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An Empirical Investigation of the relevance of Investor Relations

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1. Introduction*

When reviewing the literature on the relationship between owner versus manager and the consequent impact on the formulation of corporate goals, it appe-ars that there are two distinct appro-aches. The first places the owner/investor at the centre; the sole task of the manager then being to maximise the owner's expected utility. In the second approach the owner/in-vestor is only one in a group of partici-pants, who are all trying to maximise their wealth by investing money, time or other resources in the company. These are usually labelled as the Anglo-Saxon and European concepts respectively.

The primary focus on the investor has resulted in a relatively more profit-driven style of management at US companies compared to their European counterparts. However, during the course of the past ten years, both the US and Europe show a clear shift towards market value orientation. From the angle of finan-cial theory this is clearly a step forward, market value being more closely related to cash flows and to the risk/return trade-off than is the profit-approach[1]. Based on the position of investors in the company, this market value appro-ach resulted in an equity valuation orientation in the US, and a company valuation orientation in Europe. However, many European based international companies have shifted their focus towards the equity valuation orientation over the last few years. This shift from profit to market value is evidenced by the growing number of compa-nies that include cash flow statements and shareholder value analysis in their financial annual reports.

A direct consequence of the shift to a market value orientation has been the increased importance of future cash flow analysis and investor relations (IR) policy. A well-defined IR-policy will increase information availability and reduce estimation risk resulting in a lower cost of capital and higher stock prices. Theoretically the benefits of an IR-policy are straightforward, but in practice its effects are hard to measure. This measurement problem is a major headache for company management as formulation and implementation of an IR-policy should always be preceded by a trade-off in terms of costs and potential benefits.

In this paper we will try to explore the potential benefits of an IR-policy by examining the effects of differential information on the cost of equity, and therefore implicitly on the cost of capital. From that analysis we obtain an indication of the potential effects of a structured information policy directed at (potential) investors in the company.

The structure of this paper is as follows. In section 2 we briefly discuss the differen-tial information concept. While this covers the results of the anomaly studies, our focus is somewhat different from that in the anomaly studies. Our main concern is the relati-onship between a stock's expected return and instrumental IR-policy variables. The data and re-search metho-dology are discus-sed in section 3, followed by the major re-sults in section 4. The practical implications of the results for investors and companies are dealt with in section 5, and we close the paper with the major conclusions in section 6.

[1.] Even so, this was only a small step forward. Five hundred years ago Luco Pacioli wrote in his Summa that:

(a) The most important of these is cash or any equivalent

(b) to be a good bookkeeper and ready mathematician

(c) to arrange all the transactions in such a systematic way that one can understand each of them at a glance. (see Vis and Dorsman, 1994).

Not once does the Summa employ the term profit or anything of that ilk.

2. Review of the Literature

Klein and Bawa (1977) were among the first to show that, on a theoretical level, differential information limits the portfolio diversification of an investor thereby boosting the market price of risk. Barry and Brown (1985) extended the Klein and Bawa result in a CAPM context, and showed that differential information may affect the equilibrium price of any asset.

Empirical support for this theoretical concept came from the anomaly studies which appeared in academic journals during the 'eighties. These anomaly stu-dies uncovered a large body of empirical regularities in stock markets that contradict the joint hypothesis of an efficient market and the validity of a specific equilibrium asset-pri-cing model (e.g. the CAPM and APT).

One explanation for these anomalies is differen-tial information. When seeking a unifying factor among the different anomalies, the follo-wing results may be observed: small cap stocks on average have a below-average price/earnings ratio; small caps with relative low P/Es are on average more neglected. Moreover, small cap compa-nies that have rela-tively low P/Es are on average responsible for the above-average January returns.

From this it appears that these anomaly-stocks all suffer from a below-average information production and a below-average attention of insti-tutions, private investors and financial analysts. As most anomaly studies started from a CAPM context, which assumes perfect informa-tion structures, it may be that the observed return anoma-lies merely represent an additional risk premium for bearing above-average estima-tion risk.

A major problem in testing the presence of priced estimation risk in stock returns is the construction of information variables. Given that information is a multidimensional factor, it cannot be readily observed. Use must therefore be made of information proxies. Among proxies suggested in empirical tests are the period of listing (Barry and Brown, 1984), degree of variance in opinion per analyst on any given security (Barry and Brown, 1985 and Barry and Gültekin, 1992) and the number of analysts providing research on a security (Arbel and Strebel, 1982).

