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"Exploiting Predictable Components in Returns for the US Non-Financial Corporate Sector, 1990-2002"

Abstract

Many studies have identified factors that can be used to predict stock returns to a varying degree. This paper begins by selecting a set of variables shown in previous studies to forecast changes in stock returns: the price/earnings ratio, interest rate, inflation, industrial production and the money stock. The importance of these variables in predicting excess returns in the US Non-Financial Corporate Sector is then assessed through the implementation of a stylized investment strategy. The approach taken is to simulate an investor's decisions in 'real time'. At the beginning of each time period the investor predicts excess returns using only available information at that point in time rather than the entire sample. Initially a baseline model including all variables is used to forecast stock returns. The analysis evaluates the economic significance of predictability in the stock market and shows that an investor could have exploited such evidence using a switching portfolio strategy between the market index and the risk-free rate. The investor's approach is then developed allowing the investor to search for the 'best' predictive model from the initial six variables. The performance of the switching portfolio strategy using alternative model selection criteria is then assessed.

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1. Introduction

Historically a consensus has existed amongst financial economists that movements in financial markets cannot be predicted - that changes in stock prices follow a random walk. The Random Walk Hypothesis has subsequently become a cornerstone of modern financial economics. However this has not stopped many Economists, Mathematicians and Financial Investors applying their skills to put this hypothesis to the test in order to answer the question "Is it possible for one to 'beat the market'?" Indeed a large number of these studies have concluded that stock returns *are* predictable to some degree, providing mounting evidence that it may be possible to consistently 'beat the market'. Many of these studies use time series data on financial and macroeconomic variables exhibiting clear business cycle variations. Skidelsky (1992) observes that "Keynes initiated an 'Active Investment Policy', which combined investing in real assets with constant switching between short-dated and long-dated securities, based on predictions of changes in the interest rate". Along with interest rates, these studies have also identified a number of other variables to be statistically significant for predicting stock returns: the dividend yield, price/earnings ratio, monetary growth rates, inflation and changes in industrial production[1].

The presence of predictable components in the stock market implies that the Random Walk Hypothesis can be rejected. The economic interpretation of the rejection of the Random Walk Hypothesis is controversial and has created much discussion regarding the very closely related Efficient Markets Hypothesis[2]. An alternative perspective is that the existence of predictable components of stock returns does allow superior investment decisions to be made in the longer-term. This paper evaluates the economic significance of predictability in the stock market by showing that an investor could have exploited such evidence successfully for the period 1990-2002 in the US Non-Financial Corporate Sector.

The approach taken simulates an investor's decisions using publicly available information on a set of factors believed to be relevant to predicting stock returns prior to the forecasting period of 1990-2002. The investor then estimates annual stock returns at the beginning of each investment period (a calendar year) using the same set of factors before making the next investment decision. This approach rules out the benefit of hindsight obtained through parameter estimates based on the entire sample, estimates that in reality our investor would not have been able to obtain. Each investment decision is therefore made in 'real time' – decisions are made with currently available information only. A weak assumption is made regarding the investor's beliefs over the type of financial and business cycle variables thought to be important in forecasting stock returns. The investor

[1] Campbell (1987), Fama and French (1989), and Pesaran and Timmerman (1995, 1998)
[2] See Lo & MacKinlay (1999) for an extensive discussion.

uses only historically available information in the forecasting equation to make predictions of excess returns one-period ahead. Using a switching portfolio strategy, the investor then makes a decision whether to invest in stocks or at the risk-free rate for the next investment period depending on whether predicted excess returns are positive or negative. Analysis upon the performance of the switching portfolio in comparison to a 'buy-and-hold' strategy in stocks and the risk-free rate is then reported, determining whether the predictable components in stock returns are economically exploitable. This analysis is done in the absence of transaction costs incurred when switching portfolio.

