[January effect, business cycle, lottery-type stocks and cross-section of expected returns (old name)]

Impact of business cycle on investors' preferences and trading strategies

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Abstract

A growing literature documents evidence that some investors seek stocks with lottery-type payoffs. Recently, Bali et al. (2011) find that sorting stocks by the maximum daily return (MAX) in the previous month can produce an average return difference of more than 1% per month between stocks in the lowest and highest MAX deciles. We construct a variable that identifies various stages in a business cycle and examine its impact on the profitability of the MAX trading strategy. We find that the MAX trading strategy is not profitable when the economy is bad, but highly profitable when the economy is good. This finding is consistent with the hypothesis that investors' preference vary at different economic stages. In addition, we show that the momentum strategy, buying winners and selling lowers, would not work either during a difficult time.

JEL classification: G11, G17, G12

Keywords: Extreme returns, lottery-like payoffs, cross-sectional return, predictability, January effect, business cycle

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1 Introduction

Recent literature documents evidence that many investors do not have well diversified portfolios. Odean (1999) studies return patterns before and after the purchases and sales made by overconfident investors who tend to buy securities that have risen or fallen more over the previous six months than the securities they sell. They sell securities that have, on average, risen rapidly in recent weeks. And they sell far more previous winners than losers. Goetzmann and Kumar (2008) show that individual investors hold under-diversified portfolios. The level of under-diversification is more sever among younger, low-income, less-educated, and less-sophisticated investors. In addition, the level of under-diversification is also correlated with investment choices that are consistent with over-confidence, trend-following behavior, and local bias. In particular, investors who over-weight stocks with higher volatility and higher skewness are less diversified. Using Swedish household data, Calvet, Campbell and Sodini (2003) find that although a few households are very poorly diversified, the cost of diversification mistakes is quite modest for most of the population.

Several explanations are provided in the literature to explain why some investors' portfolios are not well diversified. Overconfidence may lead some investors to hold a concentrated portfolio (Odean (1999), Goetzmann and Kumar (2008), Calvet, Campbell and Sodini (2003)). It is also possible that some investors ignore other stocks which might be more suitable for their investment objectives just because of habit or pattern. Information asymmetry may play a role as well: many individual investors are not well informed about good investment opportunities compared with sophisticated investors or institutions. Moreover, investors' preference is likely to play a big role when they select stocks to form a portfolio. The preference for skewness, i.e., many investors prefer stocks with skewed returns even the mean returns are lower for those stocks, e.g., see Chunhachinda, Dandapani, Hamid and Prakash (1997), Sun and Yan (2003). Chunhachinda et al. (1997) show that the returns of the world's 14 major stock markets are not normally distributed and document evidence that including skewness into an investor's portfolio decision causes a major change in the composition of an optimal portfolio. This indicates that investors should trade off their expected return with skewness. Along the same line, Sun and Yan (2003) study the skewness persistence and optional portfolio selection. They find that the portfolios optimally formed by using the PGP method, which allows preference for skewness, greatly enhances skewness persistence over time.

Recently, more evidence suggests that some investors might care less about extra risk. Instead, they tend to prefer more risky investments. A typical example is that some of them seek stock with lottery type payoff. A "lottery type payoff" is an investment that has a small probability to win a big payoff. Such an investment usually has a negative expected return. The chance of winning big may make it attractive to some investors.

Motivated by investors' preference for lottery type payoff, Bali et al. (2011) argue that investors who seek lottery-type stocks are attracted by stocks with extreme positive price moments in the latest memories, such as in the previous month. This would push up prices of stocks that exhibited the extreme movements in the previous months. Bali et al. (2011) demonstrate that after sorting stocks based on the maximum daily return (MAX) in the previous month, the average raw and risk-adjusted return differences between stocks in the lowest and highest MAX deciles exceed 1% per month. This provides evidence that investors' preference play a central role when choosing their portfolios which might not be well diversified.

The motivation of our study is to examine whether investors' preference for lottery-type stocks varies over the course of a business cycle. Many researchers present the evidence that investors have quite different attitudes toward investments at various economic stages: during recession or when economy is expanding. By using FinaMetrica, a measure for risk assessment, Guillemette and Finke (2014) show that the risk-tolerance may be varying. During the lasted recession started in 2007, it was quite low. The correlation between average monthly risk tolerance scores and the S&P 500 from January 2007 to May 2012, is quite strong (0.70). When economy is on an upward trajectory, investors are optimistic and could have more incentive to search all kinds of investment opportunities, including the lottery-type investments. In such a setting, we expect to see more investments on lottery-type stocks. The opposite might be true as well. During a difficult time, investors should behave more prudently and constrain from searching for stocks with more extreme payoffs. In other words, the behavior of seeking lottery type of investment should be depressed during a difficult time. We construct a variable that identifies various stages in a business cycle and examine its impact on the profitability of the MAX trading strategy as suggested by Bali et al. (2011).

