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Clustering of annual general meetings and stock returns: UK evidence

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Abstract

We find evidence of a significantly negative relationship between stock returns and the clustering of annual general meetings in the UK. The negative returns during the clustering of annual general meetings are not, however, economically significant. We caution against interpreting our results as evidence of a “new anomaly” in stock market returns.

Keywords: annual general meeting; stock return; market anomaly; market efficiency

JEL Classification: G10; G11; G12, G14

1. Introduction

In a recent study, Wang and Hefner (2014) uncover a “new anomaly” evidenced by the positive association between clustering of annual general meetings (hereafter AGMs) and stock returns in the US. However, Schwert (2003) suggests that one way to examine whether a particular returns phenomenon is a temporary anomaly is to investigate whether the pattern can be replicated in an independent sample. Consistent with this approach, this study re-examines the relationship between the frequency of AGMs and stock returns using UK data spanning the period 2004-2014.

Similar to the pattern in the US, our results show that AGMs cluster around May, June and July in the UK. However, contrary to Wang and Hefner (2014), we find a negative relationship between the monthly frequency of AGMs and stock returns, using both firm-level and aggregate market data. While our study contributes to the stream of studies on stock market anomalies, we caution against labelling the clustering effect as a “new anomaly” as our results are not inconsistent with the well-known April effect (e.g. Reinganum and Shapiro, 1987) and Halloween effect (e.g. Dichtl and Drobetz, 2014).

The remainder of this paper is organised as follows. In Section 2, we briefly discuss the relevant literature on stock market anomaly; Section 3 discusses the data collection approach; Section 4 presents the methodology; Section 5 discusses the results and Section 6 concludes the paper.

2. Literature Review

The finance literature documents a number of stock market anomalies suggesting predictability of stock returns contrary to the efficient market hypothesis. For example, the well-documented January effect suggests that the returns for the month of January are on average significantly higher than those of the remaining 11 months of the year (Rozeff & Kinney, 1976). Empirical evidence supports the tax-loss selling (Cheng & Singal, 2004) and window dressing (Haugen & Lakonishok, 1988) explanations for this phenomenon. Another variant of this phenomenon – the other January effect – suggests positive (negative) returns in January predict positive (negative) returns in the following 11 months of the year (Marshall & Visaltanachoti, 2010).

More recently, Wang & Hefner (2014) provide new evidence in support of a calendar related stock market anomaly in the US. They argue that the release of more sensitive information in months with relatively high frequencies of AGMs suggests that returns for these months should be significantly different from those of other months. In line with their argument, their results support a positive relationship between the clustering of AGMs and stock returns. It is, however, unclear whether this phenomenon is restricted to the US.

3. Data

We hand-collected 15,375 AGM dates for 2107 listed equities for the period 2004-2014 from annual reports, notices of AGMs and web searches. We also obtained stock market data from Datastream. We used the FTSE All Share Index as our benchmark. We matched our AGM dataset with the returns data using the International Securities Identification Number (ISIN), thus mitigating the possible incidence of mismatching due, for example, to change of company names. To the best of our knowledge, this is the first study, outside the US, that

draws evidence from as many AGM dates. Column 1 of Table 1 presents the monthly frequency of AGMs during the study period.

4. Methodology

We start our investigation of the relationship between the monthly frequency of AGMs and stock returns by relating monthly stock returns to a number of month specific dummy variables. Specifically, we follow Wang & Hefner (2014) in using the following regression model:

$$r_{it} = \sum_{t=1}^{12} \beta_t Month_t + \sum_{t=1}^{12} \beta_t Month_t \times EventMonth + \varepsilon_{it} \quad (1)$$

where r is the continuously compounded monthly stock returns; $Month$ is a series of calendar month dummy variables. For example, $Month$ is a dummy variable that takes the value of 1 for the month of January and 0 otherwise. $EventMonth$ is the event month dummy variable that takes the value of 1 if the firm holds an AGM in month t and 0 otherwise. We test whether the coefficients of the interaction variables are significantly different from zero suggesting that the monthly returns depend on the AGM events.

