Brunel University London

Department of
Economics and Finance

Working Paper No. 12-15

Economics and Finance Working Paper Series

Qiwei Chen

Risk and Seasonal Effects: International Evidence

September 2012

http://www.brunel.ac.uk/economics

Risk and Seasonal Effects:

International Evidence

Qiwei Chen*

Brunel University, United Kingdom

* School of Social Sciences, Brunel University, Clevand Road, Uxbridge, UK. Tel: +44-(0) 1895 267763, Email: Qiwei.Chen@brunel.ac.uk,

Abstract

Various explanations have been investigated to the January effect in existent literature, but no conclusive explanation has been given to distinguish particular explanation from others. A time-series GARCH-M model with the conditional variance as proxies for market systematic risk is applied in this paper to investigate the seasonal effects in the USA, the UK, China and Australia with different tax system and tax year end. Empirical evidence showed January effect in the USA, January and April effect in the UK, July effect in Australia and no significant seasonal effect in China. The pattern consistently links to tax year end and tax system in the sample countries. But no clear evidence has been found to support the proposition that market risk is higher or priced highly only in certain calendar month with seasonal effect. However, with an interactive dummy variable to reflect the seasonal effect added into the time-series GARCH-M model, the seasonal effects are explained away. The results in the sampled countries support the proposition that market volatility increases when it is close to the date of financial statement performance due to the uncertainty of the financial information.

JEL classification: G12

Key Words: seasonal effect; January effect; market volatility; risk pricing; GARCH

Introduction

“January effect”, which is an evidence that the mean return of common stocks is higher in most of months in January, has been one of the most intriguing topics in financial economics since Rozeff and Kinney (1976) reported evidence that the returns of common stocks in January, especially small firms, are significantly higher than those of other months during the year. Thereafter subsequent research by Reinganum (1981), Keim (1983), Roll (1983) reconfirmed that the January effect is a phenomenon more pronounced in small-capitalised companies.

While the January effect is documented worldwide, there is no consensus on what causes the anomaly. Various explanations have been advanced thereafter: tax-loss selling (Branch (1977), Dyl (1977), Reinganum (1983), Roll (1983), Ritter (1988), Chen and Singal, (2004) and Chen, Jack and Woods (2007) et al.); risk explanations: (Change and Pinegar (1989, 1990), Kramer (1994) and Sun and Tong (2010) et al.,); window-dressing (Haugen and Lakonishok (1988), (Lakonishok et al. (1991)); transaction cost (Stroll and Whaley (1983), Bhardwaj and Brooks, (1992)); liquidity (Ogden(1990)) and business cycle (Kohers and Kohli (1992) and Kramer (1994)) and microstructure explanation (Keim (1989), Menyah and Paudyal (1996) and Draper and Paudyal (1997)).

Among the above-mentioned explanations, the most extensively investigated explanation is the tax-loss selling hypothesis, according to which tax-motivated investors sell off stocks with declined prices to realise losses towards the end of tax year. The realised losses will be eligible to offset capital gain realised elsewhere, creating tax benefit to investors. The increased selling pressure will put the prices downwards at the end of tax year. Stock prices will bounce back with the relieved selling pressure and the picking-back buying trend, causing the January effect. The empirical evidence on the tax-loss selling explanation is mixed. Using U.S. data sample, Branch (1977), Dyl (1977), Schultz (1985), and Brauer and Chang (1990) all provided empirical evidence, supporting the tax-loss selling hypothesis. More recently Chen and Singal (2004) reported that tax-loss selling is the most important cause of this seasonality. While Jones, Pearce, and Wilson (1987) and Haug and Hirschey (2006) argued that tax-loss selling hypothesis is weak.

More research has extended the study into international market. Griffiths and White (1993) provide strong evidence for the influence of tax by exploiting the five day difference between the end of Canadian and US tax-years. Reinganum and Shapiro (1987) provided partial support to this hypothesis with the UK data. On the other hand, Brown et al. (1983) with Australian data, Berges, McConnell, and Schlarbaum (1984) with Canadian data, Kato and Schallheim (1985) with Japanese data and Ho (1990) with nine Asia Pacific markets data all report evidence inconsistent with the tax loss selling hypothesis.

The second explanation to this seasonality is the risk explanation. Rozeff and Kinney (1976) and Keim (1983) documented higher mean return as well as higher volatility in January. They argued that the higher volatility is due to the uncertainty linked to the impending release of financial statement information. Rogalski and Tinic (1986) found that the betas of much higher during January. All these research suggested that the higher return of common stocks in most months of January is just the reward of bearing higher risk. Fama and French (1993) explained away January effect for most of all portfolios with three-factor model, including size, book to market ratio and risk premium.

If risk is the explanatory, the question is then, whether risk is priced in every calendar month or, rather, just in January. Rozeff and Kinney (1976) argued that the risk-return trade off in January is much higher in January than in any other months of the year. Tinic and West (1984) supported this argument and posited that risk is not priced higher in January, but that it is priced only in January (Sun and Tong (2011)). Chang and Pinegar (1988) investigated the return spreads between common stocks and T-bills and found empirical evidence supporting the argument that risk is only priced in January. Wang and Chen, (2012) use ARCH (1, 1) model to investigate the information flow in the Chinese stock market.

The third explanation to January effect is "window dressing", which suggests that in order to eliminate embarrassing losers' portfolio for annual reports to investors, professionals intentionally sell off losers' portfolio prior to the end of reporting period. After this period, with the bouncing-back buying pressure, the equity prices would be "pushed" up, causing "January effect". Lakonishok et al. (1991) argued that for evaluation purpose, fund managers will "make up" their holding portfolio to improve investors' impression of investment philosophy and execution.

