearly variables are formed at the end of June in year t using accounting information from Compustat at the end of fiscal year t–1
- 1972.01 to 2017.12
- sales seasonality: the sales in quarter q of year t scaled by the annual sales in year t
  - $SEA_{qt} = SALES_{qt} / ANNUALSALES_t$
- Why Sales?
- Because this variable is always nonnegative and should not be affected either by seasonal changes in capital structure or by the presence of unusual and nonrecurring items.

2.Data

- mitigate any possible outlier impact:
- $AVGSEA_{qt}$= the average of SEA_{qt} over years t−2 and t−3
- use $AVGSEA_{qt}$ in year t−2 to predict SEA_{qt} in year t to ensure that seasonality data are available to investors at the time of the portfolio formation

Panel A: All sample

		T+ 1				T + 2	
		Low-season portfolio	High-season portfolio			Low-season portfolio	High-season portfolio
T	Low-season portfolio	$\boxed{66.13\%}$	2.34%	T	Low-season portfolio	$\boxed{50.99\%}$	5.42%
	High-season portfolio	2.28%	$\boxed{67.86\%}$		High-season portfolio	5.40%	$\boxed{53.69\%}$

Panel B: Below-median SEAACC

		T + 1				T + 2	
		Low-season portfolio	High-season portfolio			Low-season portfolio	High-season portfolio
T	Low-season portfolio	$\boxed{87.69\%}$	0.00%	T	Low-season portfolio	$\boxed{71.61\%}$	0.48%
	High-season portfolio	0.00%	$\boxed{88.63\%}$		High-season portfolio	0.42%	$\boxed{71.06\%}$

Panel C: Above-median SEAACC

		T + 1				T + 2	
		Low-season portfolio	High-season portfolio			Low-season portfolio	High-season portfolio
T	Low-season portfolio	$\boxed{56.99\%}$	3.75%	T	Low-season portfolio	$\boxed{38.10\%}$	8.72%
	High-season portfolio	3.50%	$\boxed{60.66\%}$		High-season portfolio	8.59%	$\boxed{43.18\%}$

Panel A: the fraction of those firms in the lowest and highest sales seasonality portfolios at time t that remain in the same portfolios at time t+1 and t+2.

the probability of a firm's moving from the lowest (highest) decile at time t to the highest (lowest) decile at time t+1 is less than 3%.

Panel B uses a subsample of firms below the $SEAVAR_{qt}$ median and then sorts on AVGSEA deciles.

$SEAVAR_{qt}$= the absolute value of the change in SEA_{qt} between t−3 and t−2

4.Results

- 2 parts
  - Empirical Results
    - the predictive power of sales seasonality
    - whether the volatility of quarterly sales plays a role in the sales seasonality premium
    - whether the sales seasonality premium are driven by firms’ fixed characteristics
    - whether the sales seasonality effect corresponds to existing asset pricing factors
  - Economic mechanisms

