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Sell in May and Go Away: Evidence from China

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A B S T R A C T

Using the Chinese stock market data from 1997 to 2013, this paper examines the "Sell in May and Go Away" puzzle first identified by Bouman and Jacobsen (2002). We find strong existence of the Sell in May effect, robust to different regression assumptions, industries, and after controlling for the January or February effect. However, part of the puzzle is subsumed by the seasonal affective disorder effect. We then construct a trading strategy based on this puzzle, and find that it outperforms the buy-and-hold strategy and could resist the market downside risk during large recession periods.

1. Introduction

Bouman and Jacobsen (2002) document the "Sell in May and Go Away" puzzle, which means that stocks have higher returns in the November–April period than the May–October period. Recently, Jacobsen and Zhang (2012) report that the Sell in May effect is significant in 35 out of 108 countries. Andrade et al. (2013) conduct an out-of-sample test of the Sell in May effect.[1]

In this paper we provide further evidence on the calendar anomalies by examining the "Sell in May and Go Away" puzzle that was first identified by Bouman and Jacobsen (2002) and using the Chinese

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[1] Other recent studies on equity market seasonality include Dowling and Lucey (2008), Kamstra et al. (2012) and Lu and Chou (2012), etc.

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Table 1
Descriptive statistics of the stock returns.

		All months	May–October (r_1)	November–April (r_2)
Mean		0.0098	−0.0036	0.0232
Maximum		0.3638	0.3638	0.2983
Minimum		−0.2651	−0.2651	−0.1926
Standard Deviation		0.0871	0.0909	0.0814
H_0: $r_1 = r_2$	t-Value	−2.28		
	p-Value	0.02		

Notes: The last row reports the t-test results for the null hypothesis that the returns are equal between the two periods.

stock market data from 1997 to 2013. This puzzle cannot be explained by the well-known January or February effect (Donald, 1983; Gao and Kling, 2005), nor by time-varying risk, nevertheless, it is associated with time-varying risk aversion found in Kamstra et al. (2003). This study is the first detailed work on Chinese market, the world's largest emerging market, with sample periods covering the 1997–1998 Asian crisis and the recent global financial crisis. In addition, we investigate the economic benefits with a trading strategy based on this puzzle. Different from the evidence in Dichtl and Drobetz (2014) for developed markets, we find the strategy outperforms a buy-and-hold strategy and could resist the market downside risk during large recession periods in China. Overall the findings of this study complement the evidence found in other developed and emerging markets (Andrade et al., 2013) and have special implications for those international investors as MSCI plans to add Chinese A shares to its emerging index from May 2015.[2]

2. Methodology: dummy regression

Following Bouman and Jacobsen (2002), we run a dummy regression as follows:

$$R_t = \beta_0 + \beta_1 \times \text{dummy}_t + \varepsilon_t \tag{1}$$

where R_t is stock returns and the dummy = 0 when the date t is in the May–October period, and dummy = 1 when otherwise. If the coefficient of dummy is significantly above 0, we can conclude that the stock returns of the November–April period are higher than those of the May–October period. Newey–West standard errors are used to adjust for heteroskedasticity and autocorrelation.[3]

3. Empirical analysis

3.1. Data

The data used in this paper is obtained from the GTA CSMAR (China Securities Market & Accounting Research) Database that included in the WRDS (Wharton Research Data Service). Our monthly data focuses on the Chinese A shares[4] with periods from February 1997 to December 2013, since the 10% price limit policy was not implemented before 1997. GTA CSMAR computes the monthly stock returns of the value-weighted market index to minimize the possible January effect largely caused by small companies (Bouman and Jacobsen, 2002).

Table 1 reports the descriptive statistics of our data for all months, May–October and November–April. The mean return is positive for November–April and is negative for May–October, suggesting that the summer months may generate lower returns than the winter months. Moreover, the null hypothesis that the returns are equal between these two periods is rejected at the 5% level.

