The Good and the Bad of Value Investing:
Applying a Bayesian Approach to Develop Enhancement Models

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Abstract:

Value investing was first identified by Graham and Dodd in the mid-30's as an effective approach to investing. Under this approach stocks are rated as being cheap or expensive largely based on some valuation multiple such as the stock's price-to-earnings or book-to market ratio. Numerous studies have found that value investing does perform well across most equity markets but it is also true that over most reasonable time horizons, the majority of value stocks underperform the market. The reason for this is that the poor valuation ratios for many companies are reflective of poor fundamentals that are only worsening. The typical value measures do not provide any insights into those stocks whose performance is likely to mean-revert and those that will continue along their recent downhill path.

The hypothesis in this paper is that the value stocks most likely to mean-revert are those that are financially sound. Further, it is proposed that we should be able to gain some insights into the financial strength of the value companies using fundamental accounting data. We apply a Bayesian model averaging approach to a set of fundamental accounting variables to forecast, the probability of each value stock outperforming the market. These probability estimates are then used as the basis for enhancing a value portfolio that has been formed using some valuation multiple. The positive note from our study of the US, UK and Australian equity markets is that it appears that fundamental accounting data can be used to enhance the performance of a value investment strategy. The bad news is that the sources of accounting data that play the greatest role in providing such insights would seem to vary both across time and across markets.

JEL Codes: G14, C11, C51, M40

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Section 1: Introduction

So called value investing is one of the oldest but still the one of the most commonly used quantitative approaches to investment management. It relies upon the premise that stock prices overshoot in both directions and that the resulting mispricings can be identified using one or more valuation multiples. Commonly used multiples include price-to-earnings, price-to-sales, price-to-cash flow and price-to-book. These are all very simple measures that are used to rank stocks in order to identify those that are considered cheap and which are considered expensive. The expectation being that the valuations of many of these stocks will mean-revert and so give rise to profitable investment opportunities.

Numerous studies have found that fairly simple value strategies outperform the overall market in most countries. However, it has also been found that over most reasonable time periods, the majority of the stocks included in the value portfolio actually underperform the market (see Piotroski [2000]). This reflects that the use of simple multiples to identify value stocks is very crude, in that they are unable to differentiate between the true value stocks and those that appear cheap but will only get "cheaper".

In line with the findings of Piotroski and others, we propose that fundamental accounting variables reflecting the financial strength of a company can be used to better separate the subset of “cheap” value stocks into true value stocks (i.e. those that mean revert and improve in return) and false value stocks (that are sometimes referred to as "dogs"). We develop a series of annual models based upon accounting variables, using a Bayesian model averaging technique, to forecast the probability of each value stock outperforming the market over a one year holding period. A number of investment strategies are then developed on the basis of these probability estimates, that prove to enhance the investment returns ofg the value portfolios. Our findings support our proposition that accounting variables provide information that can be used as the basis for achieving the desired separation within a portfolio of value stocks. The findings of our study provide insights into a particular usefulness of accounting information, suggest a market inefficiency in that publicly available information cvan be used to further enhance a value investment strategy and as such suggests how value managers can supplement their investment strategy.

In Section 2, we provide a more detailed discussion of the problem that we are addressing. In Section 3, we describe our data and the method employed to rank value stocks on the basis of their estimated probability of outperforming the market over a one-year holding period. The investment strategies that we employ based on these probability estimates and their performance are reported and discussed in Section 4 while Section 5 provides us with the opportunity to summarise our major findings.

Section 2: The Literature

The foundations of value investing date back to Graham and Dodd [1934] when these authors questioned the ability of firms to sustain past earnings growth far into the future. Their proposition was that analysts extrapolate past earnings growth too far out into the future and by so doing drive the stock price of the better (lesser) performing firms to too high (low) a level. A number of price (or valuation) multiples can be used to provide insights into the possible mispricings caused by flawed forecasts of future earnings. For example, a high (low) price-to-earnings multiple is indicative of the market's expectations of high (low) future earnings growth. The Graham and Dodd hypothesis is that firms who have and are currently experiencing high (low) earnings growth are unlikely to be able to sustain it to the extent expected by the market. When this earnings growth reverts towards some industry/economy-wide mean, then this will result in a revision of earning's expectations, a fall in the firm's price-to-earnings multiple and so a downward correction in its stock price. The ramification of such price behaviour for the investor is that at times certain stocks are cheap while others are expensive and one can use a number of price multiples to gain insights into this phenomenon.

Value investing where stocks are classified on the basis of one or more price multiples has gone through various cycles of acceptance over the period since the first writings of Graham and Dodd. However, it is only in the last 25 years that the success or otherwise of value investing has been subjected to much academic scrutiny. As examples, Basu [1977] evaluated earnings-to-price as a value measure; Rosenberg, Reid and Lanstein [1984] investigated price-to-book; Chan, Hamao and Lakonishok [1991] studied cash flow-to-price. A number of authors have evaluated several measures both individually and in combination (Lakonishok, Schleifer and Vishny [1994]; Dreman and Berry [1995]; Bernard, Thomas and Whalen [1997].