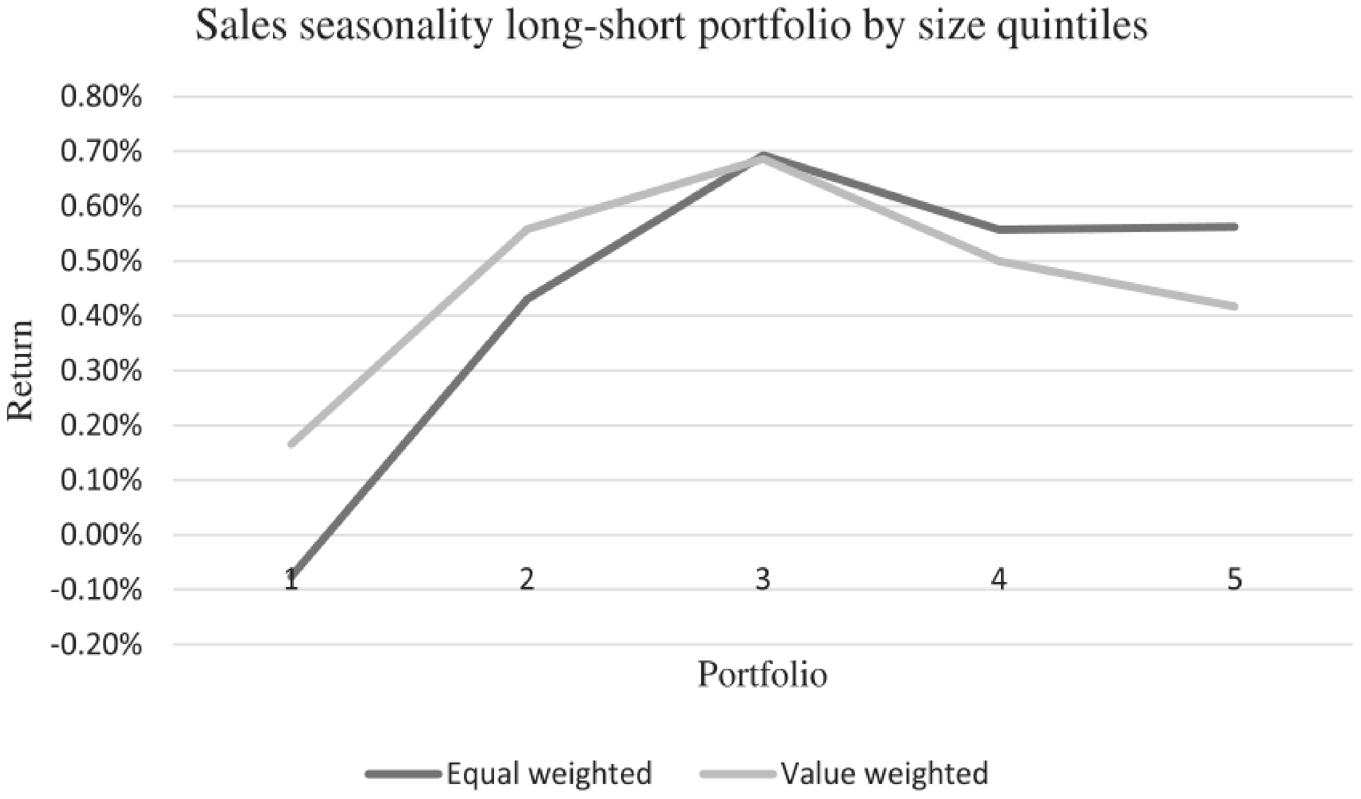
4.Results_Q1

- the predictive power of sales seasonality
- allocate stocks at the beginning of each month into deciles based on $AVGSEA_{qt}$ in year t−2

	Panel A: EW	Panel B: VW
	L-H	L-H
CAPM		
Alpha	0.26	0.65
	[2.88]	[4.32]
Mrktf	0.00	0.09
	[0.14]	[2.74]
Fama-French		
Alpha	0.27	0.74
	[2.95]	[4.98]
Mrktf	−0.01	0.03
	[−0.58]	[0.86]
SMB	0.06	0.13
	[1.98]	[2.55]
HML	−0.03	−0.22
	[−0.81]	[−4.19]
Fama-French		
Alpha	0.29	0.70
	[3.09]	[4.56]
Mrktf	−0.02	0.04
	[−0.76]	[1.18]
SMB	0.05	0.14
	[1.39]	[2.71]
HML	−0.03	−0.28
	[−0.68]	[−4.01]
RMW	−0.05	0.08
	[−1.16]	[1.10]
CMA	−0.01	0.09
	[−0.11]	[0.84]