In the next section we will describe the methodology and data we have used in our tests. The data, and the proxies in particular, can be distinguished from other studies in that we focus on estimation risk factors that are endogenous for the management, while at the same time controlling for exogenous estimation risk factors which are heavily correlated with these endogenous estimation risk factors. (See for example Arbel and Strebel, 1982; Keim, 1985; Rozeff and Kimmey, 1976).

3. Data and Research Methodology

The data set used in this paper covers the period 1968 - 1993 and consists of monthly total return observations obtained from the Palladyne database[1]. The data set we use in this paper covers the period 1968 - 1993 and consists of monthly total return observations. This resulted in 44,452 valid observations. Based on the empirical literature on stock market anomalies eleven information proxies were selected. These proxies are divisible into two groups: (exogenous) control variables and (endogenous) IR variables. Our primary focus is on the second group. The (exogenous) control variables have been added to the analysis to get more efficient estimates from the regressions (as the control variables can be correlated with the IR variables) and to obtain a better understan-ding of the potential benefits of an IR policy. The variables used in the study are:

Control variables

a. Period of listing (POL);

b. market capitalisation (SIZE);

c. relative market capitalisation (SIZEREL);

d. E/P ratio (E/P);

e. E/P differential (EPDIF);

f. stock turnover (TURN);

g. relative stock turnover (TURNREL);

h. dividend yield (YIELD).

IR variables

i. beta/volatility ratio (BETAVOL);

j. window dressing factor (SEAL);

k. relative price volatility around the earnings announcement (VOLRAT).

There may of course be other exogenous IR variables. Due to the multidimensionality of 'information' it is very hard, if not impossible to develop a perfect selection procedure for IR variables. We therefore limited ourselves in this study to variables suggested in earlier academic works.

The period of listing is the length of time in years for which a security has been listed on the ASE, and hence measures the availability of historical price and return informati-on. Size, size relative, E/P, E/P differential, turnover, relative turnover and yield have been chosen for their relationship with endogenous estimation risk and play the role of control variable. Size relative is calculated as the ratio 'size stock/average size of the stocks quoted on the ASE'. In this study E/P relative is defined as the difference between a stock's E/P ratio and the E/P ratio of the sector. The E/P relative has been added to the list of explanatory variables since earlier research suggests that E/P ratios are highly sector-dependent. In order to use E/P as an information proxy, we must control for this sector influence[2]. The same applies to the dividend yield variable. Many studies have revealed a positive relationship between a stock's dividend yield and its total return (e.g. Litzenberger and Ramaswamy, 1977; Keim, 1985). As we do not have any indication or prior knowledge as to the correlation between yield and neglect, we use the yield variable to account for potential links.

Stock turnover is motivated by the fact that informati-on processing is usually induced by buy and sell transactions. Low stock turno-ver may signal a low rate of informati-on proces-sing resulting in a relative high estima-tion risk. Along the same line as the size relative, the turnover relative can be calculated as the ratio of turnover stock/average turnover of the compa-nies quoted on the ASE.
The beta/vo-latility ratio measures the extent to which a stock is part of a well-diversified portfolio. For any stock it is defined as:

$$BETAVOL_i = \frac{\beta_i \cdot \sigma_m}{\sigma_i} \qquad (3.1)$$

with σ_m representing the volatility of the market portfolio. A high ratio means that the stock is traded by investors who give beta relatively high weight as a risk factor, i.e. only portfolio investors. These are insti-tutional investors who only consider stocks of information-rich companies. Hence, a low beta/volatility ratio indicates a firm with a relative high estimation risk.

The window dressing factor is defined as the difference between the average CAPM-residual in December and the average CAPM-residual in January, both measured over a five year period. We use CAPM-residuals instead of returns in order to control for differences in general market move-ments in December and January. The assumption behind this information proxy is that portfo-lio managers clean their portfolios at the end of the year - leading to buying pressure for the blue chips and selling pressure for the small, neglected companies. This pattern is reversed in January so that stocks with relatively low returns in December and high returns in January, can be considered 'ne-glected' and therefore suffer from an above-average estimation risk. The relative price volatility around the earnings announcement is defined as

$$VOLRAT = \frac{\sigma_{jv} - \sigma_t}{\sigma_t} \quad (3.2)$$

with σ_{iv} and σ_t being the stock's volatility in the period of the annual report release, respectively over the total period; both volatilities being on a monthly basis and calculated over a five-year period. This variable focuses on the information value of the annual report. For companies with a good information policy (and a relatively low estimation risk) the annual report holds few surprises, whereas the annual report of a neglected firm may be full of them. A relatively high surprise level usually leads to a more than average price volatility around the announcement of the annual report.