A consistent finding in these papers is that value investing is a profitable investment strategy not only in the US but also in most of the other major markets (Arshanapalli, Coggin and Doukas [1998], Rouwenhorst [1999]). This raises the question as to whether the excess returns associated with a value strategy represent a market anomaly (Lakonishok, Schliefer and Vishny [1994]) or whether they simply represent a premium for taking on extra risk (Fama and French [1992]).

Irrespective of the source of the extra returns from value investing, they do seem to exist and persist across almost all of the major world markets. Not surprisingly, this outcome has attracted a number of investment managers to integrate this form of investing into their process. This is often described as taking a contrarian approach to investing as the view is that the value stocks are out-of-favour in the market probably as the result of a period of poor performance and that their price will increase substantially when first their fundamentals, and then their price multiples, mean revert.

If this mean reversion occurred for all, or even most, value stocks, then value investing would indeed be extremely rewarding. The problem is that the majority of the so-called value stocks do not outperform the market (Piotroski [2000]). The reason being that the multiples used to identify value stocks are by their nature very crude. For example, the market may expect a firm that has been experiencing an elongated period of poor earnings to continue to do so for several more years and this will cause the firm to have a relatively low price-to-earnings multiple. Of course if the earnings do revert upwards in the immediate future, the market will revise the firm's stock price upwards and the low price-to-earnings multiple would have been reflective of a cheap stock. On the other hand, the market might have been right in its expectations and the firm's profitability may never improve in which case it is unlikely to prove to be a cheap stock. Indeed, the firm's fundamentals might even worsen and so investing in this firm on the basis of its price-to-earnings multiple would prove to be a very bad investment decision.

The point here is that the typical criteria for identifying value stocks provide little or no insight into which ones will prove to be good investments and which ones will prove to be bad investments. Fortunately for value investors, the typical longer-term outcome from following such a strategy is that a value portfolio outperforms the market even though only a minority of the stocks included in the portfolio out-perform the market. In Figure 1, we present a histogram of the excess returns over a one-year holding period for all US value stocks over our entire data period. The information contained in this figure not only confirms that the majority of value stocks underperform (the median excess return is negative) but also highlights that the average performance of the value portfolio is largely driven by a relatively small number of value stocks which achieve an extremely good performance. This is reflected by the fact that the excess return distribution of value stocks is very much skewed to the right.

This raises the question as to whether it might be possible to enhance the performance of a value strategy by developing an overlay procedure designed to separate out the true value stocks from the false value stocks. Ideally this strategy would produce an *enhanced value* portfolio with a higher proportion of stocks that outperform the market, without deleting many (preferably any) of the value stocks whose returns lie in the right-hand tail of the excess return distribution. Asness (1997) has shown that momentum provides a good basis for separating out true and false growth stocks but that it has nowhere near the same degree of success in distinguishing between true and false value stocks. As an alternative, we would suggest that accounting fundamentals might well provide a good basis for making this distinction, as ultimately it is the fundamental strength of a company that plays an important role in determining whether a company ever recovers after a period of poor performance. This conjecture has been supported by other writers such as Piotroski [2000] who has demonstrated that a check-list of nine such variables can be used to rank value stocks with a fair degree of success while Beneish, Lee and Tarpley [2000] has found that such variables are also useful for distinguishing between those stocks whose performance falls in the extreme tails of the return distribution.

The approach taken in this paper is to develop a model to distinguish between true and false value stocks in the spirit of Ou and Penman [1989]. In that paper, Ou and Penman effectively “data mined” 68 accounting variables in an attempt to build a model, using the previous 5 years of earnings performance, to predict whether a firm’s earnings would increase or decrease over the next 12 months. They used these forecasts as the basis for an apparently profitable investment strategy. A recent study has updated and extended this strategy using a Bayesian variable selection process and found that the power of these accounting variables to forecast future earnings movements has significantly dissipated since the time of the Ou and Penman study (Bird, Gerlach and Hall [2001]). However we would argue that accounting information is more likely to provide a better guide to the current financial health of a firm rather than to its future earnings-generating potential. Therefore, we believe that the Ou and Penman approach may well prove more successful in identifying those value stocks whose fundamentals are most likely to mean revert, and so provide a good basis for discriminating between the future investment potential of these value stocks.

Of course if it does prove that the performance of value investment strategies can be significantly improved by the application of a model based upon fundamental (accounting) information, then this provides another instance of the use of publicly available information to enhance investment returns. This calls into question the efficiency of markets. Further, the results of this research have interesting implications for the structuring of a funds management operation. A price multiple, such as price-to-earnings, serves as a very simple technique by which a fund manager can screen the total investable universe, to isolate a subset of that universe that has a high probability of outperforming the market. If our search for a model to differentiate between true and false value stocks has some success, then it could be used to further refine a value portfolio in order to realise even better performance. As this refinement process is based upon fundamental accounting data, this suggests that another way to proceed is to overlay a more traditional fundamental approach over the quantitative process which may involve employing analysts who review the list of value stocks in a more traditional but disciplined way.