In addition, we examine the effect of January returns on the profitability of the MAX trading strategy. A large literature documents strong evidence for the January effect. In a recent study, Chen and Jindra (2010) investigate seasonal variations and size-related differences in cross-stock valuation distribution. They adopt three stock valuation measures, two derived from structural models and one from book/market ratio. With each measure, they find that the average valuation level is the highest in mid-summer and the lowest in mid-December. Furthermore, the valuation dispersion (or kurtosis) across stocks increases towards the yearend and reverses direction after the turn of the year, suggest an increased movements in both the under- and overvaluation directions. Kang (2011) shows that the change of an information asymmetry measure, the Probability of informed Trading (PIN), is on average negative in January, which is different from the other calendar months. Based on the value-weighted index for large stocks from 1908 to 2004 and equal-weighted index for small stocks from 1927-2004, Haug and Hirschey (2005) find a persistent January-effect for small cap stocks even after the Tax Reform Act of 1986. In addition, they find the existence positive January Effect for the SMB (Small minus Big) and the HML (High minus Low) factors from Fama-French factors. However, the January Effect for the Momentum (UMD) is negative.

Because of pervasive evidence for the January effect, it is important to check whether January returns have an impact on the MAC trading strategy. Bali et al. (2011) show that the difference between deciles 1 and 10, sorted by the maximum daily returns in last month is 1.03%. We find that if based on the maximum returns in December each year to form 10 (decile) portfolios, the difference between stocks in the lowest and highest decile portfolios is a negative 3%. This may be due to the strong motive in January to buy back stocks sold in December. We find that the low returns on the MAX trading strategy in bad-economy months cannot be attributed to the January effect.

Jegadeesh and S. Titman (1993) show that buying winners and selling lover, tabbed as momentum strategy could be a profitable trading strategy. The time period covered in their paper is from 1965 to 1989. To classify a stock as winner or lowers, we sort cumulative n-month total return, n take a value from 3 to 12 months. The top 10% stocks are called winners and bottom 10% are named as lowers. The trading strategy is long stocks that perform quite well in the past and short stocks that fare badly in the past n-month. The holding period could be 3 to 12 months. Even in the footnote 4, they explain why their starting date is from 1965 (1962), we don't see why not to extend to other periods such as from 1965 to 2013 and from 1926 to 2013. Using 6-month evaluation period and 6 month holding period, the T-value for the difference between winner and losers is 2.79, i.e., significant at 1% level. However, after we extend the period from 1965 to 2013, such a strategy only significant at 10% level. From 1926 to 2013, it is no longer a profitable strategy with a T-value of 0.87 with both evaluation period and holding periods is 6-months. Again, we argue that along the business cycle an investor's attitude toward to risk vary. Based on the original period from 1965 to 1989, it covers just 4 business cycles while the period from 1965 to 2013 has 7 while from 1926 to 2013 has 15 cycles. Our empirical results indeed confirm that the so-called momentum trading strategy would not work during a difficult time.

This study contributes to our understanding of investors' preference and its pricing effect in stock market. We provide evidence that investors' preference for lottery-type stocks varies over the course of a business cycle. This is important if we examine a long time series which covers multiple business cycles. We find that the behavior seeking the Lottery-type stocks observed in Bali et al. (2011) is much stronger after removing returns in January and bad-economy months.

The paper is organized as follows. Section 2 explains data source and how to design a variable showing every stages of a business cycle. Section 3 presents our empirical results and discussions. Section 4 offers several robustness tests. The last section concludes the paper.

2 Data

Like Bali et al. (2011), we use the whole universe of CRSP (Center for Research Security Prices) database including all stocks listed on the New Stock American Exchange, American Stock Exchange and NASDAQ. The daily data is used to estimate the maximum daily returns, while the monthly data (returns) is used to estimate decile portfolio returns. For the value-weighed portfolio (decile) returns, we use the lagged market capitalization which is defined as the price times shares outstanding (abs(prc) * shrout). In this paper, we first use the same time period from 1926 to 2005 as Bali et al. (2011). Since there is no compelling reason not to extend the data to the latest available date, we extend to longer period, i.e., from January 1926 to December 2013.

The business cycle data is from the National Bureau of Economic Research center.[1] The original starting date is June 1854. Since the starting year of our stock data, from CRSP, is 1926, we remove data before 1923 for an easy presentation, see Table 2. To label each month in terms of the stage (location) in a business cycle, we design a variable called CYCLE. For a peak which means the economy is at the top of a business cycle, CYCLE takes a value of 1, while for a trough which means that the economy is in a deep recession, CYCLE is -1. Any months between those peaks and troughs, we linearly interpolate. For example, based on Table 2, July 1953 is a peak, then CYCLE for that month is 1. The next trough month is May 1954 and CYCLE will be -1. Since there are 10 months between, the incremental value will be 0.2 (2/10). Thus, for the next month after the peak month, i.e., August 1953, CYCLE will be 0.8 (1- 02), while it is 0.6 for September 1953. CYCLE value will be 1-n*2/10 for the n^{th} month after the peak month of July 1953. For more detail, see Figure 1.

[Insert Figure 1 about here]

The magnitudes of this variable, CYCLE are not important since our objective is to classify all months into different stages depends on whether a month is close to a peak (economy is expanding) or close a trough (economy is in recession). For example, a -0.5 will be close to a recession while a 0.5 will be in the stage of expansion. To classify each month into recession-month or non-recession month, we use a cut-off points such as -0.6. When a month's CYCLE

[1] http://www.nber.org/cycles/cyclesmain.html

value is less than this cut-off point, we classify it as a recession-month. For a robustness check, we vary this cut-off point, see the related section later in the paper.