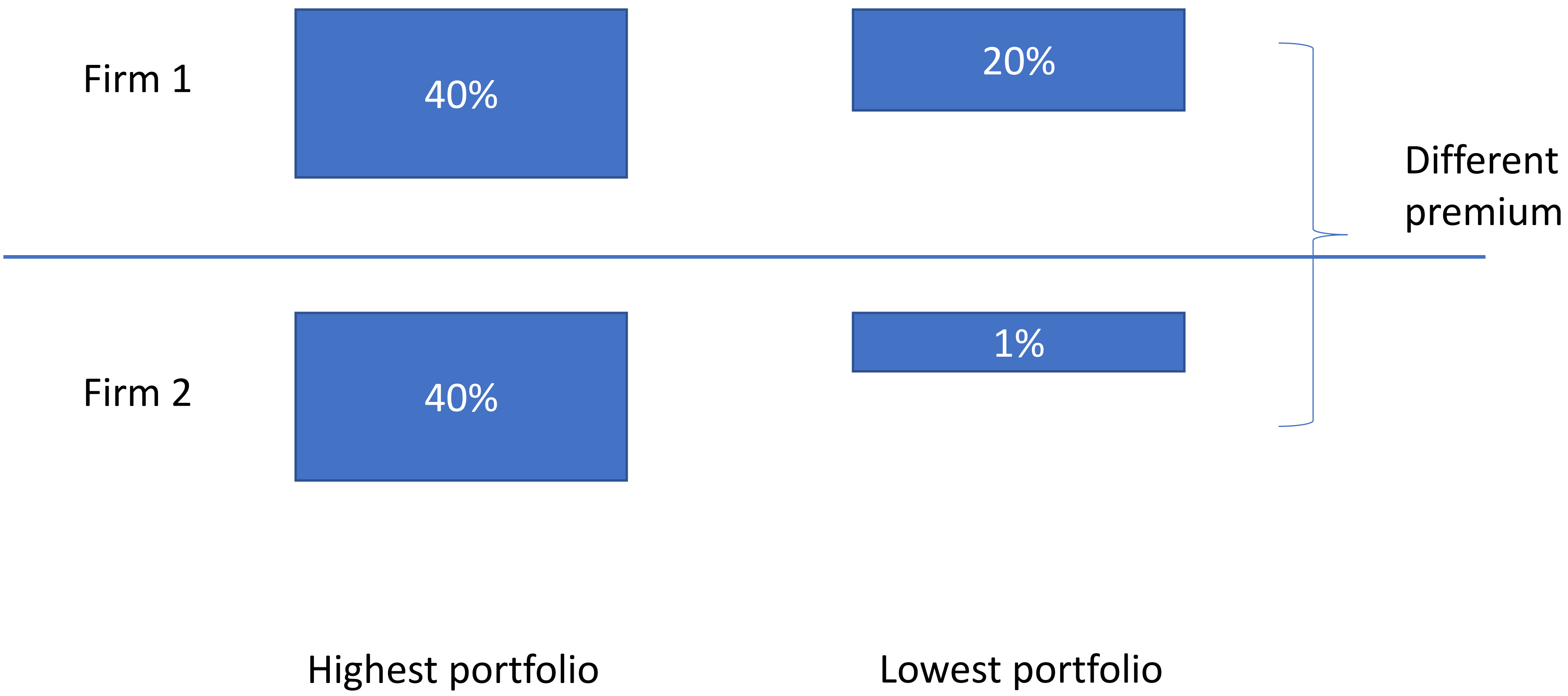
the value-weighted returns are larger than the equal-weighted returns indicates a stronger sales seasonality effect among large firms

- divide the data into size quintiles using NYSE breakpoints
- the Fama–French five-factor alphas of our long-short strategy for each size quintilethe alphas increases from quintile 1 to quintile 3 and then declines to quintile 5——the sales seasonality premium is not a small firm phenomenon



4.Results_Q2

- **whether the volatility of quarterly sales plays a role in the sales seasonality premium**



4.Results_Q2

$$SEARANGE_{qt} = \max_{n=0\ to\ 3}(AVGSEA_{q-n}) - \min_{n=0\ to\ 3}(AVGSEA_{q-n}).$$

Panel A: SEARANGE

	1	2	3	4	5	6	7	8	9	10	L-H
Alpha	−0.01	0.03	0.01	0.02	0.04	0.18	0.12	0.05	0.34	0.06	0.07
	[−0.10]	[0.40]	[0.10]	[0.23]	[0.51]	[2.06]	[1.52]	[0.51]	[2.93]	[0.62]	[0.54]

Panel B: Sales Seasonality within below-median SEARANGE

	1	2	3	4	5	6	7	8	9	10	L-H
Alpha	−0.01	−0.02	0.11	0.15	0.13	0.09	−0.05	−0.12	−0.08	−0.07	0.06
	[−0.12]	[−0.18]	[1.17]	[1.67]	[1.42]	[1.04]	[−0.53]	[−1.22]	[−0.73]	[−0.68]	[0.36]

Panel C: Sales Seasonality within above-median SEARANGE

	1	2	3	4	5	6	7	8	9	10	L-H
Alpha	0.59	0.60	0.45	0.28	−0.05	0.15	−0.12	0.02	−0.07	−0.32	0.91
	[4.82]	[4.50]	[3.82]	[2.57]	[−0.44]	[1.31]	[−0.94]	[0.17]	[−0.52]	[−2.08]	[4.92]