Section 3: Development of Models: Data and Method

In this section, we explain the basis for the Bayesian approach that we have taken to obtaining a ranking of value stocks based upon a set of fundamental variables. The objective of this exercise is to develop forecast models aimed at separating value stocks into those that are likely to outperform the market and those that are likely to under-perform. As discussed earlier, a number of different multiples can be used to separate the value stocks from the investment universe and in this study we have chosen to use book-to-market. We report our findings for three markets – the US, the UK and Australia. A combination of differing sample sizes in each of the markets and the need to have sufficient value stocks to estimate the Bayesian models has caused us to use a slightly different definition for the value stocks within the three markets – the top 25% of stocks by book-to-market in the US and the UK and the top 33% in Australia. Each year in each country a new value portfolio is chosen in accordance with these definitions.

Most of the fundamental data was obtained from the COMPUSTAT databases with some supplementation from GMO's proprietary databases[1]. The return data was also obtained from COMPUSTAT for the US stocks and from GMO for both the UK and the Australian markets. The sample of firms included in our data set each year are composed of all firms in the COMPUSTAT database from 1983 until 2001, with the exception of financial stocks and those stocks for which we had a incomplete set of fundamental and/or return data. In line with the typical financial year and allowing for a lag in the availability of fundamental data, we built the models as at the beginning of April for both the US and the UK and at the beginning of October for the Australian market. As an example in the US the first model was developed over the 3 year period from April 1983 to March 1986, which was used to estimate the probability of a particular value stock outperforming the market over the 12 month period from April 1986 to March 1987. More details of the availability of data for the three markets are provided in Table 1.

Fundamental variables

The proposition that we are evaluating in this paper is that fundamental variables that provide an insight into a company's financial strength will also provide a basis for determining those value stocks that are most likely to perform best in the future. However we do not follow the Ou and Penman approach of commencing with a vast array of fundamental variables when developing the models, but rather we have been more selective when determining the potential explanatory variables. These variables were chosen on the following grounds:

- Other writers had found the variable to be useful for differentiating between potentially cheap stocks (e.g. Beneish, Lee and Tarpley [2000]; Piotroski [2000])
- We and/or GMO have found previously that the variable had potential for differentiating between value stocks (Bird, Gerlach and Hall [2001])

The following 23 fundamental variables[2] were included when developing the US models but data restrictions meant that we were only able to include the first 18 of these variables when modelling the UK and Australian markets[3]:

1. Return on assets
2. Change in return on assets
3. Accruals to total assets
4. Change in leverage
5. Change in current ratio
6. Change in gross profit margin
7. Change in asset turnover
8. Change in inventory to total assets
9. Change in inventory turnover
10. Change in sales to inventory
11. Return on equity
12. Change in sales

[1] GMO is Grantham, Mayo, Van Otterloo, a US-based fund manager who has facilitated this research.
[2] We standardise each of the variables to have a mean of zero and a standard deviation of one.
[3] Not all of the variables were available for all years in all markets.

13. Change in receivables to sales
14. Change in earnings per share
15. Times interest covered
16. Quick ratio
17. Degree of operating leverage as measured by change in EBIT to sales
18. Degree of financial leverage measured by the change of net income to EBIT
19. GMO quality score made up of one-part the level of ROE, one-part the volatility in ROE and one-part the level of financial leverage
20. Volatility of return on equity
21. New equity issues as a proportion of total assets
22. Change in capital expenditure to total assets
23. Altman's z-score

Method of model development

The first step each year is to rank all of the stocks on the basis of their book-to-market value and then form a value portfolio using the cut-offs reported previously. The return data for these value stocks is transformed to a binary series of 1's and 0's, where a 1 indicates that the return on a particular value stock over the subsequent year is greater than the average market return for that year and a 0 indicates otherwise. This data series forms the observations in a logistic regression model. We use this model, instead of an ordinary regression model of returns on accounting variables for a few reasons. The first being that we are basically interested in separating out the better performing value stocks from those that underperform. Therefore, a technique that provides a probability estimate for each stock as to its likelihood to outperform the market average is consistent with our objective without being too ambitious. A second statistical reason for taking this approach is that it is preferable to a linear regression with returns as the dependent variable as parameter inferences based on this approach are sensitive to outliers and other interventions in the data. The return distributions with which we are dealing are positively skewed and contain several extreme returns. One option would be to delete these potential outliers and hence have more well behaved data, but this is not the preferred means to deal with the problem, as large positive or negative returns are very important in contributing to the success or otherwise of the value strategies. Another option is to model the outliers using mixture distributions, as in Smith and Kohn (1996), however this leads to outlying returns being down-weighted compared to other company returns, again this is not the preferred option.

Logistic regression is a natural model to use in this case as the observations only tell us the direction of the return compared to the average. The advantage of this is that outlying returns will not distort the regression in any way as they will still be recorded as either a 0 or a 1. In fact, if we can predict and forecast these outliers (both positive and negative) from the accounting information, then this will enhance the performance of our value portfolio. That is, the logistic regression searches for information in the accounting variables that indicates whether the company return will outperform or not, regardless of the magnitude of this performance.