3 Results and discussions

First, we repeat the analysis in Bali et al. (2011) with the CRSP data over the time period from July 1926 to December 2005. Generally speaking, we got a qualitatively similar result. Table 1 shows the result based on the raw value-weighted portfolio. For an easy comparison, the result shown in Table 2 of Bali et al. (2011) is also presented, see the second column. For a value-weighed decile, the lag monthly market capitalization is used as the weight. For the difference between the lowest and highest deciles, Bali et al. report a -1.05%, while we have a -0.62%, about 40% smaller. The T-value is also much smaller as well: -1.80 vs. -2.83. It is worth noting that based on our results the difference is statistically significant at only 10% level.

[Insert Table 1 about here]

Next, based on our arguments that December-January combination should not be included, we conduct the same analysis without January returns. After removing all January months from our final data set, the absolute difference between the lowest and highest deciles jumps, in terms of absolute value, from -0.62 to -0.95. The corresponding T-value also increases, in terms of absolute value, from -1.80 to -2.69. Now the difference between returns of two extreme decile portfolios, the lowest minus the highest, is significant at a 1% level. This result suggests that January returns, sorted by using MAX in December in the previous year, might be quite different from other months. This confirms our argument that the December-January combination should be removed from the design of Bali et al. (2011).

To further investigate January-Effect, or December-January combination, we conduct the same test on January returns only, i.e., no other months. The result from the test confirms our suspicion that January is indeed quite unique from other months. The sign of the difference is reversed and it is significant at 1% significant level. This means that January returns have a big impact on the results.

Panel B in Table 1 reports our results based on equal-weighted portfolios. The impact of the January is more striking. If using all months to estimate, the difference between the highest and the lowest max portfolio is a mere -0.13%. More importantly, it is not statistically significant, with a T-value of -0.32. However, after January months are removed, the difference is -0.87, close to -0.63 reported in Bali et al. (2011), and it is statistically significant at 1% level (T-value is -2.23). This is consistent with the current literature that small stocks suffer more severe January effect than big stocks. Compared with a value-weighted scheme, an equal-weighed one would give small firms more weights. Similarly, the difference, between two extreme portfolios, is more substantial, 8.10%, compared with 3.11% based on a value-weighted scheme when we consider January only.

[Insert Table 2 about here]

Along the same line, we look at the impact of economic stages, particularly a recession, on the profitability of this trading strategy. Our methodology of classifying a month as a bad-economy month is as follows. First, based on the historical business cycle data, we have Peak month (P) and Trough month (T) according to each business cycle. We assign the month which is Peak (P) as +1 (CYCLE=1) while the Trough month (T) is designated as -1 (CYCLE= -1). Then we linear interpolate all months between P and T. Assume that we have 10 months between P and T (n=10). After Peak, we subtract an incremental value of 0.2 (2/10=0.2) for each month after it. For example, the next month after a Peak month, it would have a value of 0.8 (1-0.2) and for the third month after P, we have a value of 0.4 (1-3*0.2). For the next Trough month (T), we have a value of -1 (1-10*0.2). In this study, we use various cut-off points to classify whether a month belongs to recession or not.

Table 3 presents the results when the mood change of investors is considered at different economic stages, i.e., during recession or non-recession periods specified in the previous section. Column 2 will be our benchmark which includes all 954 months, while Column 3 offers the result after removing all months that have a Business-Cycle value less than -0.6, our cut-off point. Remember we have assigned a -1 to month that is trough (deep recession) and +1 to peak month. For all months between, we linearly interpolate between those two extreme values of [-1, 1], see more detailed discussion in the previous section and Panel B in Table 2. Again, the absolute difference between the lowest and highest portfolios increase and the T-value level both increase. On the other hand, based on the months which are close to recessions (Trough), we could not find a significant difference between those two extremely portfolios. This confirms our hypothesis that during a recession, investors have lower appetite for lottery-type stocks.

[Insert Table 3 about here]

To consider their joint impact, we repeat our analysis by removing returns in both January and bad-economy months. The evidence for the lottery-seeking behavior is much stronger. Based on Table 4, after removing January returns and months in recessions with a cut-off point of -0.6, the difference between the lowest and highest deciles jump from 0.62% to 1.08% and its T-value jump from 1.80 to 2.98. The trend is true when we remove more months, i.e., cut-off points of -0.5 and -0.4. Those results provide additional support that investors' preference for lottery-type stocks is weak when the economy is bad.

[Insert Table 4 about here]

Jegadeesh and S. Titman (1993) show that buying winners and selling lover, tabbed as momentum strategy could be a profitable trading strategy. Based on the monthly CRSP data, our results are shown in Table 5. Like Jagadeesh and Titman (1993), the time period used in this table is from 1965 to 1989. The second column of Panel A is our benchmark. From Panel A: the benchmark plus results based on recession months only, we see that the different between winners and losers are not statistically significant at any level. This confirms our arguments that we should not put all months together to test such a trading strategy. Panel B presents the results after we excluding recession months. In the next section, we offer more evidence when we extend original Jegadeesh and Titman (1993) to 1926 (backward) and to 2013 (forward).