The cost of equity capital comprises the risk-free rate plus an additional component for 'risk'. Poor information (availability) increases investment risk, which in turn leads to a reduction of the stock price. Although it is technically speaking incorrect to label those factors that significantly increase the risk component as 'priced risk factors' we will nonetheless do so in the remainder of this study. Two major problems with analyses of 'differential information' as a risk factor are a) its multidimensionality and b) the lack of data for earlier time periods. However, we feel that the combination of empirical evidence presented in this paper and earlier theoretical academic work (e.g. Barry and Brown, 1984) provides an interesting indication of the existence of a priced 'information effect'.

The empirical tests of investor relations for companies were directed along two lines. First, a number of portfolio tests with the above mentioned information proxies as dimensions were carried out. As portfolios are formed using two dimensions and information proxies are likely to be highly correlated, it is not possible to determine the importance of each informati-on proxy from these portfolio tests. To this end several multivariate regression tests were also employed, to get an indication of the importance of each information proxy in explaining the cross sectio-nal diffe-rences in returns and excess returns on individu-al stocks, there-by controlling for all other information proxies.

The multivariate regression tests were carried out in two ways: a) in a CAPM-framework, and b) within a non-equilibrium multifactor setting. In ex post form the CAPM can be described as follows:

$$R_i = R_f + \beta_i (R_m - R_f) + e_i \quad (3.3)$$

with:

R_i = return on stock i

R_f = return on a risk free asset

R_m = return on the market portfolio

β_i = beta-factor of stock i, $Cov(R_i,R_m)/Var(R_m)$

e_i = residual return with $E(e_i) = 0$ and $Var(e_i)$ constant

With stock returns in a CAPM-framework only relating to their betas, priced estimation risk factors may show up in the residual returns. With this in mind, in the multivariate regression tests we focused on the CAPM-residuals by regressing them on the information proxies mentioned above. Supposedly, if estimation risk is priced and our information variables are good proxies, we would find some significant relationships. However, there are at least two reasons which support the use of a non-equilibrium multifactor model (in which beta is just one of many variables) over the CAPM. Firstly, a large body of recent studies cast doubt on the validity of the CAPM in explaining cross-sectional differences in returns (e.g. Fama and French, 1992). To start off with, the CAPM-residuals implicitly assume the correctness of the CAPM. Secondly, with differential information, observed betas may be biased due to differential estimation risk (Barry and Brown, 1985).

In the case of both the CAPM framework and the non-equilibrium multifactor setting we substituted a 60-months adjusted beta for the historical 60-months OLS beta. The adjusted beta is the weighted average of the 60-months historical beta of the stock and the 60-months industry beta[3]. The weights are the respective variances of the two beta estimates and used in such a way that a larger variance of the one implies a larger weight for the other beta, i.e.:

$$\beta_{adj} = \frac{\sigma^2(\beta_{ii})}{\sigma^2(\beta_{ii}) + \sigma^2(\beta_s)}\beta_s + \frac{\sigma^2(\beta_s)}{\sigma^2(\beta_{ii}) + \sigma^2(\beta_s)}\beta_{ii} \quad (3.4)$$

with:

$\sigma^2(\beta_{i,h})$ = variance of the 60-month historical beta of stock i

$\sigma^2(\beta_s)$ = variance of the 60-month historical beta of industry s

$\beta_{i,h}$, β_s = 60-month historical beta of stock i and industry s respectively