Initially the investor includes all variables in the forecasting model at each period. The model does not alter, the parameters are simply re-estimated. The paper then relaxes this assumption regarding model specification and takes account of the uncertainty that would exist regarding specification. The investor uses the original set of variables as a base set, searching for the 'best' forecasting model at each point in time – the investor imposes a recursive modelling approach. The 'best' model is determined by alternative model selection criteria. The same analysis as conducted above with the baseline model is then carried out in order to evaluate the relative performance of each selection criterion. This also allows the determination of the degree of importance for the predictability of stock returns to each one of the originally selected variables.

The plan of the paper is as follows: Section 2 describes the investor's initial approach using the baseline model and explains the choice of the factors believed to be of importance when predicting stock returns. Section 3 reports the results and measures the performance of the investor's switching portfolio strategy using the baseline model. Section 4 then develops the investor's approach using the recursive modelling framework allowing for model specification uncertainty. This section also identifies the statistical criteria used in model selection. Section 5 reports the results of the alternative model selection criteria, assessing the predictive power of the chosen variables and the economic significance of predictability in stock returns whilst Section 6 concludes with a discussion of the interpretation of the findings.

2. Predictability of Stock Returns: Identifying a Set of Factors

Consider an investor who believes that annual stock returns can be predicted by a set of financial and macroeconomic variables, and also has a strong belief in the 'true' model specification, but does not know the 'true' parameter values. The investor updates the model each year to obtain the forecast for stock returns. As time progresses the investor does not change the forecasting equation, he simply has a larger sample. At each point in time, τ, the investor makes a one-period ahead forecast of excess returns[3] for the US Non-Financial Corporate Sector using only publicly available information. The investor forecasts excess returns using a linear regression of the form:

$$\mathbf{ER_{(\tau+1)} = \beta' X_{\tau} + \varepsilon_{(\tau+1)} \qquad \tau = 1, 2, ..., t\text{-}1}$$

where $\mathbf{X_{\tau,i}}$ is a ($\mathbf{k}$+1) vector of variables selected by the investor plus a vector of ones for the intercept term. $\mathbf{k}$ denotes the number of variables chosen. In order to limit the number of regressions required for the latter part of the paper, the number of variables chosen was limited to six. The parameters of this model can then be estimated by the Ordinary Least Squares (OLS) method. OLS provides reasonably robust estimates even in the presence of non-normal errors in the forecasting equation.

As the investor is using a switching portfolio strategy it was important to analyse a period in which negative stock returns[4] were witnessed. Otherwise, the best portfolio return our investor could realise would be that from holding stocks throughout, rendering the following analysis redundant in terms of testing the ability to exploit predictability of stock returns. Therefore the period for analysis in this paper is chosen to be 1990-2002. This period witnessed the ‘Dot-com bubble’ resulting in the spectacular fall in stock prices in 2000 and large subsequent losses for investors. A much cited explanation for the crash was overvaluation - price/earnings (PE) ratios were too high. The standard argument is that as the market PE ratio went higher, the average price of a listed stock had expanded much faster than its corresponding earnings. Without fundamental justification to support them, stock prices had no choice but to tumble. Therefore it was decided to include the PE ratio as one of the variables.

In order to capture the time variation in expected returns, many studies have also looked to include a measure of inflation. Fama (1981) argues that the negative correlation between expected inflation with shocks to future economic growth, whilst stock returns are positively correlated with such shocks, leads to anticipated inflation and stock returns being negatively correlated. Therefore a short term interest rate is included as a proxy for expected inflation.

Economic theory also aids the consideration process for the inclusion of factors relevant for the frequency of the business cycle. As the business cycle moves away from a trough towards a peak, expected excess returns should be higher as expected future consumption increases. The opposite is true as the business cycle moves from a peak towards a trough. The forecasting variables included to capture the variations in the business cycle, and those identified in previous

[3] See Appendix A for definition.
[4] Or at least returns less than that from the risk-free rate.

studies, were: the change in interest rate, the change in industrial production and the rate of monetary growth. The rate of change in the narrow money stock also accounts for the impact of liquidity on stock returns.