Moreover a number of studies have contributed the cause of January effect to market microstructure, transaction cost, liquidity or even business cycle. Bhardwaj and Brooks (1992) argued that before transaction cost, low share price stocks earn abnormal returns in January, however, when transaction cost and bid-ask bias are taken into account, no positive abnormal returns are found. Menyah and Paudyal (1996) and Draper and Paudyal (1997) found that the bid-ask spreads are widened when the price of the stocks increase. Ogden(1990) attributed January effect to the high liquidity during that month; while Kramer (1994) linked January effect to business cycle.

This paper is motivated by the unique country characteristics in the UK, Australia and China and the recent work by Sun and Tong (Sun and Tong (2011)). In their paper, conditional variance has been added into time-series GARCH models to investigate the January effect in the USA market. Empirical evidence based on sample between 1926 and 2005 suggests that neither conditional nor unconditional variance is higher in January. Their results showed that it is not the higher risk itself but the higher compensation to the risk that caused January effect in the USA.

The aim of this paper is to further explore the risk explanation for seasonal effect; while at the same time, beside the USA I will extend the study into the seasonal effects in the UK, China and Australia. The difficulty in seasonal effect investigation is to construct tests that distinguish one explanation from other hypotheses that purport to explain the presence of a January premium. For example when risk is found to be significant as explanatory factor, how conclusion be drawn that tax-loss or window dressing is not one of the reasons, as January effect can be the result of the combination of various causes? In this vein, The UK, China and Australia offer an interesting testing ground to distinguish from tax-loss selling hypothesis for the reason that the tax year and tax regimes are different for these countries. While a lot of literature reported January and April effects in the UK and July effects in Australia, it is not strange that the seasonalities in these two countries would be attributed to tax-loss selling. China differs from other countries in the tax system. No capital gain tax is applied for both companies and investors in the equity market. Existent literature found no significant seasonal effect in Chinese stock market.

A lot of literature found evidence supporting the risk explanation for the January Effect. However no evidence has been given to explain why risk is higher only in January. The results of this paper contribute to the literature that evidence indicates that market volatility is higher in the calendar months linked to the financial statement announcement. This supports the risk explanation that market volatility increases due to the uncertainty of the company performance announcement. The results indicate that the seasonal effects in the four sample countries are due to the compensation for the increased market volatility linked to the financial information release.

Data and Methodology

Data

The tests use monthly equally weighted return series comprise of all listed stocked in the UK, the USA, Australia and China. The data sample of the UK is from January, 1971 to June, 2012; the data sample of the USA is from January, 1973 to June, 2012; the data sample of Australia is from January, 1981 to June, 2012 and the data sample of China is from January, 1991 to June, 2012. All return index data is collected from Datastream, and the return of equity is calculated as:

$$R_{it} = \ln(RI_{it}) - \ln(RI_{it-1})$$

where R_{it} is the monthly return of all listed equities, and RI is the return index of all listed equities.

And the monthly return of each countries is calculated as the equally weighted return of all the listed equities in the market, as Sun and Tong (2011) mentioned that Ritter (1988) argued that if the value-weighted return series is used, no January effect is observed.

Methodology

1. For each country regression model with calendar month dummies will be run to examine the seasonalities.

$$R_t = \alpha_0 + \alpha_i calendarmonthdummies_t \quad (1)$$

where R_{it} is the monthly equally weighted return of all the listed equities in each different country.

Calendar month dummies include 11 calendar month dummies from January to November, and the constant α reflects the return of December. Calendar month dummy takes the value one for the specified month and zero otherwise. For example

January dummy is equal to 1 for equally-weighted average return of all listed equities for January and 0 otherwise.

2. Following Sun and Tong (2011), the basic GARCH (1, 1) model with a seasonality dummy is structured as follows:

$$R_t = \alpha_0 + \alpha_1 R_{t-1} + \alpha_2 seasonaldummy_t + \varepsilon_t \quad \varepsilon_t | \phi_{t-1} \sim N(0, h_t) \tag{2}$$

$$h_t = \beta_0 + \beta_1 h_{t-1} + \beta_2 seasonaldummy_t + \beta_3 \varepsilon_{t-1}^2$$

where seasonal dummy is a dummy variable to be included when the seasonality incurs. h_t is the variance of ε_t, which is conditional upon the information set ϕ at time t-1 and is following an ARMA(1, 1) process (Sun and Tong, 2011).

This widely used model has been adopted by many studies to reflect asset return dynamics. In the mean equation of this GARCH (1, 1) model, the seasonal dummy variable is regarded to be able to capture a possible seasonality in the return series. If seasonality exists, regression result should show significant α_2. For example, positively significant α_2 suggest that the return of January is significantly higher than other calendar months during the year. The conditional variance in the variance equation, as claimed by Rogalski and Tinic (1986), works as a proxy of the anticipated market risk by investors. The same as the example above, if the risk is higher in January, we should observe positively significant β_2 in the variance equation.

3. GARCH-M model will be used to test for the risk explanation:

$$R_t = \alpha_0 + \alpha_1 R_{t-1} + \alpha_2 seasonaldummy_t + \alpha_3 h_t + \varepsilon_t \tag{3}$$

$$h_t = \beta_0 + \beta_1 h_{t-1} + \beta_2 seasonaldummy_t + \beta_3 \varepsilon_{t-1}^2$$

In the GARCH-M model, the conditional variance has been added into the mean equation.

If risk is the driving factor for the seasonality, as a proxy of the anticipated market risk, the conditional variance should have explanatory power for the seasonal dummy. Therefore when conditional variance is included in the mean equation, the coefficient of the seasonal dummy α_2 should become insignificant or, at least, smaller than the α_2 in Model 2.