The motivation for this adjustment is that previous research showed that the cyclical patterns in beta witnessed in the Netherlands, resulted in an explanatory power of the standard OLS-beta close to zero. This 'mean reversion' phenomenon shows a certain resemblance with the well-known seven/eight year business cycle, although the beta cycles seem to be somewhat shorter on average. These two test frameworks described above, give two regression models which need to be estimated:

$$\varepsilon_{i,t} = \gamma_0 + \sum_{j=1}^{11} \gamma_j \cdot I_{i,j,t} + \xi_{i,t} \qquad (3.5A)$$

$$R_{i,t} = \alpha_0 + \alpha_1 \cdot \beta_{i,t} + \sum_{j=2}^{12} \alpha_j \cdot I_{i,j,t} + \nu_{i,t} \qquad (3.5B)$$

with:

$\varepsilon_{i,t}$ = CAPM residual of stock i in period t
$\gamma_0, \gamma_j, \alpha_0, \alpha_j$ = regression coefficients
$I_{i,j,t}$ = information proxy j of stock i in period t
$\xi_{i,t}$, $\nu_{i,t}$ = residual term with E(·) = 0 and Var(·) = x
$R_{i,t}$ = return of stock i in month t
$\beta_{i,t}$ = adjusted beta of stock i in month t

[1] This database comprises stock prices, dividends, stock splits, offerings and financial accounting data of virtually all companies quoted on the Amsterdam Stock Exchange.
[2] Even so, low P/Es - to take an example - could also indicate something amiss with IR in this particular sector. However, for the time being, with no pointers in this direction, it seems unlikely. But this eventuality is covered by inclusion of 'E/P absolute' even after introduction of 'E/P relative' into our framework.
[3] The beta-adjustment method chosen in this paper can be regarded as a modification of the beta-adaptation technique suggested by Vasicek (1973).

4. Results

Prior to conducting the regression tests a number of portfolios were constructed in order to obtain a first impression of the relationship between our IR variables and stock returns. These portfolio tests were used to control for size, as this appeared to be the most important control variable.

Table 1 shows the monthly returns of several size-matched BETAVOL-portfolios[1.] It appears that return differences between BETAVOL-portfolios are more pronounced than the returns differences of the size categories. Put differently, improving on BETAVOL within a specific size category appears to be more interesting than getting bigger within a specific BETAVOL category.

Another remarkable result following from Table 1 is the performance of the first size quintile (the smallest companies), in that these are companies with the lowest returns. A likely explanation is that these stocks are held by a small number of investors, including the management of the company, who rarely trade their stock. As this small group of investors is usually very well informed, these small stocks can pose a major risk to the average investor. Hence, the low returns should not be interpre-ted as a reflection of a below-average risk profile.

Tables 2 and 3 report the monthly returns of the size-matched VOLRAT and the size-matched SEAL portfolios respectively. Working from either table we can arrive at similar conclusions to those in Table 1. The return differences between the VOLRAT and the SEAL portfolios seem to be more obvious than those between the size portfolios. Inspection of the second and sixth columns of Tables 1, 2 and 3 enables the conclusion that, on average, BETAVOL and VOLRAT are both slightly more important than SEAL. All the same, from the economic perspective, the return differences between B1/B5, V1/V5 and SE1/SE5 are all worth realising.

This analysis does not permit us to separately determine the specific importance of the IR variables. Firstly, the three IR variables we use in our test can be correla-ted so as to lead to similar results in the portfolio tests. Secondly, BETAVOL, VOLRAT and SEAL can all be correlated to some omitted variables that are exogenous from the manage-ment angle, thereby overstating the benefits of an IR policy.

To deal with these problems we employed a number of multivariate regression tests with the information-related variables described in section 3. As mentioned in section III we have two available model specifications to test the significance of the IR variables: the CAPM related framework (Equation 3.5A) and the non-equilibrium multifactor framework (Equation 3.5B). In Table 4 the results of both models are reported. Although the coefficients of the statistically significant variables in both regression frameworks have the expected sign, the non-equilibrium multifactor framework performs better than the CAPM framework, which is indicated by the better R^2 and t-values.

Table 1: Monthly average returns for size-matched BETAVOL portfolios, 1968 - 1993.

	B1	B2	B3	B4	B5	B TOT
S1	0,006	0,002	0,000	0,004	0,004	0,003
S2	0,017	0,013	0,012	0,010	0,004	0,012
S3	0,023	0,013	0,011	0,011	0,008	0,012
S4	0,020	0,013	0,011	0,015	0,011	0,013
S5	0,016	0,011	0,012	0,011	0,009	0,011
S Total	0,014	0,009	0,009	0,011	0,008	0,010

Note: Portfolio S1/B1 contains the smallest stocks with the lowest BETAVOL value and portfolio S5/B5 contains the largest stocks with the biggest BETAVOL value.