- **Panel A:** value-weighted returns sorted on $SEARANGE_{qt}$
- **Panel B/C:** examine the effect of sales volatility on sales seasonality premium
- split the sample into high and low volatility groups based on $SEARANGE_{qt}$ and then form deciles based on $AVGSEA_{qt}$ in year t−2

4.Results_Q3

- **whether the sales seasonality premium are driven by firms' fixed characteristics**
- verify that the sales seasonality premium are driven by firms' fixed characteristics(i.e., product market dynamics) and not by unusual recent changes in quarterly sales:
- form portfolios based on $AVGSEA_{qt}$ in year t−n(n=2~20)

	Equal weighted			Value weighted		
n	CAPM	FF3	FF5	CAPM	FF3	FF5
2	0.28 [2.35]	0.29 [2.43]	0.35 [2.85]	0.82 [4.27]	0.88 [4.66]	0.86 [4.36]
3	0.41 [3.41]	0.43 [3.59]	0.50 [4.01]	0.62 [3.00]	0.70 [3.48]	0.74 [3.56]
4	0.36 [3.25]	0.36 [3.30]	0.46 [4.06]	0.76 [3.85]	0.84 [4.49]	0.90 [4.58]
14	0.67 [5.44]	0.66 [5.37]	0.71 [5.51]	0.59 [3.05]	0.58 [2.95]	0.67 [3.34]
15	0.71 [5.61]	0.72 [5.61]	0.76 [5.71]	0.50 [2.59]	0.48 [2.44]	0.51 [2.53]
20	0.66 [4.46]	0.67 [4.46]	0.69 [4.44]	0.46 [2.39]	0.46 [2.37]	0.48 [2.35]

- forming portfolios using stale measures of $AVGSEA_{qt}$ do not change our main findings——the sales seasonality premium is a fixed firm characteristic priced in the cross-section of stock returns.

4.Results_Q4

- **whether the sales seasonality effect corresponds to existing asset pricing factors**

		sales seasonality		
		Low	Medium	High
Size	Big	B/L	B/M	B/H
	Small	S/L	S/M	S/H

- the sales seasonality factor: SEAF=$\frac{1}{2}$(SH+BH-SL-BL)
- ①Pearson’s correlation coefficients
- ②Sharpe ratio
- ③Fama Macbeth

4.Results_Q4

Panel A: Pearson correlations							
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

Panel B: Sharpe ratios			
Variable	Mean%	Std dev.	Annualized Sharpe ratio
Mrktf	0.56	0.045	0.434
SMB	0.19	0.030	0.221
HML	0.36	0.029	0.428
UMD	0.66	0.044	0.524
CMA	0.31	0.020	0.551
RMW	0.28	0.023	0.426
SEAF	0.31	0.015	$\boxed{0.746}$

- ①the sales seasonality factor to be uncorrelated with the range of important asset pricing factors in the literature.
- ②SEAF has the strongest performance relative to the Fama-French factors.