Therefore the following set of variables was decided upon:

$$\mathbf{X_t = \{PE_{(t)}, RFR\_3M_{(t)}, D3M_{(t)}, INF_{(t)}, DIP_{(t)}, DM1_{(t)}\}}$$

where **PE** is the Price/Earnings ratio of the US Non-Financial Corporate Sector, **RFR_3M** is the 3-Month Treasury Bill Rate (annualised), **D3M** is the year on year change in **RFR_3M**, **INF** is the annual rate of inflation, **DIP** is the year on year change of the Industrial Production Index, and **DM1** is the year on year change in the M1 narrow money stock[5]. The quality of data reported for these variables can be considered of good quality going back to 1960[6]. It was therefore decided to use the period 1960-1989 as the initial sample for estimation.

Examination of the data reveals immediately one of the central problems of financial econometrics - the presence of a unit root. Tests show that it is not possible to reject the presence of a unit root in the PE ratio, Inflation rate, year on year change in the M1 narrow money stock and the 3-month Treasury Bill series at a 5% level[7]. It is therefore likely that a degree of forecasting accuracy is lost. However it was still decided to include these variables as previous studies have found predictability of excess returns from these variables, and also due to the consideration that the failure to reject the presence of a unit root may be due to the span of the data.

The graphs show the 1970s to be a very volatile period. The primary cause for this was oil price shocks. Inflation increased sharply in 1973 before falling in 1976 before increasing once more to its peak for the period, in 1980. The interest rate, used as a means to control inflation, followed a similar pattern. The PE ratio fell heavily in 1974. Excess returns fell to its lowest point in 1974. Although it is probably not strictly true to call this an extreme value[8], it was decided to include a dummy for the year of 1974. This dummy is included in all regressions.

It was assumed that all data was available at the end of each period thus enabling annual calculations of each variable required for the forecast of the following period.

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[5] See Appendix A for more details.
[6] No missing datapoints, nor major changes in reporting methodology.
[7] See Appendix for charts of all explanatory variables and the results of these tests for the presence of a unit root.
[8] A traditional criterion for an extreme value is a value greater than 3 standard deviations from the mean.

3. Reporting the Results Using the Baseline Model

Figure A8 displays annual excess returns for the US Non-Financial Corporate Sector for 1990-2002. A peak is observed in 1991 before a decline, resulting in excess returns becoming negative in 1994. The ensuing boom, incorporating the 'dot-com bubble', can be seen with the dramatic fall occurring when this 'burst' in 2000. Excess returns remain negative for the remainder of the period, decreasing even further in 2002. Therefore there is plenty of scope in this period for an investor to 'beat the market' by switching his portfolio between stocks and the risk-free rate.

Table A8 summarises the regression results, estimated on annual data, for the entire forecast period. The regression includes all of the business cycle variables identified in the previous section and a dummy for 1974. The extent to which excess returns are predictable through the use of these variables is evident from the table. Out of the six variables included in the regression, only the lagged PE ratio is found to be significant at the 1% level. The year on year change in the M1 money supply is significant at a 10% level.

The coefficient for the lagged PE ratio is negative - as the lagged PE ratio increases, a fall in excess returns follows in the next period. This may reflect mean reversion of the PE ratio. Lagged inflation and lagged year on year change in the M1 money supply also enter with negative coefficients, as to be expected from economic theory. The interest rate and year on year change of the interest rate enter the equation with positive coefficients as expected but appear to be very weakly correlated to excess returns. The year on year change in the Industrial Production Index has a negative coefficient. Theory would suggest that the coefficient should be positive, however depending upon the stage of the business cycle a negative coefficient can easily be explained. If the business cycle is at a peak (trough) then a decline (increase) in excess returns is expected the next period. It is possible that the timing of the data captures these turning points in the business cycle. The year on year change in the Industrial Production Index does appear to be weakly correlated with excess returns in any case.