However, Equation 1 does not directly examine the relationship between stock returns and the frequency of AGMs. We address this by estimating the parameters of the following regression equation:

$$r_t = \alpha_1 + \beta_1 AGM_t + \varepsilon_t \quad (2)$$

where r is the continuously compounded average monthly stock returns; AGM represents two alternative variables – the number of AGMs in month t as a percentage of total AGMs in the year, and a dummy variable that takes the value of 1 if month t falls in period May through July (cluster months) and 0 otherwise (non-cluster months). In both cases, a

significant coefficient of the AGM variable will support the hypothesis of an AGM cluster effect on stock returns.

To examine whether the frequency of AGMs contemporaneously signals the direction of returns in the overall stock market, we examine the relationship between returns on the FTSE All Market Index and the frequency of AGMs. Our analysis of this relationship proceeds in two ways. First, we use the bin tests to uncover the correlation, if any, between returns and the frequency of AGMs¹. However, because the bin tests only indicate the direction of the association between variables without attaching a precise measure of this association, we further examine the relationship between market returns and the frequency of AGMs while controlling for the January effect and (April) tax-loss effect using the following regression model:

$$r_t = \alpha_1 + \beta_1 M_t^{Jan} + \beta_2 M_t^{Tax} + \beta_3 AGM_t + \varepsilon_t \quad (3)$$

where r is the continuously compounded monthly market returns, M^{Jan} is the January effect dummy variable which equals 1 for the month of January and 0 otherwise; M^{Tax} is the tax-loss effect dummy variable that takes the value of 1 for the month of April and 0 otherwise, consistent with the fact that the UK fiscal year starts (and ends) in the month of April.

5. Results and Discussion

Table 1 reports the monthly distribution of AGMs and average stock returns. Column 2 of the table indicates the three-month period spanning May to July accounts for 50.1% of the AGMs justifying our classification of these months as the cluster months. Column 5 of Table 1 shows that the average monthly returns were negative for each month of the AGM cluster period. While we do not include the month of April in our cluster month, consistent with the result reported by Wang & Hefner (2014) and the April effect, we report positive average stock returns of 1.41% for the month of April. The authors associate their reported positive

¹ See Cao & Wei (2005) and Saunders (1993) for a description of these tests.

April stock returns to AGM clustering in the US. However, the explanation is more

Calendar Month	Number of annual general meetings	Percentage of total meetings	Average Monthly returns (%) (Continuous)	Average Monthly returns (%) (Simple)
1	2	4	5	6
	UK	UK	UK	UK
January	582	3.8	1.36	2.67
February	490	3.2	1.18	2.20
March	639	4.2	-1.22	0.53
April	1329	8.6	1.41	7.31
May	3134	20.4	-1.82	-0.78
June	2404	15.6	-2.19	-1.18
July	2162	14.1	-0.85	0.62
August	684	4.4	0.33	1.53
September	1355	8.8	-0.66	0.65
October	661	4.3	-2.19	0.26
November	1003	6.5	-1.85	2.23

confounding for our UK evidence given that April marks the end and turn of the fiscal year in the UK suggesting that the positive stock returns may be evidence of the tax-loss effect in which investors adjust their portfolios in response to changes in government tax policies (see, for example, Baker & Limmack, 1998).

Table 1: The distribution of annual general meetings and stock returns

December	932	6.1	0.22	1.49
Total	15,375			

The table reports the monthly distribution of annual general meetings and stock returns and market returns for the period 2004-2014.

Table 2 presents the result from the estimation of a modified version of Equation 1 without the interaction variables. Consistent with the January effect and the tax-loss effect, we report significantly positive mean monthly returns for the months of January and April. The results also indicate significantly negative average returns for the AGM cluster months. However, the negative stock returns reported for the AGM cluster months is also consistent with weather-related Halloween effect in which stock returns are higher in the November-April period than the May-October period (see, for example, Bouman & Jacobsen, 2002; Dichtl & Drobetz, 2014; Guo et al., 2014), suggesting that the AGM clustering effect, if any, may not be a new anomaly as suggested by Wang and Hefner (2014).