[2] http://www.reuters.com/article/2014/03/12/china-msci-idUSL6N0M921D20140312.
[3] We also test an ARMA-GARCH model and allow for a thick tailed distribution to avoid the possible biases caused by autocorrelation, heteroscedasticity, and non-normal distributed stock returns, our conclusion remains.
[4] A shares are for domestic investors and B shares are for foreigners investors.

Table 2
Dummy regression results.

	Constant	Sell in May effect
Coefficient	0.0232***	0.0268**
t-Value	2.87	2.21

Notes: Result is for the regression (1).
T-statistics is adjusted by the Newey–West standard errors.
** Denotes significance at the 5% level.
*** Denotes significance at the 1% level.

Table 3
Sell in May effect results for industries.

Industry	Mean return		Sell in May effect
	May–October	November–April	p-Value
Wholesale and retail store	−0.0059	0.0220	0.0420
Culture	0.0032	0.0278	0.2260
Agriculture and forestry	−0.0085	0.0216	0.0740
Conglomerate	−0.0087	0.0182	0.1100
Real estate	−0.0011	0.0231	0.1320
Finance	−0.0042	0.0230	0.1650
Information technology	−0.0069	0.0249	0.1000
Catering	−0.0061	0.0211	0.0490
Transportation	−0.0095	0.0221	0.0110
Construction	−0.0027	0.0267	0.1120
Hydroelectric	−0.0122	0.0222	0.0060
Manufacturing	−0.0075	0.0238	0.0210
Mining	−0.0022	0.0330	0.0780

Notes: This table reports the dummy regression (1) results for 13 industries. The last column shows the p-value associated with the dummy variable, adjusted by the Newey–West standard errors.

3.2. Empirical results

3.2.1. Test the existence of the Sell in May effect

Table 2 shows the dummy regression results for the Sell in May effect. For the regression model (1), the dummy variable is positively significant at the 5% level, supporting the assertion that the Sell in May effect exists in the Chinese stock market. The stock returns in the May–October period are significantly lower than those in the November–April period.

3.2.2. Industry-specific factor

In this section we test whether the Sell in May effect is mainly driven by some industries, for example, firms in Agriculture industry may perform differently in the summer and winter due to their business nature. Following Jacobsen and Visaltanachoti (2009), we separate the market by industry classification and run the one at a time dummy regressions for each industry index. Thirteen main industries are the Information technology, Culture industry, Catering industry, Transportation, Mining, Agriculture and forestry, Wholesale and retail store, Manufacturing industry, Real estate, Construction, Hydroelectric, Conglomerate industry and Finance.

The industry-by-industry regression results are reported in Table 3.[5] The mean return for the November–April periods is larger than that for the May–October periods for all thirteen industries. Interestingly, the mean return for the summer months is negative for twelve industries and is positive for the winter months for all industries. To save space, the last column reports only the p-value associated with the dummy variable, more than three-fifths of industries exist significant Sell in May effect at the 10%

[5] Available industry indices data sample periods are from July 2001 to December 2013, slightly different from the whole market.

Table 4
Sell in May effect controlling for the January or February effect.

	Coefficient	*t*-Value
Panel A: January effect		
Sell in May effect	0.0256**	1.98
January effect	0.0071	0.31
Panel B: February effect		
Sell in May effect	0.0238*	1.75
February effect	0.0179	1.25

Notes: T-statistics is adjusted by the Newey–West standard errors.

level. The effect is weak for the Culture, Real estate and Finance industries and is especially strong for the Hydroelectric, Transportation and Manufacturing industries.

Overall we conclude that the Sell in May effect in the Chinese stock market is not biased toward few industries. The finding that the effect is stronger for some industries than other industries provides additional implications for portfolio industry allocation.