The adjusted R-squared for the regression is 0.24. This may be slightly misleading due to the inclusion of the dummy for 1974. Excluding the dummy from the regression, the adjusted R-squared value is 0.13, which falls into line with findings for the US stock market[9]. In terms of diagnostic tests, the model can be considered robust with tests for the presence of no serial correlation, correct model specification and normality of the residuals all being accepted. In addition the White Heteroskedasticity test with no cross terms is also passed[10].

[9] Pesaran & Timmerman (1998)
[10] See Tables A8-A11 and Figure A9 in the appendix for full results.

Figure A10 compares predicted and actual excess returns[11]. The predicted excess returns are less volatile than the actual values, and although the fall in stock returns in 2000 appears to have been captured, several periods experience opposite movements between the two series. The movement of predicted excess returns is incorrect for three out of the first four time periods but is correct for the remainder of the period. More importantly for the performance of the switching portfolio strategy, the sign for excess returns is correct for ten of the thirteen forecasted periods. As a simple measure of fit the R-Squared of the model for each year has been graphed in figure A14. The R-Squared begins at around a value of 0.47. This decreases to a level of 0.3 in 1999, before improving to a value of around 0.37 in 2002. Figure A18 displays the recursive standard errors for the estimated equations. The recursive standard errors trend upwards steadily throughout the period – the standard error for the first estimation in 1990 is 0.149, estimation in 2002, at the end of the forecast period, has a standard error of 0.163. The predictive power of the model declines. This is in contrast to the findings provided by the predicted sign changes. The incorrect predictions of the sign of excess returns were only found at the beginning of the forecast period.

In order to measure the economic value of the predictability of stock returns, a stylized investment strategy is considered in which an investor switches portfolio between the asset (one representing the market, one representing the risk-free rate), with the highest forecasted expected return for the next period. Short selling is not considered in order to avoid bankruptcy risks. Table A25 displays the results for a scenario in which transaction costs are not incurred. The performance measures for a buy-and-hold strategy in the market index (US Non-Financial Corporate Sector index[12]) and the 1-year treasury constant maturity rate (RFR_12M) are displayed. If liquidity was not an issue for the investor and a decision was made to tie up the portfolio in risk-free assets with a longer term rate for the entire duration of the forecast period, it is likely that the return would be greater than the risk-free buy-and-hold strategy displayed in the table. However, it was chosen to 'roll' the 1-year treasury constant maturity rate as an investment decision is made at the beginning of each period as to whether the investor places the portfolio in stocks or invests at the risk-free rate.

The market portfolio returns a mean of 13%, almost 8% higher than the mean return on the risk-free portfolio of 5%. As to be expected, this higher mean return is associated with a higher level of risk. The standard deviation of the annual returns on the market portfolio is 20%. This is twenty times greater than that of the risk-free portfolio which was only 1% for the period 1990-2002. The investor makes the decision to invest in stocks if the forecast equation predicts excess

[11] The calculation of predicted excess returns was performed in Excel.
[12] It is assumed that a portfolio can easily be constructed with identical average return and volatility.

returns to be positive. If the prediction of excess returns is negative then the investor will invest at the risk-free rate. The performance of this switching portfolio strategy can be seen alongside the buy-and-hold performances. The switching portfolio strategy has a mean return of 16%, greater than the mean return from the market. Our investor would have seen his initial wealth of $100,000 increase to $654,141 by switching portfolio as indicated by the baseline model, in contrast to $383,650 and $188,666 returned by the market and the risk-free rate respectively. However, even though this mean return is higher, volatility is lower. The standard deviation of the annual returns of the switching portfolio strategy is 15%, 5% lower than the 20% associated with a buy-and-hold strategy of the market portfolio. A method of comparing two portfolios is to use the Sharpe ratio. The Sharpe ratio is commonly used in finance. It is a measure of risk adjusted return and is calculated by dividing excess returns for the period by the volatility (standard deviation) for the period. The Sharpe ratio therefore increases when excess returns increase relatively to the level of volatility. Further examination of Table A25 shows that the Sharpe ratio for the buy-and-hold strategy of the market portfolio is 0.3955. The Sharpe ratio for the switching portfolio is just over double this at 0.7978. Therefore by switching portfolio our investor gains significant return-to-risk ratio improvements.