Table 2 also reports the results of the estimation of Equation 1. The event month interaction variables are statistically significant only for the months of May and September both of which are within and outside the cluster period, respectively. Specifically, firms holding their AGMs in May (September) experience significantly greater returns of about 0.5% (1.0%) than firms without an AGM in these months. Overall, the results presented in Table 2 do not seem to support the idea that average monthly stock returns depend on AGM events.

Table 2: Regression Results: Annual General Meetings and Stock Returns

Independent variables	returns	t-value	returns	t-value
	(1)	(2)	(3)	(4)
January	0.014 ^{***}	11.44	0.013 ^{***}	11.05
February	0.012 ^{***}	10.71	0.012 ^{***}	10.47
March	-0.012 ^{***}	-9.96	-0.012 ^{***}	-9.78
April	0.014 ^{***}	11.01	0.014 ^{***}	10.16
May	-0.018 ^{***}	-16.30	-0.019 ^{***}	-14.98
June	-0.022 ^{***}	-19.55	-0.022 ^{***}	-17.91
July	-0.008 ^{***}	-7.99	-0.009 ^{***}	-7.74
August	0.003 ^{***}	3.05	0.003 ^{***}	2.79
September	-0.007 ^{***}	-5.43	-0.007 ^{***}	-5.81
October	-0.022 ^{***}	-16.10	-0.022 ^{***}	-15.91
November	-0.019 ^{***}	15.14	-0.189 ^{***}	-14.72
December	0.022 [*]	1.89	0.002 ^{**}	1.91
January*EventMonth			0.050	0.89
February*EventMonth			0.006	0.76
March*EventMonth			-0.001	-0.18
April*EventMonth			0.007	1.50
May*EventMonth			0.005 [*]	1.79
June*EventMonth			-0.002	-0.53
July*EventMonth			0.002	0.73
August*EventMonth			0.006	0.96
September*EventMonth			0.010 ^{**}	2.14
October*EventMonth			0.004	0.55
November *EventMonth			0.003	0.64
December*EventMonth			-0.001	-0.23
N	208,190		208,190	
Adjusted R ²	0.0080		0.0080	

The table reports the result of the ordinary least squares regression of monthly stock returns on event month dummy variables. January is the dummy variable that takes the value of 1 for the month of January and 0 otherwise. The dummy variables for February through December follow the same definition. EventMonth is a dummy variable that takes the value of 1 if the company held an AGM month t and 0 otherwise. The reported t-values are based on robust standard errors. The asterisks *, ** and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

Table 3 reports the results of the regression of average stock returns on the frequency of AGMs (Equation 2). The monthly average stock returns were calculated for the (12) calendar months and the (132) month-year combinations. The results in columns 1 and 3 of Table 3 support a negative relationship between stock returns and the frequency of AGMs. For example, the result shows that a 1% change in the frequency of AGMs results in significantly negative monthly returns of 0.1% and 1.4% for the 12-month and 132-month regressions, respectively. These results are qualitatively and quantitatively similar in the regressions in which the independent

variable is the *AGM* dummy variable. The results suggest that average monthly returns are significantly lower for AGM cluster months than the non-cluster months.

Table 3: Regression Results: The Frequency of AGMs and Stock Returns

Independent Variables	returns (1)	t-value (2)	Returns (3)	t-value (4)	returns (5)	t-value (6)	returns (7)	t-value (8)
Intercept	0.0045	0.64	0.0057	0.99	-0.0016	-0.33	-0.0007	-0.15
AGM	-0.0011***	-2.40	-0.0135***	-2.52				
Cluster					-0.0146***	-2.46	-0.0149**	-1.96
<i>N</i>	12		132		12		132	
Adjusted R ²	0.22		0.03		0.23		0.02	

The table reports the results of ordinary least squares regression of monthly average stock returns on the frequency of annual general meetings. *AGM* denotes the monthly percentage of annual general meetings. *Cluster* is a dummy variable that takes the value of 1 for the cluster period - May, June and July - and 0 otherwise. The t-values are based on robust standard errors. The asterisks ** and *** indicate statistical significance at the 5% and 1% levels, respectively.