[Insert Table 5 about here]

4 Robustness tests

Many authors point out that the January effect is essentially a size effect and exists only for small capitalization stocks. Lakonishok and Smidt (1988) study the January Effect by using DJIA (Dow Jones Industrial Average), a price-weighted market index. They could not find the January Effect. This is confirmed by Haug and Hirschev (2005) who use the value-weighted market index from 1980 to 2004. On the other hand, Haug and Hirschev (2005) find the January Effect using the CRSP equal-weighted market indices from 1927 to 2004. Based on this conclusion, we divide all our stocks into big stocks and small stocks and rerun the same tests discussed in the previous section. The results are shown in Table 4.

[Insert Table 6 about here]

Table 6 shows the impact of January-Effect on risk-adjusted results: alpha which is based on Fama-French-Carhart's 4-factor model. The period is from July 1926 to December 2005, like Bali et al. (2011). The holding period is 12 months. From the table, we could find that the impact of the January-effect on the value-weighted portfolio is negligible. All T-values are significant at 1% even for the portfolios formed based on the daily maximum returns in December. The T-value for all months is 11.80, the T-value is 11.50 for all non-December months, while the corresponding value for December is 5.46.

The last three columns of Table 5 offer the results based on the equal-weighted scheme. Obviously, the T-values drop significantly. The T-value drops from 12.51 to 2.08 for all months, and from 11.50 to 1.98 for all non-December months. Noticeably, for portfolios formed based on the maximum daily return observed in December with a holding period of 12 months, the difference between two extreme max portfolios is no-longer significant. This result is consistence with the current literature that January-effect has a much bigger impact on small stocks and an equal-weighted scheme puts more weights on small stocks then a value-weighed scheme.

[Insert Tables 7 and 8 about here]

There is no reason why the momentum would not work beyond the original period of 1965 to 1989. Table 7 shows the results over such a period. When the evaluation and holding periods are both 6 months, the return difference between winner and loser portfolios is only marginally significant, i.e., at 10% level. Based on recession months with a moderate cut-off points such as -0.7 and -0.6, the difference switches sign, from positive to negative. More importantly, when choosing recession months using a cut-off point of -0.5, the difference is negative and significant at 5% level. This means the opposite trading strategy is true: we could buy lower and sell winner during a difficult time. Panel B of Table 7 confirms that after we excluding recession months, the momentum strategy returns to a profitable trading strategy. Table 8 shows the results covering all CRSP available period, from 1926 to 2013. The results are more striking: during a difficult we might reverse our momentum strategy. Our conclusion is that the momentum trading strategy is not profitable during recession.

5 Conclusions

A number of researchers find that for many investors their portfolios are not well-diversified. One of the reasons is that those investors seek stocks with lottery-type payoffs. Recently, Bali et al.'s (2011) empirical results show that after sorting stocks based on the maximum daily return (MAX) in the previous month, the average raw return differences between stocks in the lowest and highest MAX deciles exceed 1% per month. Their empirical results confirm that the preference of lottery-type stocks would lead to a non-optimal portfolio selection. They also show that including the MAX variable would reverse the puzzling negative relation between return and idiosyncratic volatility shown in Ang et al. (2006, 2009).

In this paper, we hypothesize that investors' preference for lottery-type stocks varies over the course of a business cycle, in particular, such preference is weak when the economy is bad. We construct a variable that identifies various stages in a business cycle and examine its impact on the profitability of the MAX trading strategy. We find that the MAX trading strategy is not profitable when the economy is bad, but highly profitable when the economy is good. This finding supports that investors' preference for lottery-type stocks is weak when the economy is bad. In addition, we find excluding January returns increases the profitability of the MAX trading strategy.

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Table 1: Impact of January effect on decile portfolio returns from July 1962 to December 2005. Decile portfolios are formed every month from July 1962 to December 2005 based on the Max daily returns of the previous month. The table reports the Value-weighed portfolio returns and the weight is the lagged market capitalization (abs(prc) * shrout). N is the number of the observations.
The third column, in both Panels A and B, is from Bali et al. (2011) Table 1. The rest is from this paper. The fourth and fifth column, under "All months", are the replicate of the third column. Columns 6 and 7 are the results after we have removed January portfolio returns which aee based on the Max in December of the previous year. The last column shows the decile returns only in January.

Panel A: V-W portfolio monthly average returns								
	Bali et al. (2011)		This paper					
			All months		Exclude January		January only	
		Max*	N=954	max	N=875	max	N=79	max
Low MAX	1.01	1.30	0.87	1.40	0.81	1.39	1.49	1.52
2	1.00	2.47	1.00	2.36	0.96	2.35	1.43	2.46
3	1.00	3.26	1.10	3.10	1.05	3.09	1.73	3.22
4	1.11	4.06	1.02	3.82	0.94	3.81	1.82	3.98
5	1.02	4.93	0.98	4.62	0.91	4.60	1.86	4.82
6	1.16	5.97	1.20	5.54	1.07	5.51	2.63	5.80
7	1.00	7.27	1.06	6.69	0.87	6.66	3.01	7.07
8	0.86	9.07	0.92	8.30	0.71	8.25	3.28	8.80
9	0.52	12.09	0.82	10.95	0.57	10.88	3.52	11.78
High MAX	-0.02	23.60	0.25	20.11	-0.14	19.92	4.60	22.2
10-1	-1.03		-0.62		-0.95		3.11	
Difference	(-2.83)		(-1.80)		(-2.69)		(2.69)	