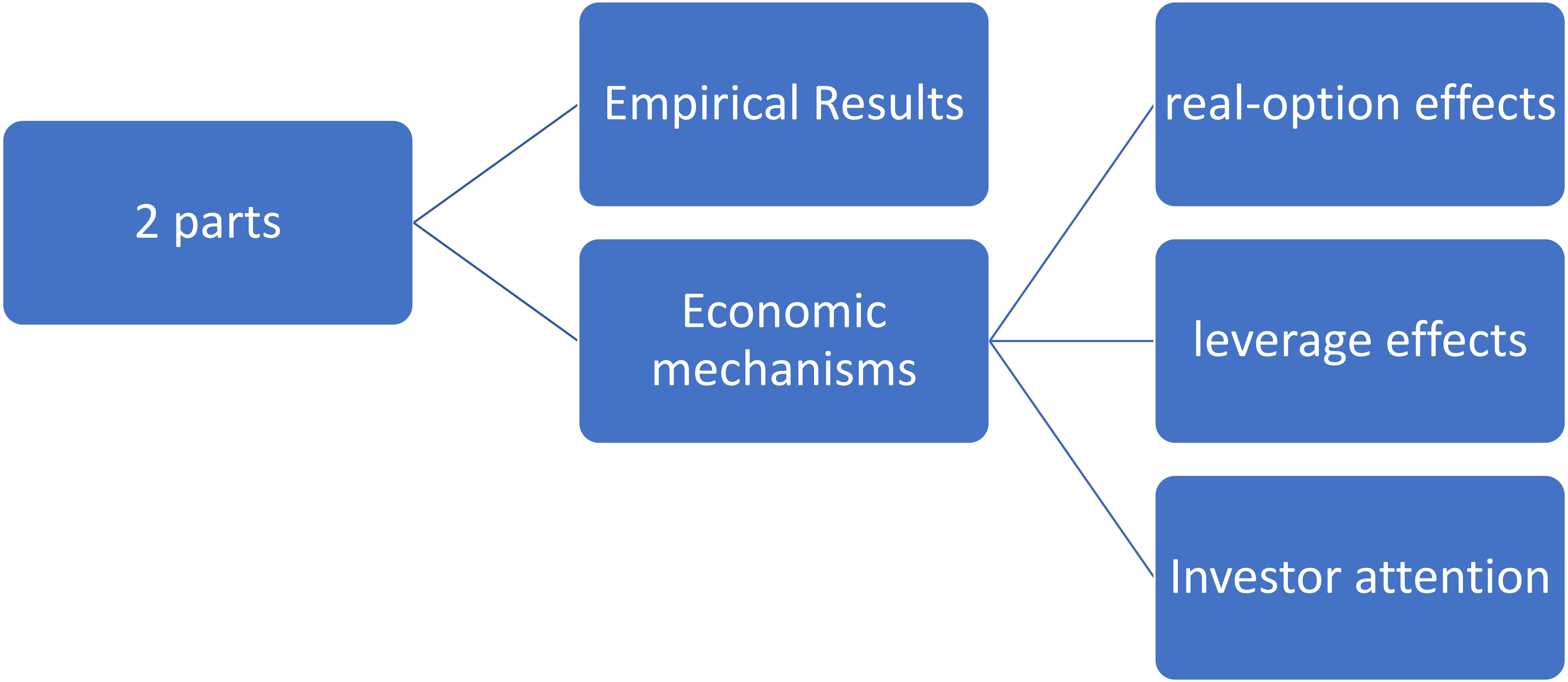
4.Results_Q4

	Full sample		Small firms		Big firms	
	Model 1	Model 2	Model 1	Model 2	Model 1	Model 2
Intercept	0.917	0.919	1.025	1.026	0.711	0.713
	[3.47]	[3.47]	[3.41]	[3.41]	[3.44]	[3.45]
SEA	−0.087	−0.093	−0.057	−0.067	−0.193	−0.184
	[−4.36]	[−5.04]	[−2.41]	[−3.11]	[−7.29]	[−7.61]
LogME		−0.179		−0.176		−0.045
		[−2.08]		[−2.19]		[−1.09]
BM		0.183		0.181		0.130
		[3.34]		[3.01]		[2.67]
IA		−0.236		−0.263		−0.114
		[−6.84]		[−6.58]		[−3.34]
GPA		0.126		0.131		0.089
		[2.62]		[2.39]		[2.00]
MOM		0.130		0.131		0.163
		[1.61]		[1.56]		[2.07]
OA		−0.030		−0.022		−0.016
		[−0.91]		[−0.59]		[−0.53]
HS 36		0.200		0.194		0.139
		[5.95]		[5.53]		[3.52]

① sales seasonality is negatively correlated with future stock returns.

② the sales-seasonality premium is not a small firm phenomenon

4.Result


2 parts
Empirical Results
Economic mechanisms
real-option effects
leverage effects
Investor attention

4.Result_T1

- **real-option effects**
- Berk et al.(1999): if firms significantly increase their investment around their high sales seasons, then their expected returns should be lower during these periods because they have converted most of their growth opportunities into assets in place
- sales seasonality and proxies for corporate investment （+）
- **IAQ:** the relative change in total assets from quarter q−1 to q.
- **IACQ:** the change in current assets from quarter q−1 to q with respect to total assets of quarter q−1 .
- **PPEQ:** the change in net property, plant, and equipment fixed assets from quarter q−1 to q with respect to total assets of quarter q−1 .
- **INVQ:** the relative change in inventories from quarter q−1 to q with respect to total assets of quarter q−1