Table 4 reports significantly negative correlation between the frequency of AGMs and stock market returns for three of the four bin cases that we examine (3-Bin, 4-Bin and 5-Bin). Using the 5-bin case, for example, the *Z*-score result of the test of difference in mean returns between Bin 5 (months with the greatest frequency of AGMs) and Bin 1 (months with the lowest frequency of AGMs) is significantly negative at the 5% level. The result suggests that monthly market returns are about 2.2% significantly lower for months with a high frequency of AGMs relative to months with a low frequency of AGMs. Consistent with this result, the proportion of months with positive stock returns also reduces significantly as the frequency of AGMs increases.

Finally, we present the result of estimating Equation 3 in Table 5. We find no evidence in support of the January effect or tax-loss effect (April effect). Our data supports a significantly negative relation between market returns and the frequency of AGMs at the 10% level. This relationship is however economically insignificant as the monthly negative returns of 0.01% translates into an annualised negative returns of about 0.12% which would not justify an investment strategy and its associated transaction costs that requires investors exiting the market in the cluster months. As Schwert (2003 p 242) notes, if anomalous returns behaviour is not definitive enough for an efficient trader to make money trading on it, then it is not economically significant.

Table 4: Bin Test of Correlation between the Frequency of AGMs and Market Returns

	Bin 1	Bin 2	Bin 3	Bin 4	Bin 5	Z-score (high, low)
Panel A: Mean Return						
Two Bin	0.0039 (113)	0.0017 (19)				-0.20
Three Bin	0.0060 (99)	0.0023 (21)	-0.0145 (12)			-1.68*
Four Bin	0.0045 (86)	0.0020 (27)	0.0186 (12)	-0.0273 (7)		-2.06**
Five Bin	0.0052 (75)	0.0011 (30)	-0.0147 (12)	0.1273 (8)	-0.0275 (7)	-2.11**
Panel B: Percentage with Positive returns						
Two Bin	0.6106 (69)	0.4737 (9)				-1.11
Three Bin	0.6262 (62)	0.5714 (12)	0.3333 (4)			-2.03**
Four Bin	0.6395 (55)	0.5185 (14)	0.5833 (7)	0.2857 (2)		-1.98**
Five Bin	0.6400 (48)	0.7407 (20)	0.3333 (4)	0.500 (4)	0.2857 (2)	-1.97**

The table reports the results of the bin tests of the correlation between monthly market returns and the frequency of AGMs. Panel A reports the mean return for each of the bins and the z-statistic of the test of difference of means between the bin with the highest frequency of AGMs and the bin with the lowest frequency of AGMs. Panel B reports the percentage of positive returns for each of the bins and the z-statistic of the test of difference of proportions between the highest bin and the lowest bin. The asterisks * and ** indicate statistical significance at the 10% and 5% levels, respectively.

Table 5: Regression Results of Market Returns on the Frequency of AGMs

Independent Variables	returns	t-values
Intercept	0.0119*	1.95
M^{Jan}	-0.0184	-1.47
M^{Tax}	0.0144	1.18
AGM	-0.0001*	-1.73
N	132	
Adjusted R^2	0.02	

The table reports the results of ordinary least squares regression of market returns on the monthly frequency of AGMs. M^{Jan} is the January effect dummy takes a value of 1 for the month of January and 0 otherwise M^{Tax} is the tax-loss effect dummy variable that takes the value of 1 for the month of April and 0 otherwise. The asterisks * indicates statistical significance at the 10% level. The sample covers the period 2004-2014.

6. Conclusion

The study examines the relationship between stock returns and the frequency of annual general meetings. Our results suggest evidence of AGMs clustering around May to July in the UK. We find a significantly negative relationship between stock returns and the monthly frequency of AGMs. If viewed as a market timing signal, our results suggest that investors exit the market during the AGM clustering months contrary to the signal suggested by Wang and Hefner (2014) for the US. However, the loss in value during the cluster months is economically insignificant to justify additional transaction cost. In addition, the results presented in this study are not inconsistent with the Halloween effect. Therefore, we caution against interpreting our results as evidence of a “new anomaly” in stock returns.

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