Panel B: E-W portfolio monthly average returns

	Bali et al. (2011)		This paper					
			All months		Exclude January		January only	
		Max*	N=954	max	N=875	max	N=79	max
Low MAX	1.29	1.30	1.17	1.27	0.94	1.26	3.77	1.37
2	1.45	2.47	1.32	2.36	1.13	2.35	3.47	2.47
3	1.55	3.26	1.43	3.11	1.20	3.1	3.91	3.24
4	1.55	4.06	1.42	3.84	1.16	3.82	4.32	4.01
5	1.49	4.93	1.44	4.63	1.14	4.62	4.7	4.84
6	1.49	5.97	1.46	5.56	1.09	5.54	5.55	5.84
7	1.37	7.27	1.35	6.73	0.92	6.70	6.09	7.09
8	1.32	9.07	1.31	8.36	0.77	8.31	7.22	8.87
9	1.04	12.09	1.23	11.11	0.58	11.02	8.42	12.06
High MAX	0.6	23.60	1.04	21.92	0.07	21.62	11.87	25.18
10-1	-0.64		-0.13		(-0.87)		8.10	
Difference	(-2.83)		(-0.32)		(-2.23)		(4.80)	

*Note: the values under Max are from Bali et al. (1011). However, they do not specify whether those values are value-weighted or equal-weighted.

Table 2: Business cycle and a new variable called CYCLE

The business cycle data is from the National Bureau of Economic Research center. The original starting date is June 1854.[2] Since our stock data start from 1926, we remove data before 1923, see Panel A below. For a peak, we assign a positive 1 while for a trough, we assign a negative 1. Any months between those peaks and troughs, we linearly interpolate, see Panel B below. P for Peak and T for Trough. T(t-1) is for the pervious Trough and P(t-1) is for the previous Peak.

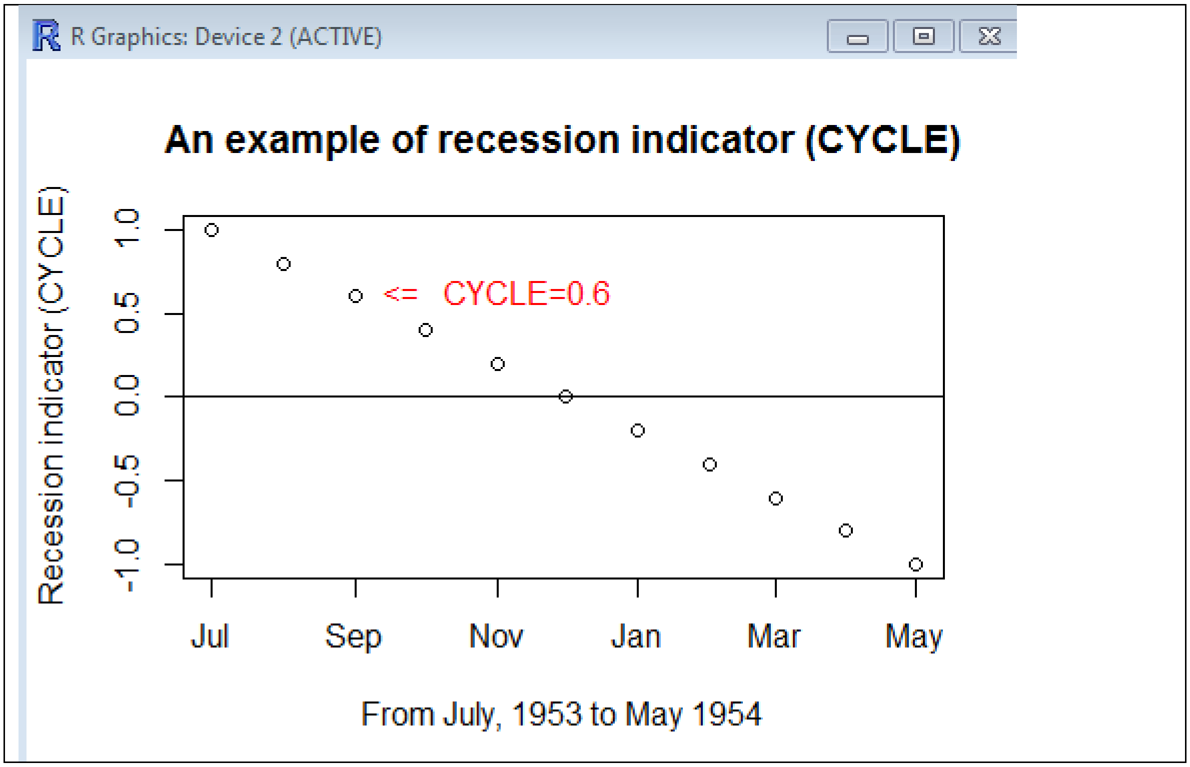
Panel A: Business cycle					
		Contraction	Expansion	cycle	
Peak (P)	Trough (T)	P to T	T(t-1) to P	T(-1) to T	P(t-1) to P
May 1923(II)	July 1924 (III)	14	22	36	40
October 1926(III)	November 1927 (IV)	13	27	40	41
August 1929(III)	March 1933 (I)	43	21	64	34
May 1937(II)	June 1938 (II)	13	50	63	93
February 1945(I)	October 1945 (IV)	8	80	88	93
November 1948(IV)	October 1949 (IV)	11	37	48	45
July 1953(II)	May 1954 (II)	10	45	55	56
August 1957(III)	April 1958 (II)	8	39	47	49
April 1960(II)	February 1961 (I)	10	24	34	32
December 1969(IV)	November 1970 (IV)	11	106	117	116
November 1973(IV)	March 1975 (I)	16	36	52	47
January 1980(I)	July 1980 (III)	6	58	64	74
July 1981(III)	November 1982 (IV)	16	12	28	18
July 1990(III)	March 1991(I)	8	92	100	108
March 2001(I)	November 2001 (IV)	8	120	128	128
December 2007 (IV)	June 2009 (II)	18	73	91	81