4. The above GARCH-M model is structured to investigate risk explanation for the seasonalitites. When result shows that the risk is not significant higher, there is another hypothesis which argues that it is not the higher risk but the highly priced risk premium that drives the seasonalities, To test this hypothesis, the third GARCH model is adopted from Sun and Tong (2011):

$$R_t = \alpha_0 + \alpha_1 R_{t-1} + \alpha_2 seasonaldummy_t + \alpha_3 h_t + \alpha_4 h_t * seasonaldummy_t + \varepsilon_t \tag{4}$$

$$h_t = \beta_0 + \beta_1 h_{t-1} + \beta_2 seasonaldummy_t + \beta_3 \varepsilon_{t-1}^2$$

In this model, interaction of seasonal dummy has been used with the conditional variance in the mean equation, therefore different mean-variance relationship in the calendar month when seasonality occurs is allowed. If the risk has been priced highly in certain calendar month, α_4 would be expected to be significantly positive. While at the same time, if the interactive dummy has explanatory power for the seasonality, α_2 in Model 4 should be insignificant and even smaller than α_2s in Model 3 and Model 2. Quasi-maximum likelihood estimator has been used in estimation, since standardized residuals are usually not normally distributed.

Results

1. Seasonal effects

Model 1 is run first to check if there is any seasonality exists in the four sample countries. Empirical results presented in Table 1 are consistent with most existent literature. In the USA, the mean monthly return in January during the sample period between January, 1973 and June, 2012 is 5.09%, which is significantly higher than the average monthly return of all other months. In the UK, the results support Gultekin and Gultekin (1983), Reinganum and Shapiro (1987) and Chen, Jack and Wood, (2007) that the seasonalities incur in both January and April. The mean return of January is 2.56% and the return of April is 2.34%. While at the same time, interestingly that with our sample period, the seasonality incurs only in July in Australia with a mean return of 2.97%; and no seasonality has been present in China during the sample period.

However, in the UK, the capital gain tax year end is 4th, April for small business and 31st, December for medium to large sized companies; in the Australia, the capital gain tax year end is 30th, June; while in China, there is no capital gain tax imposed till now. This fact seems to support the tax-loss selling hypothesis explanation for the seasonalities. The results of the two sub-sample periods are consistent with the results of the whole sample, except that consistent with previous literature that the magnitude of the coefficients has reduced in the latter period, suggesting that the trend of the seasonality is decreasing. The finding of Chinese market is consistent with Zhang and Li (2007) that before 1997, January effect only exists in small-sized firms; while after 1997, no significant seasonal effect has been found.

2. Conditional Volatility

Table 2 present the results of the standard GARCH (1, 1) model on the full sample period for the four sample countries: the USA, the UK, China and Australia. This enables us to confirm the results of Model 1 and whether the conditional variance, as a proxy of risk, is higher in January (or other specific month having seasonal effect suggested by Model 1). The listed results confirm the results for Model 1. The result on the sample of the USA is consistent with Sun and Tong's result that in January, the mean return of equally-weighted index of NYSE is 4.44% higher than the average monthly return of -0.36% in all other months, which is positively significant at 1% significant level with a T-value of 6.71. While contrary to the finding of Sun and Tong (2011), the coefficient β_2 in the variance equation is positively significant, suggesting that the conditional variance of January is significantly higher than that of other months during the year. Therefore the result suggests that market risk is one of the driving factors of the January effect in the USA during the sample period.

Same as the result of Model 1, for the UK, the seasonal effect occurs in both January and April. In January, the mean return is 3.16% higher than the mean return of 0.29% in the other months; and in April, the mean return is 1.68% higher than the average return in the other months. Both results are positively significant at 1% significant level. While it can be found from the results, for the UK, that conditional variance is not significantly higher in either of January or April, suggesting that market risk can't explain the seasonal effect in the UK during the sample period.

The result of Australia is consistent with the result of Model 1 as well. Besides, the conditional variance, as a proxy of market risk, is not significantly higher in July in Australia. The result of China is the same with no significant higher market risk occurs in any of the calendar month.

Besides the full sample, the test is conducted on two sub-sample periods, one for the first half of the sample period, and the other for the more recent period. Most of all the results are the same as the whole sample period.

3. Market risk test with GARCH-M Model

The results of the GARCH-M Model have been presented by Table 3. With the conditional variance added into the mean equation, there is no significant change to the magnitude of the coefficient of the dummy variable of the seasonal effect, suggesting that market risk is not an explanatory factor to the seasonalities in the four sample countries. In the USA, α_2 ,although gets smaller, is still significant at 1% significant level with a T-value of 5.24; In the UK, for January effect, α_2 is 0.0308, still positively significant at 1% level; and for April effect, α_2 is 0.0313, which is positively significant at 1% level as well. The same result is concluded for Australia, with a positively significant coefficient of 0.0379, the market risk seems not to be able to explain July effect during the sample period. Test has been conducted on every single month during the year in China to check the possible seasonality[1], and no seasonality has been detected.

4. Market value interacted with seasonal dummy variable/s

In Model 4 interactive dummy variable of the month/s with seasonal effect is added into GARCH-M model. Extremely interesting results shown in Table 4 are generated. In the USA, the results of sample period between 1973 and 2012 are consistent with Sun and Tong (2011). When interactive dummy variable is added into the mean equation, the coefficient of January dummy becomes even smaller and, most importantly, only marginal significant at 10% level. α_2 is 0.041 with a T-value of 1.90. Interesting results were found both in the UK and Australia. The coefficient α_2 decreases to 0.0199 with a T-value of 0.46. However the difference between the UK and the USA result is that the interactive dummy is not significant in the UK, implying that although the coefficient of January dummy has become insignificant, market risk has not been highly priced in January.

Another interesting founding is that besides January, interactive dummy variable can explain other seasonal effects in either the UK or Australia. The coefficient α_2 has significantly decreases to be insignificant with the interactive dummy in the mean

[1] For simplicity, just certain months with lower p-value is exhibited.

equation. For the April effect in the UK, the coefficient α_2 has decreases to be insignificant at 0.0369. While at the same time, for the July effect in Australia, the coefficient α_2 has decreases to be insignificant at 0.016.

The test is conducted in both the sub sample periods and the results are robust. From all the results presented, it seems that with the interactive dummy variable added in to GARCH-M model, the seasonal effects in our four sample countries with different tax implication can be explained. However, the results did not support the argument that in certain calendar month, the market risk has been priced highly. As the seasonal effects are consistent with the tax year end and tax system in the four sampled countries, the results support the proposition that market volatility increases when it is close to the financial statement announcement period due to the uncertainty attached to company performance.