The model is a dynamic logistic regression model, where the observations, y_t, record whether each firms' annual return is higher than the market return in that year ($y_t = 1$), or smaller ($y_t = 0$). The probability of out-performing the market is allowed to change over time. i.e.

$$P(y_t = 1) = \pi_t \text{ , } t = 1, \ldots, n$$

This is the probability that we will attempt to forecast in our analysis. That is, given returns and fundamentals over the previous 5 years, we will forecast these probabilities for value stocks in the forthcoming year. Using the standard logistic link function, the log-odds of outperforming the market is modelled as a simple linear regression as follows:

$$\log (\pi_t/1-\pi_t) = z_t = X_t\beta + e_t \text{ , } t = 1, \ldots, n$$

where the errors, e_t, are normally distributed i.e. $e_t \sim N(0, \sigma^2)$. The row vector X_t contains the values of the 23 accounting variables for observation (stock) t, lagged by one year. For example, when considering US returns for stocks in the year April, 1996 to March, 1997, the accounting variables used in the vectors X_t are those available as at the end of March, 1996, for each stock in the value portfolio for 1996 (April, 1996 – March, 1997). This allows us to have the required accounting information available at the time when we make the one year ahead forecasts and hence avoids any look-ahead bias.

We start with the set of 23 fundamental variables described above from which we wish to forecast the probability of each value stock outperforming the market. One approach for doing this would be to select one single 'optimal' model, say using a stepwise regression (Ou and Penman [1989]), but there are several well-known drawbacks from applying this technique, as pointed out in Weisburg [1985], among others. As an alternative we could use standard model selection techniques such as the Akaike or Schwartz information criterion (AIC, SIC) to select our model. However, this would require calculating the criterion function for each of the approximately 8 million (2^{23}) potential models we have here. While this may be theoretically possible, it is impractical and could be quite inefficient, especially if many of the models have very low likelihood. Another drawback is that parameter uncertainty is ignored in the criterion function; that is, parameters are estimated and then 'plugged in' to the criterion function as if they were the true parameter values for that model. A further drawback of choosing a single model is pointed out by Kass and Raftery (1995), who discuss the advantages of 'model averaging' when dealing with forecasting problems. The advantage is especially apparent when no single model is significantly best, or stands out from the rest, in terms of explaining the data. This model averaging approach is nicely facilitated by a Bayesian analysis as detailed in the Bayes factor approach of Kass and Raftery (1995), who also showed how to use this approach for model selection. This Bayes factor approach involves estimating the posterior likelihood for each possible model and then using these to either select one optimal model (using maximum posterior likelihood) or combining the forecasts of each model by model taking a weighted average, weighting by the posterior probability of each model. These two Bayes factor approaches have the further advantage, over the criteria based techniques mentioned above, that we could use the Occam's razor technique to reduce the model space in a logical, efficient fashion. However, for the Kass & Raftery approach, a Laplacian transformation is needed to estimate the actual posterior likelihood for each model, relying on a normal approximation to the posterior density for each model. This approximation is required because the logistic regression model is a generalised linear model, see Raftey (1996). In other words, we are assuming that the sampling distribution for each parameter in the model is normally distributed. In addition, non-informative priors on model parameters cannot be used with this approach, a proper prior distribution must be set. Rather than take this restrictive approach, we favour a more efficient technique allowing us to explicitly and numerically integrate over the possible parameter values and potential model space, without relying on approximations or proper priors, in an efficient manner.

Recent advances in Bayesian statistics allow the use of Markov chain Monte Carlo (MCMC) techniques to sample from posterior densities over large and complex parameter and model spaces. These techniques allow samples to be obtained that efficiently traverse the model space required without having to visit each and every part of that space. When we are dealing with over 8 million models these techniques allow us to efficiently examine a sub-sample of these models by directly simulating from the model space. The Bayesian variable selection techniques for ordinary regression were illustrated by Smith and Kohn [1996], who designed a highly efficient MCMC sampling scheme, extending the original work in the area by George and McCulloch [1993]. In order to undertake the required analysis for this paper, we have adapted the Smith and Kohn [1996] MCMC technique for a logistic regression model, as in Gerlach, Bird and Hall [2002]. This technique allows us to directly simulate from the model space conditional upon the sample data, accounting for both parameter and model uncertainty in estimation. As we are dealing with a generalised linear model here, we cannot explicitly integrate out all model parameters from the posterior density, so we cannot explicitly find the posterior density of each model, as in Smith and Kohn [1996]. However, we can estimate the relative posterior likelihood for each model selected in the MCMC sample as in McCulloch and George [1993], using the proportion of times each model is selected in the MCMC sample. This will allow us to either (i) select the most likely model based on the MCMC output; OR (ii) forecast the probability of outperforming the market using the model averaging approach outlined in Kass and Raftery [1995]. We take approach (ii) in this paper. The MCMC sampling scheme, model selection and model averaging techniques are outlined in Appendix A.