4.Result_T1

Panel A: Investment variables								
Period	*IAQ* 1973–2016		*IACQ* 1973–2016		*PPEQ* 1973–2016		*INVQ* 1973–2016	
SEA_q	0.011 [13.25]		0.009 [12.39]		0.001 [8.14]		−0.005 [−15.10]	
SEA_{q+1}		0.012 [15.73]		0.008 [12.34]		0.001 [15.41]		0.004 [16.17]
Observations	242,519	236,351	234,672	228,690	241,857	235,729	234,779	228,826
R^2	12.26%	12.49%	10.12%	10.20%	20.13%	20.26%	11.15%	10.48%

- the coefficients are positive and statistically significant
- firms invest more prior to, and during, their high-sales seasons.

4.Result_T2

- **leverage effects**
- the possibility that firms use the higher cash flows generated during high seasons to reduce their leverage, thereby leading to a reduction in expected returns
- sales seasonality and changes in leverage （-）

- proxies for changes in leverage ratios:
- the change in book leverage (**BLChange**) from quarter q−1 to q
- market leverage (**MLChange**) from quarter q−1 to q
- book leverage: total debt divided by total assets
- market leverage: total debt divided by total market capitalization

4.Result_T2

Panel B: Financing variables				
	BLChange		*MLChange*	
Period	1973–2016		1973–2016	
SEA_q	−0.004		−0.001	
	[−15.40]		[−7.88]	
SEA_{q+1}		0.002		0.003
		[6.55]		[14.14]
Observations	215,852	210,159	221,333	215,577
R^2	6.15%	5.26%	9.19%	9.48%

① both measures of leverage are negatively correlated with $SEA_{i,q}$——firms pay off a portion of their debt during their high seasons while increasing their leverage during their low seasons.

② firms increase their leverage prior to their high season——the increase in investment around high-sales seasons shown in Panel A is being financed with debt.

4.Result_T3

- **Investor attention**
- Merton, 1987:when stocks become neglected, some investors end up with portfolios that overweight the neglected stocks, which exposes them to excessive idiosyncratic risk. These investors require a risk premium:
- R_k-R_k^*=$\delta x_k \sigma_k^2 \frac{(1-q_k)}{q_k} \frac{R_k^*}{R_k}$
- R_k: the incomplete information expected return
- R_k^*: the complete information expected return
- δ: the representative investor’s degree of risk aversion
- x_k: the fraction of the market portfolio invested in security k
- σ_k^2: idiosyncratic volatility of security k
- q_k: the fraction of all investors who know about security k
- sales seasonality and proxies for the level of investor attention （+）

4.Result_T3

- proxies for investor attention

① $\ln(ATTE)$: the natural log of one plus the number of nonrobot views of EDGAR documents in quarter q of year t

② $\ln(AdsDollar)$: the natural log of one plus the total advertising expenses in quarter q of year t

③$\ln(AdsUnits)$: as the natural log of one plus the total advertising units in quarter q of year t

④ $\Delta breadth$: the change in the number of institutional investors from period q−1 to q

Period	$ln(ATTE)$ 2003–2015	$ln(ADSdollar)$ 1995–2017	$ln(ADSunits)$ 1995–2017	$\Delta Breadth$ 1980–2017
SEA_q	0.048	0.136	0.085	0.006
	[7.902]	[7.583]	[8.860]	[3.557]

all positively correlated with $SEA_{i,q}$ —— stocks tend to be neglected during low seasons——investors receive a risk premium when stocks are temporarily neglected

4.Result_T3

- ①size; ②idiosyncratic volatility; ③AVGSEA

Size and volatility portfolios					
Fama-French three-factor model	Low IVOL	High IVOL	*Fama-French five-factor model*	Low IVOL	High IVOL
Low ME	0.0700 [0.681]	0.0991 [0.587]	Low ME	0.0766 [0.731]	0.1743 [1.007]
High ME	0.2614 [2.217]	0.7335 [4.717]	High ME	0.2126 [1.757]	0.7664 [4.786]

- the Fama-French five-factor alpha for this portfolio is the only one that has a t-value over 2

5.Conclusions

- ①sales seasonality to be a strong predictor of future returns, which is driven primarily by large firms.
- “the sales seasonality premium” exists independently of previously documented seasonal anomalies
- ②investment and financing effects may be viable channels for the sales seasonality premium.
- low-season firms may have higher returns due to lower levels of investor attention.