3.2.3. January or February effect

As January effect is reported to generate higher returns (Donald, 1983) and January is included in the winter months, the Sell in May effect may be the result of the January effect. To relieve the concern, in this section we run the dummy regression by adding a dummy variable for January to control for the January effect.

$$R_t = \beta_0 + \beta_1 * \text{dummy1}_t + \beta_2 * \text{dummy2}_t + \varepsilon_t \tag{2}$$

where dummy1 is for the Sell in May effect and dummy2 is for the January effect. Thus, dummy2 = 1 when the date t is in January and dummy2 = 0 when otherwise. Panel A of Table 4 reports the results. We can see that no evidence was found to support the January effect in the Chinese stock market and the Sell in May effect is not disguised by the January effect.

Gao and Kling (2005) notice that the stock returns are higher in February than most other months since the Chinese new year is typically in February. Panel B of Table 4 reports the new results by replacing the dummy2 for February. Similarly, the Sell in May effect still exists, although its significance decreases to the 10% level.

3.2.4. Time-varying risk or time-varying risk aversion

The persistence of the Sell in May effect cannot be explained by either the January or February effect. Another rational alternative is: can time-varying risk or time-varying risk aversion explain this puzzle?

Table 1 indicates that returns are less volatile in the November–April period. Further, using monthly data of two macroeconomic proxies CPI (Consumer price index) and IPI (Industrial production index) representing inflation and real output from 199,701 to 201,312, we find that volatilities in the November–April period are 0.0077 and 0.0459 respectively, compared with 0.0044 and 0.0329 in the May–October period. These observations provide evidence that time-varying risk is unlikely to justify the puzzle.[6]

SAD (seasonal affective disorder) provided by Kamstra et al. (2003) has been shown to be tied to variation in risk aversion and have a substantial effect on stock market cycle (Kamstra et al., 2012). The SAD effect suggests low returns in the late summer/early fall as people become blue with shorter days, and high returns in the late winter/early spring as people recover from SAD. Kramer and Weber (2012) show further evidence from an experiment on individuals risk taking across the seasons. We test the SAD effect by including the Onset/Recovery (OR) index that represents changes in the proportion of people suffered from SAD (Kamstra et al., 2003, 2012).

[6] We thank the anonymous referee for pointing out this suggestion.

Table 5
Sell in May effect controlling for the SAD effect.

	Coefficient	*t*-Value	Coefficient	*t*-Value
Constant	0.0098	1.46	0.0172*	1.80
Sell in May effect			0.0148	0.87
OR	−0.0668**	−2.24	−0.0444	−1.22

Notes: OR is the Onset/Recovery (OR) index that represent changes in the proportion of people suffered from SAD.T-statistics is adjusted by the Newey–West standard errors.

Table 6
Sell in May trading strategy performance.

	Sell in May strategy	Buy-and-hold strategy
Return	13.03%	7.50%
Sharpe ratio	0.6002	0.2199
Maximum drawdown	27.00%	69.30%
Downside deviation	2.98%	5.34%
Historical VaR (95%)	6.86%	11.20%
Leland's alpha	8.69%	

Notes: This table reports the trading performance of a trading strategy compared with a buy-and-hold strategy.

Table 5 reports the regression results considering for the SAD effect. The coefficient for OR is negatively significant, as ORs are lower and negative in winter and spring, a negative OR coefficient thus indicates higher returns for these months. The correlation between the Sell in May dummy and OR is −63.97%. The signs of coefficients keep unchanged when regressing on both the Sell in May dummy and OR, although they become less insignificant possibly due to multicollinearity. In addition, the result that OR has a stronger coefficient than the Sell in May dummy suggests that part of the Sell in May effect is subsumed by the SAD effect, and therefore time-varying risk aversion could provide a rational explanation for the Sell in May puzzle, different from the finding in Lu and Chou (2012).

3.2.5. Trading implication

In this section we further investigate the trading implication based on the Sell in May effect. We construct a trading strategy that buys the Chinese stock market at the beginning of November and sells it at the end of April of the next year. We save the capital in a bank earning a risk-free floating deposit rate from the beginning of May to the end of October.[7] Our benchmark is a buy-and-hold strategy.