Conclusion

The seasonal effect has been continuously discussed. Various explanations have been investigated. The difficulty of this topic is to conduct a test which can distinguish specific explanation from others. This paper is motivated by the idea to test the risk explanation of seasonal effect with four different countries (the USA, the UK, Australia and China) with different tax regimes and tax year end.

When GARCH-M model with interactive seasonal dummy is applied, the seasonal effects can be explained. The empirical evidence supports the risk explanation for the seasonal effects. The results differ from Sun and Tong (2011) that no empirical evidence has been found that the market risk is priced higher in the calendar months linked to seasonal effects.

The existent research of the risk explanation has partially explained seasonal effect in the world wide. However no evidence has been given to the question that why the risk is higher only in January. The results of this paper provide implication to this question. The results of sample period imply that market return volatility increases when it closes to financial statement announcement. Because of the uncertainty linked to the company performance, investors will sell equities to avoid possible risk, leading to the increasing market volatility. The results strongly indicate that the seasonal effect, which is defined as the fact that in certain calendar month, the mean return of the market is significantly higher than other months through the year, is due to the compensation of the higher market volatility. The increased market volatility is linked with the uncertainty of the announcement of the financial statement. Future research can be linked to both trading volume and potential motivation for tax-loss selling.

Reference

Berges, A., J. McConnell, J. and Schlarbaum, G. G., 1984, "The turn-of-the-year in Canada", *Journal of Finance*, 39, 185–92.

Bhardwaj, R.K. and Brooks, L.D., 1992, The January anomaly: effects of low share price, transactions costs, and bid-ask bias, *Journal of Finance*, 47, 552-575.

Branch, B., 1977, "A tax-loss selling trading rule", *Journal of Business*, 50, 198–207.

Brauer, G. A. and E. C. Chang, 1990, "Return seasonality in stocks and their underlying assets: Tax-loss selling versus information explanations", *Review of Financial Studies*, 3, 255–80.

Brown, P., Keim, D. B., Kleidon, A. W. and Marsh. T. A., 1983, "Stock return seasonalities and the tax-loss selling hypothesis", *Journal of Financial Economics* , 12, 105–27.

Chang, E. C., and Pinegar, L. M., 1989, "Seasonal fluctuations in industrial production and stock market seasonal", *Journal of Financial and Quantitative Analysis*, 24, 59–74.

Chang, E. C., and Pinegar, L. M., 1990, "Market seasonal and prespecified multifactor pricing relations", *Journal of Financial and Quantitative Analysis*, 25, 517–533.

Chen, H. and Singal, V., 2004, "All things considered, taxes drive the January effect", *Journal of Financial Research*, 27(3), 351-372.

Chen, Q., Wood, A and Jack, L., 2007, Tax-loss selling and seasonal effects in the UK, *Applied Financial Economics*, 17, 1027-1035.

Draper, P. and Paudyal, K., 1997, Microstructure and seasonality in the UK equity market, *Journal of Business Finance and Accounting*, 24, 1177-1204.

Dyl, E. A., 1977, "Capital gains taxation and year-end stock market behavior", *Journal of Finance*, 32, 165–75.

Griffiths, M. and White, R., 1993, "Tax-induced trading and the turn of the year anomaly: an intraday study", *Journal of Finance*, 48, 575-598.

Gultekin, M.N., and Gultekin, N.B., 1983, Stock market seasonality: international evidence, *Journal of Financial Economics*, 12, 469-82.

Haugen, R. A. and Lakonishok, J., 1988, "The incredible January effect: The stock market's unsolved mystery", Homewood, IL: Dow Jones-Irwin.

Ho, R.K., 1990, "Stock return seasonalities in Asian Pacific Markets", *Journal of International Financial Management and Accounting*, 2, 47-77.

Kato, K. and Schallheim, J. S., 1985, "Seasonal and size anomalies in the Japanese stock market", *Journal of Financial and Quantitative Analysis*, 20, 243–60.

Keim, D. B., 1983, "Size related anomalies and stock return seasonality: Further empirical evidence", *Journal of Financial Economics*, 12, 13–32.

Keim, D. B., 1989, "Trading patterns, bid-ask spreads, and estimated security returns: The case of common stocks at calendar turning points", *Journal of Financial Economics*, 25, 75–97.

Kohers, T. and Kohli, R. K., 1992, "The yearend effect in stock returns over business cycles: A technical note", *Journal of Economics and Finance*, 16, 61–68.

Kramer, C., 1994, "Macroeconomic seasonality and the January effect", *Journal of Finance*, 49, 1883–1891.

Menyah, K. and Paudyal, K., 1996, The determinants and dynamics of bid-ask spreads on the London Stock Exchange, *Journal of Financial Research*, 19, 377-394.

Lakonishok, J., Shleifer, A., Thaler, R. and Vishny, R., 1991, “Window Dressing by Pension Fund Managers”, *American Economic Review*, 81(2), 227–231.

Ogden, J. P., 1990, “Turn-of month evaluations of liquid profits and stock returns: A common explanation for the monthly and January effects”, *Journal of Finance*, 45, 1259–1272.

Reinganum, M. R., 1981, “Misspecification of capital asset pricing: Empirical anomalies based on earnings’ yields and market values”, *Journal of Financial Economics*, 9, 19–46.

Reinganum, M.R. and Shapiro, A.C., 1987, “Taxes and stock return seasonality: Evidence from the London Stock Exchange”, *Journal of Business*, 60, 281-295.

Ritter, J., 1988, Buying and selling behavior of individual investors at the turn of the year, *Journal of Finance*, 43, 701-717.

Ritter, J. R. and Chopra, N., 1989, “Portfolio rebalancing and the turn-of the-year effect”, *Journal of Finance*, 44, 149–166.