4. Introducing a Recursive Modelling Framework and the Model Selection Criteria

The previous section provides evidence that our investor, using the baseline model, could economically exploit the predictability of stock returns. However, these findings beg the question as to whether further improvements can be made. First, consider the summary of results for the baseline regression over the entire period 1960-2002. These show that only two of the selected six variables were significant at a 10% level in predicting stock returns. Therefore can the specification of the model be improved? Can variables be omitted? Secondly, consider the monetary returns from table A25. Although wealth at the end of the forecasting period for the switching portfolio strategy was $654,141, in 1999 we can see that the market portfolio had a value of $675,836. This value was subsequently partially wiped out by the crash in 2000, but had it then been invested at the risk-free rate in 2000 until 2002, the value at the end of the forecasting period would have been substantially greater than that realized by our investor using the indications provided by the baseline model.

The approach now taken is to treat the set of six variables selected in Section 2 as a base set from which our investor now searches for the best predictive model when making each investment decision. The assumption that our investor is certain over the 'true' form of model specification is dropped. As time progresses and the number of historical observations increases, the investor has the ability to change the forecasting equation. The reason for this may be a reflection of the learning process of the investor or alternatively a change in the underlying data generating process.

Each regression includes an intercept and the dummy for 1974 as before. This time though the investor runs a regression for each combination of the six variables. As each variable can be either included or excluded, our investor runs $2^6 = 64$ regressions each year. Again our investor uses OLS estimation.

The choice by the investor as to which model is the 'best' is subject to three statistical model selection criteria. The three chosen were Adjusted R-Squared, Akaike's Information Criterion (AIC) and Schwarz's Bayesian Information Criterion (SBC). These criteria assign different weights to the 'parsimony' and 'fit' of the models. Each model is considered as equally likely in each period. The selection of model in one period does not restrict the model choice in following periods.

5. Performance of the Switching Portfolio Strategy Using Alternative Model Selection Criteria

Tables A12-A24 provide a summary of each of the equations estimated over the period 1990-2002. The models selected by each of the three criteria are highlighted for each year of estimation. Figures A11-A13 plot the predicted excess returns and the actual excess returns. As to be expected each one of the series selected by the alternative model selection criteria display significantly less volatility than that of actual excess returns. Both the AIC and SBC forecast the correct sign for excess returns in ten of the thirteen periods. The Adjusted R-Squared criterion fares only slightly worse correctly predicting the sign in nine periods. All three criteria provide correct forecasts of the sign of excess returns after 1994. The recursively estimated standard errors of the selected models are charted in figures A19-A21. As seen in the results for the baseline model, the standard errors steadily trend upward throughout the forecasting period, although the models selected by SBC trend to a lesser degree. The models selected by the AIC and the Adjusted R-Squared criteria in 1990 have a standard error of around 0.145. The model selected by the SBC has a standard error of just over 0.150. All three criteria select the same model in 2002 with a standard error of just under 0.160. All three criteria select a model in 1994 that reduces the standard error, all followed with a significant increase in 1995. Although all three model selection criteria correctly predict the sign of excess returns in the post-1994 period, the upward trend of the standard errors indicate that the variables in the base set are not picking up a possible change to the data generating process. This period coincides with the creation of the 'dot-com bubble'.