The MCMC technique is performed for data in a series of overlapping five-year windows (eg 1987-1991, 1988-1992) that span the whole sample. Information in each 5 year sample is used to forecast the performance for the value portfolio in the subsequent year. The first step is to form a value portfolio of stocks for each year of the entire sample period (for the US this is 1983-2001). Then, returns for stocks in the value portfolios for each of the years in a particular 5 year window, e.g. 1987-1991 (1987 for the US means April, 1987 – March, 1988 and thus this five year window extends from April 1987 to March 1992), are grouped together and transformed to 0's and 1's based on whether they realise a return higher or lower than their respective year's average market return. The MCMC technique is then used to match these returns in a logistic regression model to the 23 accounting variables taken for the same value stocks over the 5-year period lagged one year, 1986-1990 (for the US in 1986, say, this means the accounting information available at the end of March, 1987, measured over the year 1986). This means that stock returns in each year are linked to accounting variables in the previous year and hence will be publicly available at the time of investing. The statistical forecasts of the probability that each value stock in the subsequent year (1992 here) will outperform the market average (for that year) are obtained as explained below:

The MCMC technique is an iterative sampling scheme, sampling over the model and parameter space. For each iteration, the following steps are performed:

(i) a particular model is sampled from the posterior distribution of all possible models, conditional upon the model chosen at the last iteration and the subsequent estimated parameter values (see appendix for details). This step employs the likelihood over the 5-year sample period, plus the prior distribution discussed below and in the appendix. Each model represents a particular subset of the 23 explanatory variables.

(ii) Parameter values (regression coefficients) are then sampled from their posterior distribution conditional upon the model chosen in (i) and the 5 year sample data.

(iii) The chosen model and parameter values in (i) and (ii) are then used to generate probability forecasts for each value stock, using the fundamental variables selected in the model. If we are forecasting 1992 (April, 1992 – March, 1993) for the US data, these will be the accounting variables available at the end of March, 1992.

This process of choosing a model, estimating coefficients and generating probability forecasts is repeated for 25,000 iterations. At the end of the sampling run, we average the last 20,000 forecasted probabilities for each value stock to obtain a model-averaged estimate of the stock's forecasted probability of outperforming the market over the subsequent 12 months.

This analysis is repeated for each year in the US from 1986 to 2001 with the forecast models being based on the previous 5 years of data. The exceptions to this are the early years of 1986 and 1987 when three and then four years of data are used to develop the models in order to maximise the number of years over which we can test our approach.

Prior information

Where prior information is available, this can be incorporated into the estimation procedure in a natural way so that optimum posterior estimates are obtained. For example if the variable 'return on assets' proves important information in distinguishing between true and false value stocks over a number of years, then we can incorporate this into our model development process for subsequent years by commencing with a stronger prior that this variable should be included in the model. We did incorporate this option into our procedure by applying a set of rules each year when setting the prior probabilities. These rules were based upon the posterior probabilities obtained for each of the 23 accounting variables in the previous 5-year period. The rules are discussed in detail below.

(i) set the prior equal to 0.65 if the previous 5 year posterior probability is above 0.65;

(ii) set the prior equal to the previous posterior probability, if that posterior is between 0.35 and 0.65;

(iii) set the prior equal to 0.35 if the previous posterior probability is less than 0.35.

We could simply have used the posterior probability for each variable from the last time we estimated the model (the previous 5 year window) as our prior distribution for the next set of 5 years of data. However, we felt this was not an optimal strategy as variables with very high posterior probabilities (say, > 0.95) in previous years would rarely be dropped from the newly selected model whereas variables with low posterior probabilities (say, <0.05) in previous years would struggle to be selected in the model, even if they had a large or strong effect over the new sample period. We consider the prior settings above to be a compromise that will allow changes in the market to be captured relatively quickly, while still weighting our results in favour of previously successful or important variables. The first estimation run for the year 1986, when there is no prior data or prior model, has a flat prior on these probabilities (i.e. they are all set to be 0.5).

The Effects of Variables

The model averaging procedure described above results in every variable having some impact, however small, in the model developed in each of the years over which we are forecasting the probabilities. In order to shed some light on what proved to be the more important fundamental variables in our models, we provide information in Table 2 on the number of forecast years in which each variable plays a major role in the forecasting of these probabilities, where a major role is defined as being included in the model selected most often by the MCMC sampling scheme (i.e. the model with the largest posterior probability). With respect to the US models, 17 of the 23 variables are included at least once as an important variables in the 16 models selected, with each model containing on average slightly in excess of 5 important variables and the number of important variables included in any one model varying between two and seven. Only two variables prove to be important in more than half of the models with 7 variables being included as important variable on six or more occasions. The most commonly included important variables are the return on assets (13 times), the GMO quality score (11 times), the quick ratio (8 times), return on equity (7 times), and the change in ROA, the change in the current ratio and accruals (each 6 times). These variables represent a mixture of indicators of the earnings power of the company (ROA, ROE and the change in ROA) and of short-term and long-term financial strength (quick ratio, change in current ratio, accruals and the GMO quality score).

The overall impression that one would gain from reviewing Table 2 is the frequency with which there are changes in the variables that are designated as being important. Although there is persistence over time in the variables being selected, there are different variables in different time periods playing important roles. To a certain extent this is a disappointing outcome as one would like to see more constancy in the combination of variables included in the models over time. We investigated applying a model each year composed of the best six variables as listed above but its ability to achieve the desired separation of value stocks was significantly inferior to the approach reported in this paper. Table 3 shows the standardised regression coefficient for each variable in each forecast year, while table 4 shows the posterior probability for each variable having a non-zero effect in each forecast year. It is interesting to note the time patterns in the most important models and variables. While variables do have different effects in different time periods, there is clearly a time pattern in the magnitude and direction of these effects, suggesting the models estimated here are not spurious nor 'data-mined'.