Roll, R., 1983, “On computing mean returns and the small firm premium”, *Journal of Financial Economics*, 12, 371–386.

Rogalski, R. and Tinic, S., 1986, Capital market seasonality: risk mismeasurement, *Financial analyst Journal*, 63-70.

Rozeff, M. S. and Kinney,W. R., Jr., 1976, “Capital market seasonality: The case of stock returns”, *Journal of Financial Economics*, 3, 379–402.

Schultz, P., 1985, "Personal income taxes and the January effect: Small firm stock returns before the War Revenue Act of 1917: A note", *Journal of Finance*, 40, 333–43.

Stoll, H. R. and Whaley, R. E., 1983, "Transactions costs and the small firm effect", *Journal of Financial Economics*, 12, 57–80.

Sun, Q. and Tong, W. H. S., 2010, "Risk and the January effect", *Journal of Banking and Finance*, 34, 965-974.

Wang, R. and Chen, J. , 2012, " ARCH effects, trading volume and the information flow interpretation: empirical evidence from the Chinese stock markets", *Journal of Chinese Economics and Business Studies*, 10:2, 169-191.

Zhang, B. and L, X., 2007, "Do Calendar Effects Still Exist in the Chinese Stock Markets?", Journal of Chinese Economic and Business Studies , 4:2. 151-163.

Table 1 Test of seasonal effects in the four sample countries

coefficients		α_1 (January)	α_2 (February)	α_3 (March)	α_4 (April)	α_5 (May)	α_6 (June)	α_7 (July)	α_8 (August)	α_9 (September)	α_{10} (October)	α_{11} (November)	α_0 (December)
Sample countries	The USA (01/1973-06/2012)	0.051*** (3.92)	0.012 (0.94)	0.012 (0.90)	0.016 (1.27)	0.011 (0.88)	0.001 (0.06)	0.0025 (0.20)	0.0005 (0.04)	-0.01 (-0.77)	-0.018 (-1.41)	-0.006 (-0.44)	-0.011 (-1.24)
	The UK (01/1971-06/2012)	0.025** (2.12)	0.004 (0.36)	-0.008 (-0.72)	0.023** (1.94)	-0.008 (-0.65)	-0.021 (-1.80)	-0.015 (-1.27)	-0.003 (-0.27)	-0.026** (-2.16)	-0.021* (-1.77)	-0.013 (-1.06)	0.008 (0.91)
	China (01/1991-06/2012)	0.054 (1.35)	0.074* (1.85)	0.04 (1.06)	0.05 (1.25)	0.059 (1.47)	-0.007 (-0.18)	0.051 (1.25)	0.037 (0.91)	0.013 (0.32)	-0.0036 (-0.09)	0.075* (1.85)	-0.023 (-0.81)
	Australia (01/1991-06/2012)	0.0035 (0.22)	-0.018 (-1.11)	-0.009 (-0.56)	-0.0004 (-0.030	-0.022 (-1.39)	-0.038** (-2.36)	0.030** (1.93)	0.006 (0.40)	-0.007 (-0.43)	-0.027* (-1.68)	-0.016 (-0.97)	0.006 (0.53)
Sample countries	The USA (01/1973-12/1990)	0.043*** (2.39)	0.0133 (0.74)	0.0035 (0.20)	0.002 (0.14)	-0.0008 (-0.05)	-0.0022 (-0.12)	-0.0035 (-0.19)	-0.0101 (-0.56)	-0.0217 (-1.20)	-0.036** (-1.97)	-0.016 (-0.89)	0.0054 (0.42)
	The UK (01/1973-12/1991)	0.04** (2.40)	0.017 (1.03)	0.0075 (0.45)	0.027 (1.58)	-0.008 (-0.45)	-0.008 (-0.47)	-0.0036 (-0.21)	-0.002 (-0.13)	-0.015 (-0.87)	-0.024 (-1.41)	-0.013 (-0.79)	0.008 (0.68)
	China (01/1991-12/2001)	0.0875 (1.45)	0.0779 (1.30)	0.0803 (1.33)	0.0965 (1.60)	0.1179* (1.96)	0.03405 (0.57)	0.0664 (1.10)	0.0893 (1.48)	(0.0344 (0.57)	0.04492 (0.75)	0.1119* (1.86)	-0.0476 (-1.12)
	Australia (01/1991-12/1996)	-0.0136 (0.64)	-0.00896 (-0.42)	0.0029 (0.14)	0.0220 (1.04)	-0.0099 (-0.47)	-0.0287 (-1.36)	0.043** (2.04)	0.0264 (1.25)	-0.0022 (-0.10)	-0.0294 (-1.39)	-0.0185 (-0.87)	0.0027 (0.18)
Sample countries	The USA (01/1991-06/2012)	0.0549*** (2.92)	0.0118 (0.64)	0.0201 (1.09)	0.0306 (1.65)	0.0239 (1.29)	0.0046 (0.25)	0.0087 (0.46)	0.0112 (0.60)	0.0015 (0.08)	-0.0013 (-0.07)	0.0047 (0.25)	-0.0283** (-2.13)
	The UK (01/1992-06/2012)	0.01 (0.59)	-0.009 (-0.55)	-0.255 (-1.50)	0.02 (1.18)	-0.008 (-0.47)	-0.036** (-2.12)	-0.028* (-1.64)	-0.004 (-0.26)	-0.039** (-2.26)	-0.019 (-1.10)	-0.012 (-0.72)	0.007 (0.61)
	China 01/2002-06/2012	0.0145 (0.27)	0.0673 (1.26)	-0.0022 (-0.04)	-0.0036 (-0.07)	-0.0087 (-0.16)	-0.0559 (-1.05)	0.0316 (0.58)	-0.0269 (-0.49)	-0.0131 (-0.24)	-0.0628 (-1.15)	0.0306 (0.56)	0.00661 (0.17)
	Australia (01/1997-06/2012)	-0.0075 (-0.30)	-0.0276 (-1.11)	-0.02212 (-0.89)	-0.0246 (-0.99)	-0.03602 (-1.45)	-0.04845 (-1.95)	0.0144 (0.57)	-0.0164 (-0.65)	-0.0126 (-0.50)	-0.0251 (-0.99)	-0.01284 (-0.51)	0.00992 (0.55)