Figures A15-A17 provide the R-Squared for each of the selected models. Not surprisingly the models selected by SBC generally have a lower R-Squared throughout the period. The R-Squared of a model can only be increased with the addition of a variable to the equation. The lower value of the R-Squared is likely to be a reflection of the more parsimonious model selection of the SBC. The SBC places a higher penalty on additional regressors compared to the other two criteria. Figures A22-A25 show the inclusion frequency of the four variables most commonly included in the models selected by the three criteria. It is clear that typically the number of regressors selected by SBC is less than the number selected by the other two criteria.

Throughout the period of 1990-2002, none of the criteria select a model that includes the interest rate. The change in the interest rate is only selected by the Adjusted R-Squared criterion in the years of 1990, 1995 and 1996. This supports the evidence from the baseline model results in which the interest rate and change in interest rate were weakly correlated with excess returns. Table 1 provides percentages detailing how often each criterion selects each variable from the base set.

The lagged PE ratio is the most important of the base set of variables for predicting excess returns – it is included in over 80% of the alternatively selected models. The AIC and the Adjusted R-Squared criteria select this variable each year with the exception of 1999. The SBC selects the lagged PE ratio in all years other than 1998 and 1999. As expected the Adjusted R-Squared criterion often selects models with more variables than the other two criteria. The lagged rate of inflation and the lagged year on year change in the Industrial Production index are included in models selected by Adjusted R-Squared almost throughout the period whilst the AIC only selects these variables at the beginning of the period. The SBC does not include these variables at all. Only the Adjusted R-Squared criterion selects a model including the year on year change in the M1 money stock at the beginning of the forecast period. However the importance of this variable increases towards the end of the forecast period with both the AIC and Adjusted R-Squared criteria consistently selecting models including the variable. The SBC also selects the variable occasionally towards the end of the forecast period. In 1999 all three criteria select the model that only includes the year on year change of the money stock from the base set.

Only in 1999 and 2002 do all three of the model selection criteria select the same model. This results in the three alternative selection criteria predicting differing excess returns across the forecast period. However if the predicted signs match for each period, the switching portfolio strategy would result in the same final wealth for the investor, leaving the comparison of the performance of the alternative model selection criteria with a rather ambiguous conclusion. This is not the case as can be seen from figures A27-A29. The figures show the different investment patterns for the alternative selection criteria. All three criteria begin in 1990 by indicating that our investor should place his portfolio at the market index. Both the SBC and Adjusted R-Squared criteria then indicate to switch the portfolio to the risk-free rate in 1992. The AIC however indicates that the portfolio should remain invested at the market index. The AIC and the Adjusted R-Squared criteria both signal in 1993 that the investment decision is to invest at the risk-free rate. The SBC however does not indicate this. All three model selection criteria predict the same sign for excess returns for the rest of the period from 1994 onwards. Table 2 displays the mean return, volatility and Sharpe ratio over the entire forecast period for the three alternative selection criteria, the baseline model and the buy-and-hold strategies.

All three selection criteria provide greater average returns than the market. This higher average return is not associated with higher risk. The Sharpe ratio for all three is significantly higher than that of the market as a result of higher average returns and lower volatility. The SBC and AIC both have a higher Sharpe ratio than the baseline model. The Adjusted R-Squared criterion however has a lower Sharpe ratio than the baseline model although it does still represent an increase of return-to-risk when compared to the market index. The SBC accrues the investor the greatest end of period wealth, a value higher than the peak of the market. This is despite forecasting the incorrect sign for excess returns in three of the thirteen periods.

6. Conclusion

The analysis has identified several predictors of excess returns in the US Non-Financial Corporate Sector. The lagged PE ratio proved to be an important factor alongside the year on year change in the M1 money stock. The analysis has also identified the rate of inflation and the year on year change in the Industrial Production Index as significant predictors of excess returns although to varying degrees and dependent upon model selection criteria. It was therefore possible for an investor to have used forecasts from modelling these variables to improve upon the return-to-risk offered by the market by using a switching portfolio strategy.