Data restrictions limited the number of potential variables that could be considered for inclusion in both the UK and Australian models and meant that even some of those included were not available in all of the years. Only 8 variables prove to be important in one or more of the UK models with there being on average 3 important variables in any year, which is about half the number of variables typically designated as important in the US models. There are only two variables which are included in more than a half of the UK models (change in gross profit margin appears in all 8 models while growth in sales appears in 5) with only the latter proving important in both the other two markets considered. In the case of Australia, 7 variables appeared at least once as important variables in any of the seven models with on average only 2 variables being included in each model. The important variables that appear in three or more models are growth in sales (4) and degree of operating leverage (3) of which only the former is a consistently important variable in the UK models.

There is really no evidence of any consistency in the actual variables that have a strong influence across the three markets. ROA is the only variable that comes close to being of universal importance appearing at least once in a model in each country and appearing in over 50% of all models. The only other variable that may have been of consistent importance if it had been more generally available is the GMO quality score which appeared in more than 70% of the US models. Although these variables continue the theme of profitability and financial strength being important for the subsequent performance of value stocks, the lack of consistency in the variables playing an important role in these models remains a major issue for further study.

Section 4: Results

We conducted almost identical analysis on each of the US, UK and Australian markets using the Bayesian model averaging method as outlined in the previous section. The output from this process provided us with an estimate of the probability of each value stock outperforming the market over the subsequent 12 months. In this section, we describe various methods for using these probability estimates with the objective of enhancing the value strategy. We initially restrict our discussion to the US findings as these are based on a much larger data set both in terms of the period covered (16 years of results) and the sample size of companies (on average, slightly in excess of 900 each year). An additional advantage of the US data set is that it traverses two cycles in terms of the performance of value stocks and thus is much better placed to identify whether our models are capable of enhancing a value investment strategy (see Figure 3).

Investment Strategies: The US Models

Our objective is to develop an investment strategy, based upon the probability estimate of each particular stock outperforming the market (which we will henceforth refer to as the value stock's P value), that is capable of discriminating between the good and poor performing value stocks. The two strategies on which we will concentrate are drawn from the tails of the distribution of the P values[4]:

- rank all value stocks in terms of their P value and only invest in either those that rank in the top quartile (top25%) or bottom quartile (bot25%)
- only invest in those value stocks which have a P value greater than 0.6 (P>0.6) and those value stocks with a P value less than 0.4 (P<0.4)

Returns

We would propose that the greatest information lies in the tails of our probability estimates (P values) and so the strategies chosen should provide evidence of the ability of the models to differentiate between the good and poor value stocks. Our findings on the performance of these strategies for both equally weighted and market weighted portfolios are summarised in Table 5 (see also Figures 2 and 2A). In both cases our probability estimates provide a reasonable separation between the returns generated by the good value portfolios (either top25% or P>0.6) and the poor value portfolios (bot25% or P<0.4) irrespective of whether the returns are calculated using equally weighted or market weighted portfolios. The top25% strategy approximately doubles the added value realised by the value strategy and outperforms the bot25% strategy by approximately 3% pa. The P>0.6 strategy trebles the added value realised by the value strategy and achieves an even greater separation from the P<0.4 strategy.

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[4] We also investigated the strategies of (i) investing in the top 50% and (ii) investing in the stocks where P > 0.5. While still generating positive returns compared to the average market return, the results were neither as consistent nor as positive in return as the strategies discussed above.

Risk

The superior performance of the P>0.6 strategy as compared to the top25% strategy comes at the cost of more highly concentrated and more risky portfolios as can be seen from an examination of Table 5. The information contained in this table suggests that differential risk across the various portfolios may at least partially explain some of the variation in performance, particularly of the equally-weighted portfolios. However, the added value of the value enhancement is unlikely to be fully explained by the differential risk[5]. In the remainder of the discussion of the performance of the US models, we will concentrate on the top25% strategy which although slightly less rewarding represents a more diversified and more implementable strategy than the P>0.6 strategy[6]. In Figure 3 (Figure 3A) the year-by-year returns of the top25% portfolio are compared with those of the market and value portfolios for equally weighted (market weighted) portfolios. In both cases, the top25% strategy outperforms the value portfolio in 12 of the 16 years examined with most of the poor performance coming in the early 90's.

A major change in the models occurred in 1994 with a number of variables with strong effects up to that date (e.g. the quick ratio, change in inventory turnover) diminishing in importance (see table 3), these effects being replaced by stronger effects from a number of different variables (e.g. accruals, change in liquidity). It is interesting to note that the worst performance seemingly came at the end of one model regime and the performance since the establishment of the new regime has been particularly good. This suggests that the model averaging procedure may have problems in reacting quickly to changes in the markets. In response to this we have attempted to train the models applying shorter windows than the 5-year moving windows discussed in this paper; we tried both a 2 year and a 3 year window. However, reducing the size of the window actually resulted in lower returns being realised. Another option that we have not pursued up to this stage is increasing the frequency of rebalancing the portfolio from annual to possibly quarterly. Although this may be an option within the US market, it would not be possible in other markets where information on the explanatory variables only becomes available once a year.