Panel B: variable called CYCLE (business status) the first several months			
date	CYCLE	date	CYCLE
19261001	1.000	19270801	-0.538
19261101	0.846	19270901	-0.692
19261201	0.692	19271001	-0.846
19270101	0.538	19271101	-1.000
19270201	0.385	19271201	-0.905
19270301	0.231	19280101	-0.810
19270401	0.077	19280201	-0.714
19270501	-0.077	19280301	-0.619
19270601	-0.231	19280401	-0.524
19270701	-0.385	19280501	-0.429

[2] http://www.nber.org/cycles/cyclesmain.html

Figure 1: An example on how recession indicator (CYCLE) works

Based on Table 2, we know that July 1953 is a Peak while the next trough is May 1954. Thus, CYCLE takes a value of 1 in July 1953 while its value -1 for May 1954.



The related R codes are given below.

```
date1<-as.Date('19530701',"%Y%m%d")
date2<-as.Date('19540501',"%Y%m%d")
x<-seq(date1,date2,"months")
n<-length(x)
y<-seq(1,-1,by=-2/(n-1))
plot(x,y, main="An example of recession indicator (CYCLE)",xlab = "From July, 1953 to May 1954", ylab = "Recession indicator (CYCLE)")
 abline(h=0,v=0)
text(x[5],0.63, "<=   CYCLE=0.6", col=2)
```

Table 3: Impact of Business Cycle on the portfolio returns sorted by the previous month MAX daily returns

Decile portfolios are formed every month from July 1926 to December 2005 based on the Max daily returns of the previous month. The table reports the Value-weighed portfolio returns and the weight is the lagged market capitalization (abs(prc) * shrout). The second column will be our benchmark. N is the number of monthly observations.

For the peaks we would have a value of 1, such as October 1926 and for Trough, we have a value of -1, such as November 1927. Any month between a Peak and a Trough, we conduct a linear interpretation. When a cut-off point is -0.5, it means that we would remove any month which has a Business Cycle less than -0.5.

V-W portfolio returns					
		Cut-off point			
	Benchmark	-0.5		-0.6	
	All months (N=954)	Remove bad months (N=716)	Bad months only (N=238)	Remove bad Months (N=759)	Bad months only (N=196)
Low MAX	0.87	0.56	1.81	0.58	1.99
2	1.00	0.69	1.91	0.70	2.24
3	1.10	0.71	2.26	0.71	2.63
4	1.02	0.61	2.23	0.59	2.67
5	0.98	0.57	2.23	0.56	2.65
6	1.20	067	2.81	0.66	3.30
7	1.06	0.49	2.78	0.49	3.28
8	0.92	0.42	2.43	0.40	2.96
9	0.82	0.22	2.60	0.28	2.91
High MAX	0.25	-0.25	1.78	-0.19	1.98
10-1 Difference	-0.62	-0.81	0.03	-0.77	0.01
	(-1.80)	(-2.27)	(-0.04)	(-2.20)	(-0.01)

Table 4: Impact of Business Cycle and January effect on the portfolio returns sorted by the previous month MAX daily returns

Decile portfolios are formed every month from July 1926 to December 2005 based on the Max daily returns of the previous month. The table reports the Value-weighed portfolio returns and the weight is the lagged market capitalization (abs(prc) * shrout). The second column will be our benchmark.

For the peaks we would have a value of 1, such as October 1926 and for Trough, we have a value of -1, such as November 1927. Any month between a Peak and a Trough, we conduct a linear interpretation. When a cut-off point is -0.5, it means that we would remove any month which has a Business Cycle less than -0.5.