Table 2 Test of the seasonal effect on the monthly equally-weighted return series with standard GARCH (1, 1) model

Period	01/1973-06/2012	01/1971-06/2012	01/1971-06/2012	01/1981-06/2012	01/1991-02/2012	01/1973-12/1990	01/1971-12/1990	01/1971-12/1990	10/1981-12/1996	01/1991-12/2001	01/1991-06/2012	01/1991-06/2012	01/1991-06/2012	01/1997-06/2012	01/2002-06/2012
No. of Obs	**462**	**485**	**485**	**365**	**245**	**227**	**251**	**251**	**191**	**131**	**233**	**245**	**245**	**185**	**125**
Country	**The USA January**	**The UK January**	**The UK April**	**Australia July**	**China February**	**The USA January**	**The UK January**	**The UK April**	**Australia July**	**China May**	**The USA January**	**The UK January**	**The UK April**	**Australia July**	**China February**
α_0 (constant)	**-0.0036***	**0.0029**	**0.0036***	**-0.004**	**0.0017**	**0.00005**	**0.009*****	**0.004**	**0.0006**	**0.0171**	**-0.006*****	**-0.002**	**0.0004**	**-0.009***	**-0.0042**
	(-1.73)	**(1.39)**	**(1.93)**	**(-1.64)**	**(0.21)**	**(0.02)**	**(3.77)**	**(1.55)**	**(0.10)**	**(1.02)**	**(-2.97)**	**(-0.48)**	**(0.19)**	**(-1.81)**	**(-0.36)**
α_1 (R_{t-1})	**0.351*****	**0.321*****	**0.308*****	**0.380*****	**0.0736**	**0.26*****	**0.253*****	**0.32*****	**0.208****	**0.0374**	**0.435*****	**0.39*****	**0.38*****	**0.39*****	**-0.0024**
	(8.49)	**(6.78)**	**(7.6)**	**(7.95)**	**(0.96)**	**(5.69)**	**(4.30)**	**(4.51)**	**(2.02)**	**(0.32)**	**(7.93)**	**(5.40)**	**(6.34)**	**(5.15)**	**(-0.002)**
α_2 (Seasonal Dummy)	**0.0444*****	**0.032*****	**0.0168*****	**0.052*****	**0.0331**	**0.06*****	**0.036*****	**0.017***	**0.05*****	**0.0489**	**0.027*****	**0.021***	**0.024****	**0.05*****	**0.069****
	(6.71)	**(4.89)**	**(2.63)**	**(5.83)**	**(1.18)**	**(4.33)**	**(4.80)**	**(1.75)**	**(2.92)**	**(0.85)**	**(3.83)**	**(1.87)**	**(2.59)**	**(3.31)**	**(2.56)**
β_1 (h_{t-1})	**0.618*****	**0.233*****	**0.1229*****	**0.102***	**0.1233**	**-0.026**	**0.28****	**0.19****	**-0.018*****	**0.0127**	**0.353*****	**0.156***	**0.16****	**0.107***	**0.075**
	(5.06)	**(2.61)**	**(2.67)**	**(1.69)**	**(0.98)**	**(-1.08)**	**(2.01)**	**(2.11)**	**(-11.74)**	**(0.18)**	**(3.92)**	**(1.81)**	**(2.19)**	**(1.70)**	**(0.57)**
β_2 (Seasonal Dummy)	**0.102*****	**-0.096*****	**-0.427**	**-0.017**	**-1.13*****	**0.5708**	**-1.08**	**-6.69**	**-0.586**	**0.3605**	**-1.999**	**-0.86**	**1.603**	**-1.038**	**-0.971**
	(3.04)	**(-5.64)**	**(-0.10)**	**(-0.01)**	**(-8.23)**	**(1.07)**	**(-1.67)**	**(-0.001)**	**(-0.33)**	**(0.11)**	**(-0.001)**	**(-0.001)**	**(0.86)**	**(-0.16)**	**(-0.001)**
β_3 (ε^2_{t-1})	**0.808*****	**0.686*****	**0.799*****	**0.6356*****	**0.76*****	**-0.265**	**0.63*****	**0.69*****	**0.2602**	**0.744**	**0.57*****	**0.76*****	**0.78*****	**0.76*****	**0.2889**
	(4.02)	**(6.82)**	**(11.11)**	**(2.91)**	**(3.22)**	**(0.55)**	**(4.38)**	**(5.38)**	**(0.17)**	**(0.48)**	**(6.72)**	**(6.68)**	**(8.74)**	**(4.20)**	**(0.72)**

The following GARCH (1, 1) model is applied to the equally-weighted market return series: $R_t = \alpha_0 + \alpha_1 R_{t-1} + \alpha_2 seasonaldummy_t + \varepsilon_t \quad \varepsilon_t | \phi_{t-1} \sim N(0, h_t)$

$h_t = \beta_0 + \beta_1 h_{t-1} + \beta_2 seasonaldummy_t + \beta_3 \varepsilon^2_{t-1}$; where seasonal dummy is a dummy variable to be included when the seasonality incurs. h_t is the variance of ε_t, which is conditional upon the information set ϕ at time t-1 and is following an ARMA(1, 1) process

*, **, *** indicate statistical significance at the 10%, 5% and 1% level respectively

Table 3 Test of the seasonal effect on the monthly equally-weighted return series with GARCH-M model