Table 2: The monthly average returns of the size-matched VOLRAT portfolios, 1968 - 1993.

	V1	V2	V3	V4	V5	V TOT
S1	0,001	0,003	-0,001	0,002	0,009	0,003
S2	0,009	0,005	0,009	0,013	0,021	0,012
S3	0,009	0,009	0,013	0,014	0,017	0,012
S4	0,010	0,011	0,013	0,010	0,019	0,013

S5	0,011	0,008	0,010	0,012	0,015	0,011
S Total	0,008	0,008	0,009	0,010	0,016	0,010

Note: The V1/S1 portfolio contains the smallest stocks with the lowest volatility ratio, and the V5/S5 portfolio contains the largest stocks with the biggest volatility ratios.

Table 3: The monthly average returns of the size-matched SEAL portfolios, 1968 - 1993.

	SE1	SE2	SE3	SE4	SE5	B TOT
S1	-0,007	0,008	0,002	0,002	0,013	0,003
S2	0,011	0,011	0,014	0,014	0,017	0,012
S3	0,013	0,011	0,013	0,009	0,019	0,012
S4	0,014	0,003	0,011	0,016	0,018	0,013
S5	0,011	0,001	0,013	0,011	0,013	0,011
S Total	0,009	0,007	0,011	0,010	0,016	0,010

Note: The SE1/S1 portfolio contains the smallest stocks with the smallest SEAL values, and portfolio SE5/S5 contains the largest stocks with the biggest SEAL values.

None of the two regressions suffers from autocorrelation patterns in the residuals, as the DW-statistic is close to two. However, inspection of the residual plots reveals a severe heteroskedasticity problem, leading to inefficient estimators in the regression equations. To deal with the volatility clustering in the residuals we also employed some Weighted Least Squares (WLS) regressions.[2] Given that the non-equilibrium multifactor framework actually performed better than the CAPM framework, we only used the regression model 3.5B. To control for potential 'error in the variables' disturbances we employed the WLS regressions both on the individual stock level and the portfolio level, using size-sorted portfolios in the latter case.

The results of the WLS regressions on individual stock level are shown in Table 5. As can be seen, all three IR variables are significant at the one-percent level, even after controlling for many exogenous information-related variables. To save space only the variables that are statistically significant are reported. As in the portfolio analysis, BETAVOL and VOLRAT perform slightly better than SEAL. Hence, enlarging the number of institutional investors and upgrading (in terms of more regular and timely) the information policy should be a major concern for the IR manager.

Table 4: The relation between information related proxies and return/CAPM-residual, 1968-1993; t-statistics between brackets.

.INFORMATION PROXY	CAPM-RESIDUAL	RETURN(Eq 3.5B)
CONSTANT	-0,005 (-3,03)	-0,023 (-7,32)
SIZE	0,012 (11,95)	0,025 (21,27)
SIZEREL	-0,003 (-0,98)	-0,025 (-6,57)
TURN	-0,007 (-6,98)	-0,017 (-14,18)
TURNEL	-0,011 (-2,10)	0,005 (0,86)

E/P	0,000 (0,65)	0,001 (3,66)
EPDIF	0,000 (0,96)	-0,002 (-3,81)
YIELD	0,042 (5,26)	0,062 (6,98)
POL	0,0001 (0,62)	0,000 (2,06)
BETA	----	0,033 (12,06)
BETAVOL	-0,017 (-5,55)	-0,035 (12,06)
VOLRAT	0,013 (6,40)	0,018 (8,00)
SEAL	0,050 (6,20)	0,041 (5,91)
DW-STATISTIC	2,09	1,95
R^2	0,015	0,026

The results of the WLS regressions on the size-sorted portfolios are reported in Table 6. Since portfolio formation implies a substantial reduction in observations, it is not surprising that all t-statistics are lower than those reported in Table 5. As a result our IR variable SEAL is no longer significant. However, our IR variables BETAVOL and VOLRAT are still significant on the five-percent level. At first glance, taking account of the reduction in observations, there is apparently little difference between Tables 5 and 6, implying that there is no severe 'error in the variables' problem. To summarise, taking into account heteroskedasticity and potential 'error in the variables' disturbances plus a potential correlation between the IR variables and some exogenous information related variables, it appears that our IR variables could explain a statistically significant portion of the cross sectional differences in stock returns. This despite the fact that the SEAL variable dropped from the list in the WLS regressions on size sorted portfolios.