Less-concentrated Strategies

The strategies that we have discuss to date involve either going long the top quartile (or less) of value stocks or running a long/short portfolio with the top and bottom quartiles of the value stocks. Such strategies may not prove suitable for many investors as they involve investing in

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[5] When we calculated a Jensen (1969) performance measure for the enhanced value portfolios, the risk adjustment explained less than half of the added value from these strategies.

very concentrated portfolios with an average holding of less than 60 stocks in the case of the US (and considerably less in other markets). We investigated a number of different ways to use the probability estimates from our models to produce much less concentrated portfolios and report below the performance of two such strategies:

1. **80%+** where the bottom quintile of stocks is dropped from the value portfolio
2. **Enhanced 80%+** where the bottom quintile of value stocks is dropped from the portfolio and the top quintile is given a double weighting

The performance of these strategies for US stocks are reported in Table 6. The enhancement to the performance of the value portfolio realised by these strategies lie in the range of 0.5% to 0.7% pa. Although such an improvement is small in absolute terms, it represents about a 50% improvement in the added value achieved by the value portfolio and comes at a reduced level of risk. The source of the additional added value is fairly equally split between overweighting the value stocks whose P values lie in the top quintile and avoiding investing in those value stocks whose P values lie in the bottom quintile. We also investigated using the same strategies above substituting 90% for 80% in 1. and 2. above. Again the results were positive in return but not as consistent nor as strong as those reported for the 80% strategies

Sources of Improved Performance

The original problem that we highlighted in terms of value stocks is that the majority of these stocks underperform the market over 12 month holding periods. Our objective has been to enhance a value investment strategy largely by increasing the proportion of stocks included in our enhanced portfolio that outperform the market. Indeed, we have been successful in better differentiating between the good and bad value stocks as the success rate of the top25% portfolios is 4% above that of the value portfolio while that of the bot25% is 3% below. In order to throw more light on the source of the improved performance of the enhanced value portfolios, we present in Figure 4 the histograms of the excess returns of the value portfolio (see Figure 1) along with those of the top25% portfolios and the bot25% portfolios. An examination of these histograms show that the improvement in performance has largely been achieved by the top25% strategy moving the original value distribution to the right by avoiding investing in a number of what prove to be bad value stocks. This is achieved without sacrificing investing in many (although unfortunately not all) of the very good value stocks which fall in the right tail of the excess return distribution for the value portfolios. The percentiles of the excess return distribution for the value stocks, plus the top25% and bot25% portfolios, over the entire forecast period is presented in Table 7. This clearly shows, as

[6] In 2000 and 2001, there are no value stocks with a P value greater than 0.6.

discussed above, that the value distribution has been pushed to the right (except in the extreme right tail) by the top25% selection strategy. Similarly, the bot25% portfolio pushes the value portfolio distribution to the left (negative). The value portfolio typically sits right in the middle of the percentiles for the top25% and bot25% strategies. Further evidence of this performance is presented in table 7, showing the forecast accuracy of the 3 investment strategies. The top25% strategy improves the forecast performance by 3% over the value strategy, in terms of correctly forecasting that a stock will outperform the average market return. The bot25% strategy is correct 59% of the time in picking stocks that will under-perform the average market return.

In Table 8, we report the book-to-market and size characteristics of the two extreme quartiles of the enhanced value stocks. The evidence for the US suggests that the typical value stock is relatively small and, of course, has a high book-to-market ratio. The average book-to-market ratio of the stocks included in the top25% and bot25% portfolios are almost identical to that for the stocks in the value portfolio. However, the median size of stocks included in the top25% (bot25%) portfolio is much larger (smaller) than the median value stock. Therefore, the higher added value of the top25% portfolio has been achieved holding a larger cap portfolio and without resorting to holding an increased proportion of the cheaper value stocks.

Investment Strategies: The UK and Australian Models

Both the UK models and the Australian models can be used to produce enhanced value portfolios which perform at least as well if not better than the portfolios created using the US models. In Table 9 we report on the risk and returns from applying the top25% strategy to equally weighted portfolios[7]. In the case of the UK, the top25% portfolio adds in excess of 2.5%pa to the performance of the value portfolio while a long/short portfolio based on the top25% and the bot25% earns almost 10% pa. Further, this quite respectable added value is achieved without any significant increase in total risk and at a level of market risk which is less than one. The improved performance in the case of Australia is slightly inferior to that for the UK with the top25% strategy enhancing the return on the value portfolio by about 0.75%pa and the long/short strategy based on the top25% and the bot25% returning 7%pa. Again, this improved performance comes without any significant increase in risk.