Period	01/1973-06/2012	01/1971-06/2012	01/1971-06/2012	01/1981-06/2012	01/1991-02/2012	01/1973-12/1993	01/1971-12/1993	01/1971-12/1993	10/1981-12/1996	01/1991-12/2001	01/1994-06/2012	01/1994-06/2012	01/1994-06/2012	01/1997-06/2012	01/2002-06/2012
No. of Obs	**462**	**485**	**485**	**365**	**245**	**227**	**251**	**251**	**191**	**131**	**233**	**245**	**245**	**185**	**125**
Country	**The USA January**	**The UK January**	**The UK April**	**Australia July**	**China February**	**The USA January**	**The UK January**	**The UK April**	**Australia July**	**China May**	**The USA January**	**The UK January**	**The UK April**	**Australia July**	**China February**
α_0 (constant)	**-0.013**	**-0.0015**	**-0.0027**	**-0.0049**	**-0.024**	**-0.054**	**0.002**	**0.0015**	**-1.515**	**0.4736**	**-0.105*****	**0.014****	**-0.007**	**-0.032**	**-0.0517**
	(-1.99)	**(-0.34)**	**(-0.47)**	**(-0.11)**	**(-0.44)**	**(-0.75)**	**(0.41)**	**(0.29)**	**(-0.03)**	**(7.02)**	**(-2.45)**	**(2.26)**	**(0.33)**	**(-1.02)**	**(-1.17)**
α_1 (R_{t-1})	**0.401*****	**0.338*****	**0.313*****	**0.379*****	**0.036**	**0.304*****	**0.30*****	**0.14**	**0.326*****	**0.0289**	**0.359*****	**0.41*****	**0.42*****	**0.41****	**-0.1024**
	(7.49)	**(6.85)**	**(4.71)**	**(6.51)**	**(0.45)**	**(3.71)**	**(4.43)**	**(1.39)**	**(2.90)**	**(0.24)**	**(4.43)**	**(5.14)**	**(6.04)**	**(4.81)**	**(-1.17)**
α_2 (Seasonal Dummy)	**0.045*****	**0.0308*****	**0.028*****	**0.05*****	**0.090****	**0.0335**	**0.055*****	**0.022****	**0.425**	**0.353**	**-0.011*****	**0.017****	**0.038*****	**0.04*****	**0.1515**
	(5.24)	**(3.57)**	**(3.79)**	**(3.52)**	**(2.09)**	**(1.06)**	**(3.28)**	**(2.43)**	**(0.04)**	**(1.11)**	**(-2.45)**	**(2.26)**	**(2.62)**	**(2.59)**	**(1.40)**
α_3 (h_t)	**1.46**	**1.341**	**1.569**	**-4.27**	**3.89**	**1.21**	**-1.62**	**1.95***	**4.74**	**3.30**	**-0.423**	**-3.18**	**-3.05**	**-3.607**	**0.8184**
	(1.15)	**(0.59)**	**(0.51)**	**(-0.59)**	**(1.34)**	**(0.69)**	**(-1.31)**	**(1.74)**	**(0.04)**	**(0.67)**	**(-0.44)**	**(-1.22)**	**(-0.56)**	**(-0.36)**	**(1.04)**
β_1 (h_{t-1})	**0.316*****	**0.307**	**0.239**	**0.075**	**0.09**	**0.759**	**1.71**	**0.44**	**-2.33**	**-0.332**	**2.247***	**-4.65****	**-2.81**	**1.04**	**-0.434**
	(2.91)	**(1.73)**	**(1.39)**	**(0.57)**	**(0.93)**	**(0.79)**	**(1.63)**	**(0.83)**	**(-0.52)**	**(-0.74)**	**(1.76)**	**(-2.19)**	**(-0.51)**	**(1.12)**	**(-0.68)**
β_2 (Seasonal Dummy)	**0.41**	**0.643**	**-0.316**	**-0.209**	**-1.54*****	**0.569**	**1.29****	**-1.11****	**-0.262**	**0.557****	**-1.04*****	**-0.72**	**0.256**	**-0.3285**	**-0.383**
	(1.03)	**(0.59)**	**(-0.63)**	**(-0.59)**	**(-4.46)**	**(1.07)**	**(2.11)**	**(-2.07)**	**(-0.56)**	**(1.89)**	**(-3.09)**	**(-1.15)**	**(0.42)**	**(-0.63)**	**(-0.64)**
β_3 (ε^2_{t-1})	**2.26****	**-0.880**	**-0.484**	**4.03**	**-2.13**	**0.046**	**0.426**	**0.578**	**0.0005**	**-0.0003**	**0.508*****	**0.312****	**0.18**	**0.147**	**0.1909**
	(2.14)	**(-0.36)**	**(-0.63)**	**(0.40)**	**(-1.41)**	**(0.59)**	**(1.58)**	**(1.55)**	**(0.03)**	**(-0.30)**	**(3.51)**	**(2.05)**	**(1.62)**	**(1.50)**	**(0.62)**

The following GARCH-M model is applied to the equally-weighted market return series: $R_t = \alpha_0 + \alpha_1 R_{t-1} + \alpha_2 seasonaldummy_t + \alpha_3 h_t + \varepsilon_t$ $\varepsilon_t | \phi_{t-1} \sim N(0, h_t)$

$h_t = \beta_0 + \beta_1 h_{t-1} + \beta_2 seasonaldummy_t + \beta_3 \varepsilon^2_{t-1}$; where seasonal dummy is a dummy variable to be included when the seasonality incurs. h_t is the variance of ε_t, which is conditional upon the information set ϕ at time t-1 and is following an ARMA(1, 1) process. *, **, *** indicate statistical significance at the 10%, 5% and 1% level respectively