Table 5: Results of the WLS regression of return on several information proxies, 1968 - 1993 -individual stock level

VARIABLE	COEFFICIENT	T-VALUE
CONSTANT	-0,00222	-7,366
SIZE	0,00243	30,884
SIZEREL	0,00230	-14,453
VASI	0,00333	12,560
BETAVOL	-0,00440	-11,552
VOLRATIO	0,00172	7,623
YIELD	0,00611	6,645
SEAL	0,00320	4,741

EPRAT	0,00019	3,442
EPRELSEC	-0,00020	-3,549
POL	0,0000	2,540
TURN	-0,00165	-30,930

Table 6: Results of the WLS regressions of stock return on several information proxies; 1968-1993 - size sorted portfolios

VARIABLES	COEFFICIENT	T-VALUE
CONSTANT	-0,00458	-3,351
SIZE	0,0329	11,306
SIZEREL	-0,0258	-6,811
TURN	-0,0231	-10,443
VASI	0,0774	5,388
EPRAT	0,0085	3,095
EPRATSEC	-0,0080	-2,493
BETAVOL	-0,0906	-4,043
VOLRATIO	0,0385	2,946

1. It appeared that the probability distributions of all IR variables could be well approxi-mated by a normal distribution. We used this approximation to construct our portfolios, by dividing the probability distributions of the IR variables in five equally spaced (in density terms) parts. In our portfolio tests each part represents a portfolio.

2. Additional analysis revealed that the size factor and a seasonal pattern in returns explained the heteroskedasticity in residuals.

5. Practical Implications

It follows from section 4 that our IR variables BETAVOL, VOLRAT and SEAL can be considered priced risk factors which explain a statistically significant portion of cross sectional differences in returns. However, that information alone is not sufficient to support some kind of a formal IR policy. As mentioned at the start of this paper, all decisions around formulation and establish-ment of an IR policy should be preceded by a cost-benefit trade-off. This implies that potential benefits need to be expressed in terms of returns or cash. To that end the portfolio analysis discussed in section 4 was used.

Holding the size category constant, the potential reduction in expected returns resulting from a shift from B1/V5/SE5 towards B5/V1/SE1 was calculated. Before calculating the total effect certain assumptions concerning the correlation between the three IR variables were made. If it is assumed that the three variables are non-correlated, the total benefit can be calculated by adding up the three separate effects.

However, if IR variables are correlated such an approach would give an overstatement of the total effect. For the period 1968 - 1993 an average 0,02 correlation between IR variables was found. Although that would support summing the three separate effects, the total benefit was conservatively calculated as the average of the three separate effects. This yielded the following results:

Size category	Reduction in expected monthly return
S1	0,40
S2	1,03
S3	1,16
S4	0,73
S5	0,43

Transforming the benefits to an annual return, the reduction in expected returns due to IR ranges from 5% (S1) to 14% (S3). In the light of these benefits it appears that an IR policy yields a net benefit for almost all companies. Moreover, one has to bear in mind that a well formulated IR policy has more instrumental variables than have been addressed in this study. Seen in this perspective the results may even understate the potential benefits of an IR policy.

6. Summary and Concluding Remarks

In this paper the potential benefits of a well-formulated and established IR policy were analysed. For that purpose three IR related proxies were constructed: the beta/volatility ratio, the volatility around the release of the annual report related to the volatility over the total period, and the sensitivity of a stock to window dressing by institutions.

From the regressions it followed that these IR proxies could be interpreted as priced risk factors that explain a statistical significant portion of cross sectional differences in returns. This notion is unaffected even after controlling for exogenous information related variables.

Finally, the potential benefit of an IR policy in terms of a reduction in expected returns was estimated. Conservative estimates ranged from 5% to 14%, which means that it is hard to find a company for which IR is not worth the effort. It would be an interesting topic for future research to create and test a wider range of IR proxies. Another interesting study would be the examination of the effectiveness of an IR policy in bull and bear markets.

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