The investor selected just six variables initially. The analysis shows that the interest rate is not important for predicting stock returns. This variable was thus excluded from the models selected recursively. However this analysis does not allow the inclusion of any other variables outside of the initial base set. The investor was unable to search for predictors beyond the six variables initially selected. The dividend yield has been the focus of much research on this topic providing significant evidence that it is important for the prediction of stock returns. Alongside the dividend yield, other measures of inflation, other interest rates and the oil price could all be identified by further analysis to be genuine predictors. The inclusion of all these variables in a new base set would offer greater confidence in the results on the significance of these factors in terms of predicting excess returns.

Also, in order to provide more robust results a longer time period would need to be analysed. The best performing selection criteria calculated incorrect signs for excess returns for three periods out of thirteen. If the wrong sign had been predicted at the end of the 1990-2002 period by the predictive equations the performance of the switching portfolio strategy could look very different. Forecasting accuracy will deteriorate if the upward trend continues that is observable in the standard errors of all three model selection criteria, and the baseline model. As the time period for forecasting is extended the likelihood of an incorrect sign of excess returns being predicted increases.

Finally, these findings are made in the absence of transaction costs. Over the period studied in this paper it is doubtful that realistic transaction costs would have altered the results. Final wealth would certainly be lower but the switching portfolio strategy would still outperform the market. The reason for this is due to the extremely high returns made in the market at the end of the 1990s. In the absence of the ‘dot-com bubble’ and the associated high returns, it has to be considered that transaction costs may drastically alter the results, especially if our investor was to increase the frequency of the investment decisions. Thus the potential number of ‘switches’ required for the portfolio increases, accruing higher transaction costs. ■

Table 1

Percentage of periods where a regressor is included in selected forecasting equations

The results are based on annual excess return equations selected and estimated recursively over the period 1990-2002. Each year the set of regressors that maximise a given model selection criterion was determined and used to forecast stock returns one year ahead. The regressors are PE(-1) = Price/Earnings ratio lagged one period, 3M(-1) = 3-month Treasury Bill rate lagged one period, D3M = Year on year change of the 3-month Treasury Bill rate, INF(-1) = Inflation rate lagged one period, DIP = Year on year change in the Industrial Production Index, and DM1 = Year on year change in the M1 narrow money stock.

	Percentages					
Selection Criteria	**PE(-1)**	**3M(-1)**	**D3M(-1)**	**INF(-1)**	**DIP(-1)**	**DM1(-1)**
Akaike	92.3	-	-	30.8	30.8	46.2
Schwarz	84.6	-	-	-	-	23.1
Adjusted R-Squared	92.3	-	23.1	84.6	76.9	53.8

Table 2

Performance measure for the US Non-financial corporate sector switching portfolio relative to the 'Buy-and-Hold' strategy in the market and the risk-free rate (Annual results: 1990 to 2002)

The decisions when to switch portfolios between the market and the risk-free rate are based upon recursive least squares regressions of annual excess returns on an intercept term, a dummy for 1974 and a subset of regressors selected according to alternative statistical model selection criteria. The results are based on zero transaction costs when switching portfolios. The Sharpe Index adjusts the excess return on the portfolio under consideration for total risk. The final wealth figures assume that the investor begins with $100,000 at the beginning of 1990 and reinvests portfolio income each year. S.D. is standard deviation.

	Market	**Risk-Free**	**All regressors**	**Akaike**	**Schwarz**	**Adj R-squared**
Mean return	12.85	5.01	16.45	16.88	17.09	16.29
S.D. of return	0.20	0.01	0.15	0.15	0.14	0.15
Sharpe's Index	0.40	-	0.80	0.84	0.86	0.78
Final Wealth ($)	**383,650**	**188,666**	**654,141**	**688,477**	**705,061**	**641,295**

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