V-W portfolio monthly mean returns after removing January and bad months				
	Benchmark	Removing January returns and cut-off		
	All months (N=954)	-0.6 (N=696)	-0.5 (N=657)	-0.4 (N=606)
Low MAX	0.87	0.51	0.50	0.58
2	1.00	0.62	0.65	0.71
3	1.10	0.63	0.66	0.77
4	1.02	0.49	0.52	0.64
5	0.98	0.44	0.46	0.57
6	1.20	0.49	0.52	0.63
7	1.06	0.30	0.32	0.43
8	0.92	0.18	0.24	0.35
9	0.82	0.02	0.01	0.06
High MAX	0.25	-0.57	-0.64	-0.06
10-1 Difference	-0.62	-1.08	-1.13	-1.18
	(-1.80)	(-2.98)	(-3.07)	(-3.08)

Table 5: Impact of Business cycle on the momentum strategy (period: 1965 to 1989)
The time period from 1965 to 1989, the same as Jagadeesch and Titman (1993). The evaluation and holding periods are both 6 months. The second column could be viewed as the benchmark, i.e., without considering the impact of business cycle.

Panel A: all months (column 2) and recession months only (columns 3 to 5)				
	All months	Recession months only		
Portfolio	Benchmark N=300	-0.6 (n=71)	-0.5 (n=79)	-0.2 (n=121)
1 (lowest)	0.0083507	0.0324023	0.0343774	0.0257860
2	0.0115772	0.0316331	0.0330300	0.0271650
3	0.0128056	0.0324372	0.0325392	0.0283382
4	0.0130453	0.0293112	0.0296024	0.0265346
5	0.0135063	0.0291558	0.0293833	0.0266545
6	0.0140789	0.0293159	0.0292069	0.0263639
7	0.0141733	0.0276224	0.0278476	0.0258203
8	0.0148593	0.0262843	0.0267355	0.0251406
9	0.0156298	0.0281534	0.0281823	0.0264196
10 (highest)	0.0168257	0.0271434	0.0277593	0.0274133
10-1	0.0084750	-0.0052589	-0.0066181	0.0016273
T-value	2.79	-0.55	-0.75	0.28
P-value	0.0057	0.5810	0.4544	0.7767
Panel B: excluding recession months				
Portfolio	-0.6 (n=268)	-0.7 (n=281)	-0.8 (n=292)	-0.9 (n=300)
1	0.0073990	0.0088989	0.0083240	0.0082748
2	0.0109670	0.0120636	0.0115768	0.0115741
3	0.0123040	0.0132738	0.0130317	0.0128044
4	0.0127029	0.0137662	0.0133451	0.0131111
5	0.0132064	0.0140553	0.0137679	0.0135104
6	0.0137478	0.0143513	0.0141503	0.0140994
7	0.0140326	0.0146223	0.0142923	0.0141504
8	0.0147831	0.0151458	0.0148347	0.0149313
9	0.0153098	0.0159141	0.0157047	0.0155736
10 (sell)	0.0169032	0.0175411	0.0169807	0.0168327
10-1	0.0095041	0.0086422	0.0086568	0.0085580
T-value	2.89	2.62	2.75	2.82
P-value	0.0042	0.0093	0.0063	0.0052

Table 6: Impact of January effect on alpha

Decile portfolios are formed every month from July 1926 to December 2005 based on the Max daily returns of the previous month. The table reports the Value-weighed portfolio returns and the weight is the lagged market capitalization (abs(prc) * shrout).

The holding period is 12 months, i.e., based on this month's MAX value we sort all stocks into 10 portfolios and hold those 10 portfolios for the next 12 months. The following regression is run based on the Fama-French 4 factor models.

$$R_{port} = R_f + \beta_1(R_m - R_f) + \beta_1 SMB + \beta_2 HML + \beta_3 MOM$$

Alpha (α) of various portfolios in percentage

Panel A: impact of January effect

	Value-weighted			Equal-weighted		
Max	All months (N=954) (%)	Removing December (N=875) (%)	December Only (79) (%)	All months (N=954) (%)	Removing December (N=875) (%)	December only (79) (%)
Low	0.394	0.395	0.384	0.563	0.564	0.552
2	0.362	0.361	0.365	0.506	0.502	0.543
3	0.391	0.395	0.348	0.501	0.5	0.504
4	0.345	0.339	0.414	0.462	0.461	0.474
5	0.306	0.308	0.283	0.419	0.421	0.402
6	0.294	0.293	0.296	0.405	0.400	0.455
7	0.242	0.249	0.161	0.343	0.347	0.294
8	0.173	0.177	0.136	0.330	0.332	0.304
9	-0.004	0.019	-0.252	0.266	0.272	0.193
High	-0.315	0.293	-0.567	0.433	0.433	0.426
1-10 difference	0.70	0.69	0.95	0.130	0.130	0.126
T-value	12.51	11.50	5.46	2.08	1.97	0.67

Panel B: impact of recession (cut-off= -0.6)

	Value-weighted			Equal-weighted		
Max	All months (N=954) (%)	Removing Recession (N=759) (%)	Recession Only (n=195) (%)	All months (N=954) (%)	Removing Recession months (N=759)	Recession months only (N=195) (%)
Low	0.394	0.345	0.585	0.563	0.495	0.826
2	0.362	0.378	0.298	0.506	0.478	0.612
3	0.391	0.387	0.407	0.501	0.499	0.507
4	0.345	0.370	0.251	0.462	0.470	0.433
5	0.306	0.316	0.271	0.419	0.423	0.403
6	0.294	0.327	0.165	0.405	0.408	0.391
7	0.242	0.272	0.124	0.343	0.338	0.361
8	0.173	0.225	-0.029	0.330	0.349	0.255
9	-0.004	0.054	-0.229	0.266	0.259	0.293
High	-0.315	-0.293	-0.402	0.433	0.383	0.625
1-10 difference	0.70	0.638	0.987	0.130	0.112	0.202
T-value	12.51	10.16	7.57	2.08	1.62	0.139

Table 7: Impact of Business cycle on the momentum strategy (period: 1965 to 2013)
This Table is the same as Table 6 except the time period: from 1965 to 2013, extension for Jagadeech and Titman (1993). The evaluation and holding periods are both 6 months. The second column could be viewed as the benchmark, i.e., without considering the impact of business cycle.