Table 4 Test of the seasonal effect on the monthly equally-weighted return series

with interactive dummy in the GARCH-M model

Period	01/1973-06/2012	01/1971-06/2012	01/1971-06/2012	01/1981-06/2012	01/1991-02/2012	01/1973-12/1993	01/1971-12/1993	01/1971-12/1993	10/1981-12/1996	01/1991-12/2001	01/1994-06/2012	01/1994-06/2012	01/1994-06/2012	01/1997-06/2012	01/2002-06/2012
No. of Obs	**462**	**485**	**485**	**365**	**245**	**227**	**251**	**251**	**191**	**131**	**233**	**245**	**245**	**185**	**125**
Country	**The USA January**	**The UK January**	**The UK April**	**Australia July**	**China February**	**The USA January**	**The UK January**	**The UK April**	**Australia July**	**China May**	**The USA January**	**The UK January**	**The UK April**	**Australia July**	**China February**
α_0 **(constant)**	**-0.01***	**-0.0014**	**-0.003**	**-0.0068**	**-0.038**	**-0.055**	**0.002**	**0.002**	**-0.137**	**-0.241**	**-0.011****	**0.006**	**0.004**	**-0.035**	**-0.3877**
	(-2.00)	**(-0.36)**	**(-0.47)**	**(-0.13)**	**(-0.54)**	**(-0.73)**	**(0.44)**	**(0.45)**	**(-0.04)**	**(-0.74)**	**(-2.45)**	**(0.86)**	**(0.22)**	**(-1.25)**	**(-0.79)**
α_1 (R_{t-1})	**0.400*****	**0.333*****	**0.324*****	**0.363*****	**0.0455**	**0.31*****	**0.29*****	**0.12**	**0.32****	**0.047**	**0.357*****	**0.34*****	**0.43*****	**0.38*****	**0.0198**
	(7.33)	**(6.18)**	**(4.26)**	**(6.01)**	**(0.55)**	**(3.71)**	**(4.46)**	**(1.04)**	**(2.78)**	**(0.38)**	**(3.84)**	**(4.58)**	**(5.82)**	**(4.52)**	**(0.22)**
α_2 **(Seasonal Dummy)**	**0.041***	**0.0199**	**0.0369**	**0.016**	**0.146**	**0.0788**	**0.04**	**-0.016**	**0.374**	**-0.283**	**0.045*****	**-0.084****	**0.052****	**0.0076**	**-0.1236**
	(1.90)	**(0.46)**	**(1.48)**	**(0.66)**	**(1.51)**	**(0.74)**	**(0.43)**	**(-0.23)**	**(0.04)**	**(-0.79)**	**(2.91)**	**(-1.97)**	**(2.31)**	**(0.14)**	**(-0.19)**
α_3 (h_t)	**1.48**	**1.144**	**1.29**	**-3.26**	**4.91**	**1.21**	**-1.75**	**1.65***	**4.34**	**1.456**	**-0.603**	**-2.76**	**-3.05**	**-2.21**	**0.986**
	(1.17)	**(0.43)**	**(0.23)**	**(-0.17)**	**(1.25)**	**(0.71)**	**(-1.35)**	**(1.69)**	**(0.04)**	**(1.24)**	**(-0.43)**	**(-0.93)**	**(-0.55)**	**(-0.24)**	**(0.0001)**
α_4 **(Interactive Seasonal Dummy)**	**-0.098**	**0.322**	**-0.29**	**0.929**	**-0.903**	**-0.807**	**0.36**	**1.28**	**0.4849**	**-0.528**	**-0.258**	**1.97*****	**-0.497**	**1.403**	**0.2766**
	(0.21)	**(0.29)**	**(-0.37)**	**(1.69)**	**(-0.54)**	**(-0.48)**	**(0.27)**	**(0.55)**	**(0.25)**	**(-0.47)**	**(-0.45)**	**(4.47)**	**(-0.69)**	**(0.84)**	**(0.30)**
β_1 (h_{t-1})	**2.23****	**-0.702**	**-0.118**	**3.61**	**-2.32**	**0.78**	**1.75***	**0.53**	**-2.43**	**-1.73**	**2.529***	**-2.02**	**-1.804**	**1.011**	**0.6558**
	(2.14)	**(-0.26)**	**(-0.03)**	**(0.48)**	**(-1.45)**	**(0.77)**	**(1.67)**	**(1.01)**	**(-0.53)**	**(-1.09)**	**(1.59)**	**(-1.27)**	**(-0.34)**	**(1.21)**	**(-1.59)**
β_2 **(Seasonal Dummy)**	**0.41**	**0.64**	**-0.325**	**-0.247**	**-1.54*****	**0.5549**	**1.30****	**-1.21****	**-0.2657**	**0.8356**	**-1.01*****	**-1.52*****	**0.195**	**-0.422**	**1.17*****
	(1.02)	**(1.10)**	**(-0.65)**	**(-0.65)**	**(-4.38)**	**(1.03)**	**(2.18)**	**(-2.10)**	**(-0.56)**	**(1.55)**	**(-2.96)**	**(-3.14)**	**(0.29)**	**(-0.86)**	**(3.81)**
β_3 (ε_{t-1}^2)	**0.315*****	**0.304**	**0.22**	**0.067**	**0.087**	**0.0481**	**0.428**	**0.598**	**0.00057**	**0.0005**	**0.525*****	**0.26****	**0.180***	**0.1512**	**0.0013****
	(2.92)	**(1.69)**	**(1.04)**	**(0.57)**	**(0.84)**	**(0.61)**	**(1.58)**	**(1.60)**	**(0.04)**	**(0.13)**	**(3.03)**	**(1.98)**	**(1.66)**	**(1.58)**	**(2.49)**

The following GARCH-M model is applied to the equally-weighted market return series: $R_t = \alpha_0 + \alpha_1 R_{t-1} + \alpha_2 seasonaldummy_t + \alpha_3 h_t + \alpha_4 h_t * seasonaldummy_t + \varepsilon_t \; \varepsilon_t | \phi_{t-1} \sim N(0, h_t)$

$h_t = \beta_0 + \beta_1 h_{t-1} + \beta_2 seasonaldummy_t + \beta_3 \varepsilon_{t-1}^2$; where seasonal dummy is a dummy variable to be included when the seasonality incurs. h_t is the variance of ε_t, which is conditional upon the information set ϕ at time t-1 and is following an ARMA(1, 1) process. *, **, *** indicate statistical significance at the 10%, 5% and 1% level respectively