We calculate the annualized Sharpe ratio and Leland (1999)'s alpha to gauge the performance of the trading strategy. Sharpe ratio is calculated as $\frac{E[r_a - r_f]}{\sqrt{\text{var}(r_a - r_f)}}$, where r_a is the strategy return, r_f is risk-free rate. Leland's alpha takes into account the deviation from normal distribution of strategy returns and equals to

$$\alpha_p = E[r_a] - \beta_p(E[r_m - r_f]) - E[r_f]$$

where r_m denotes the benchmark return; $\beta_p = \frac{\text{cov}(r_a, -(1+r_m)^{-\gamma})}{\text{cov}(r_m, -(1+r_m)^{-\gamma})}$ measures systematic risk and $\gamma = \frac{\ln(E[1+r_m]) - \ln(1+r_f)}{\text{var}(\ln(1+r_m))}$ measures the relative risk aversion. Both Sharpe ratio and Leland's alpha are finally annualized. A larger than zero Leland's alpha indicates the trading strategy generates an excess return over the buy-and-hold strategy.

Table 6 shows the trading strategy performance. Both the return and Sharpe ratio of the Sell in May strategy are higher than those of the buy-and-hold strategy. Three downside risk measures (Maximum drawdown, downside deviation and 95% historical VaR) of the Sell in May strategy are much lower

[7] Investors can buy a market index ETF to long the Chinese stock market; short selling is not allowed for individual investors.

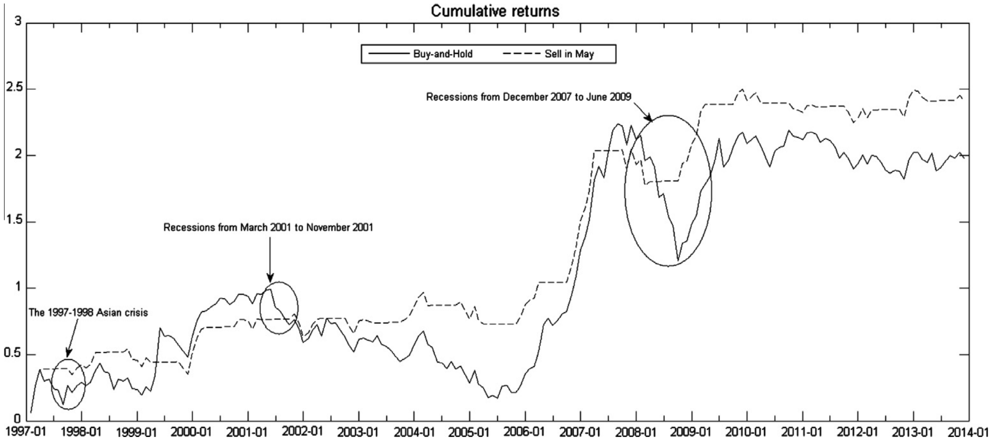

Fig. 1. Plot of Sell in May trading strategy performance. Cumulative returns of both strategies, highlighted with three recession periods.

than those of the buy-and-hold strategy, suggesting that our trading strategy could prevent investors from dramatic losses.

Fig. 1 plots the cumulative returns of both strategies. It illustrates how the Sell in May strategy could resist the market downside risk. It largely avoids the three periods identified as disasters for investors: The 1997–1998 Asian crisis, the NBER (National Bureau of Economic Research) defined recession periods from March to November 2001 and from December 2007 to June 2009.

4. Conclusion

This paper examines in detail the Sell in May effect in the Chinese A share market, the world's largest emerging market. We find that the Sell in May effect exists in the Chinese stock market. In particular, the effect does not go away for the majority of industries. It cannot be explained by different regression assumptions, or other well-known calendar effects such as the January and February effects, nor by time-varying risk, nevertheless, time-varying risk aversion approximated by the SAD effect subsumes part of the Sell in May effect. A simple trading strategy, which based on the effect, is shown to outperform the buy-and-hold strategy and can protect investors from dramatic losses during large recession. The findings of this paper provide insights to those international investors who are interested in the Chinese stock market.

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