Panel A: all months (column 2) and recession months only (columns 3 to 5)				
	All months	Recession months only		
Portfolio	All months N=588	-0.7 (n=105)	-0.6 (n=131)	-0.5 (n=150)
1 (lowest)	0.0107066	0.0297855	0.0409006	0.0436339
2	0.0111578	0.0242761	0.0317661	0.0330686
3	0.0122728	0.0230324	0.0296613	0.0303116
4	0.0123071	0.0211171	0.0274499	0.0281004
5	0.0125734	0.0210373	0.0261271	0.0266660
6	0.0127507	0.0203949	0.0249988	0.0253764
7	0.0129701	0.0202425	0.0241478	0.0245899
8	0.0130720	0.0193723	0.0222164	0.0230594
9	0.0138474	0.0223509	0.0245244	0.0248453
10 (highest)	0.0156220	0.0233321	0.0250923	0.0259135
10-1	0.0049154	-0.0064534	-0.0158083	-0.0177204
T-value	1.78	-0.99	-1.83	-2.22
P-value	0.0758	0.3250	0.0691	0.0278
Panel B: excluding recession months with different cut-off points				
Portfolio	-0.6 (n=525)	-0.5 (n=507)	-0.4 (n=482)	0.0 (n=384)
1	0.0099295	0.0089120	0.0077282	0.0029623
2	0.0112411	0.0106740	0.0097353	0.0055927
3	0.0125070	0.0121030	0.0111931	0.0072741
4	0.0125675	0.0121667	0.0115850	0.0077506
5	0.0128488	0.0124969	0.0119021	0.0084891
6	0.0130625	0.0127597	0.0123631	0.0094562
7	0.0133359	0.0130268	0.0127904	0.0101472
8	0.0135367	0.0132933	0.0129617	0.0104992
9	0.0141080	0.0139413	0.0136639	0.0112157
10 (sell)	0.0161343	0.0157622	0.0153843	0.0127306
10-1	0.0062048	0.0068502	0.0076561	0.0097683
T-value	2.13	2.32	2.54	2.99
P-value	0.0338	0.0206	0.0114	0.0030

Table 8: Impact of Business cycle on the momentum strategy (period: 1926 to 2013)
This Table is the same as Table 6 except the time period: from 1926 to 2013, extension for Jagadeech and Titman (1993). The evaluation and holding periods are both 6 months. The second column could be viewed as the benchmark, i.e., without considering the impact of business cycle.

Panel A: all months (column 2) and recession months only (columns 3 to 5)				
	All months	Recession months only		
Portfolio	Benchmark N=1054	-0.6 (n=274)	-0.5 (n=318)	-0.4 (n=371)
1 (lowest)	0.0133637	0.0408269	0.0419789	0.0376084
2	0.0119790	0.0329153	0.0337968	0.0309877
3	0.0124490	0.0319703	0.0319640	0.0293572
4	0.0127069	0.0306061	0.0302447	0.0275830
5	0.0128909	0.0286609	0.0284899	0.0260196
6	0.0129526	0.0276442	0.0273433	0.0252113
7	0.0132342	0.0266657	0.0262167	0.0245881
8	0.0131015	0.0254058	0.0250258	0.0233269
9	0.0139998	0.0262676	0.0257356	0.0241301
10 (highest)	0.0152935	0.0268992	0.0269457	0.0263019
10-1	0.0019298	-0.0139277	-0.0150333	-0.0113065
T-value	0.87	-2.17	-2.61	-2.27
P-value	0.3854	0.0307	0.0094	0.0236
Panel B: excluding recession months with different cut-off points				
Portfolio	-0.6 (n=928)	-0.5(n=885)	-0.3 (n=782)	0(n=642)
1	0.0107656	0.0105188	0.0082987	0.0058834
2	0.0099659	0.0101185	0.0080308	0.0056954
3	0.0104466	0.0105648	0.0087788	0.0066268
4	0.0109771	0.0109774	0.0095829	0.0073425
5	0.0114367	0.0113931	0.0103439	0.0084106
6	0.0114334	0.0114556	0.0104572	0.0089790
7	0.0119088	0.0119177	0.0111465	0.0097701
8	0.0119035	0.0119401	0.0112912	0.0100148
9	0.0128283	0.0129715	0.0122261	0.0112152
10 (sell)	0.0141701	0.0141819	0.0135221	0.0122465
10-1	0.0034045	0.0036631	0.0052234	0.0063631
T-value	1.52	1.59	2.25	2.56
P-value	0.1283	0.1129	0.0247	0.0108