Our original premise was that performance of value portfolios is significantly encumbered by the fact that well in excess of half of the value stocks under-perform the market. We have demonstrated in this paper that differentiating between value stocks using information derived from a number of fundamental variables would seem to offer much promise in terms of

[7] Similar results were also realised using market weighted portfolios.

improving the investment performance of such portfolios. In the case of the US, we have already demonstrated that this improved performance was largely due to being able to identify those value stocks with a greater chance of outperforming the market over the next 12 months. Similar evidence for the UK and Australian strategies are also reported in Table 10. Again the evidence supports the proposition that much of the improved performance of the value strategies has been due to being able to differentiate between the good and bad value stocks.

In order to further pursue the source of the superior performance of the enhanced value portfolio, we provide information in Table 11 of the book-to-market and size characteristics of the market portfolio and various portfolios within the value universe. Again it shows that value stocks in both the UK and Australia are on average smaller and cheaper than the average stock in the market. In the UK, the average enhanced value (top25%) stock is more expensive and larger than the average value stock while in Australia the average enhanced value stock has about the same valuation but is larger than the average value stock. As was the case with the US, the increased performance from the model enhancements does not appear to have come from taking on additional risks as measured by either size or book-to-market.

Finally, we applied the same less concentrated strategies to the UK and Australian markets as previously applied to US stocks and the results are reported in Table 12. In the case of the UK, the improvements in performance are small but are achieved with an overall reduction in risk. For Australia, the improvement in performance over the value portfolio are a significant 1.5+%pa , comes entirely from the deletion of the bottom quintile of value stocks based on our probability estimates, and involve only a very small increase in portfolio risk.

Section 5: Summary

Value investing has become a very successful investment strategy in numerous countries. However, it is consistently true that less than 50% of the value portfolio contributes to its good performance meaning the majority of value stocks underperform the market. The focus in this paper has been on developing a means to use fundamental data relating to value stocks to provide a signal to assist in distinguishing between those who current poor fundamental position will soon mean-revert from those whose financial position is most likely to continue to erode.

We used a Bayesian approach to build forecast models based on fundamental variables for the US, the UK and the Australian markets, employing both a model selection (to investigate relationships) and a model averaging (for forecasting) approach. The purpose of these models is to forecast the probability of each value stock outperforming the market over the subsequent 12 months. We used these probability estimates to provide a ranking to the value stocks to serve as the basis for a possible enhancement of a typical value investment strategy. We found in each of the three markets to which we have currently applied this technique that the probability estimates do appear to provide a basis for separating out the good from the bad value stocks and so led to an improved performance.

The overall conclusion that we draw from our analysis is that fundamental accounting data seems to be useful in differentiating between value stocks as determined by applying a traditional multiple, such as book-to-market. This contrasts with previous research that we have undertaken that questioned the usefulness of similar information in forecasting the future profitability of a firm. We suspect that these contrasting results largely reflect that accounting data is a much better source of information for determining the current financial position of a firm rather than for forecasting its profit potential. We believe that this is an aspect of accounting information that is worthy of further research.

Perhaps the only real disappointing aspect of our findings is the lack of consistency in the importance of variables both over time and between countries. We have identified at least one instance where the technique that we use to develop the models would have seemed to have problems in updating the models. One option that this suggests is more regular rebalancing but this will only have significant effect in those markets where new accounting information becomes available on a regular basis.

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Table 1

Characteristics of Samples

Country	Data Period	Ave. No. of Value Stocks Each Year	No. of Years Model Estimated
USA	4/1982 to 3/2002	229	16
UK	4/1990 to 3/2002	89	8
Australia	10/1990 to 9/2001	50	7

Table 2

Variables Included in the Various Models

	Number of times included		
Variable	US	UK	Australia
Return on assets	13	3	1
Change ROA	0*	0	1
Accruals to total assets (TA)	6*	na	0*
Change in leverage	0*	0*	0*
Change in current ratio	6*	2	0
Change in gross profit margin	2*	8	0
Change in asset turnover	2*	0*	0*
Change in inventory to TA	2*	0	0
Change in inventory turnover	3*	0*	0*
Change in sales to inventory	1*	3	0
Return on equity	8	1	0
Growth in sales	0*	5	4
Change in receivables to sales	0*	0	2
Change in earnings per share	0*	0	1
Times interest covered	0	0	2
Quick ratio	8	1	0
Degree of operating leverage	3*	0	3
Degree of financial leverage	3*	0	0
GMO's quality score	11*	na	na
Volatility of return on equity	5*	na	na
New equity issues to TAs	0	1	0*
Change in capital exp. to TA	1*	0*	na
Altman's z-score	4	na	na

*data not available for every year

Table 3

Coefficients for Each Accounting Variable in Each Forecast Year for US Models

Variable	**1986**	**1987**	**1988**	**1989**	**1990**	**1991**	**1992**	**1993**	**1994**	**1995**	**1996**	**1997**	**1998**	**1999**	**2000**	**2001**
ROA	0.35	0.19	0.08	0.21	0.29	0.24	0.17	0.41	0.39	0.28	0.30	0.41	0.20	0.21	0.07	0.05
Ch in ROA	na	0.03	0.01	-0.01	-0.01	0.01	-0.02	-0.01	-0.02	-0.04	-0.001	-0.02	-0.02	0.001	-0.005	-0.02
Accrual	na	na	na	na	na	na	na	na	-0.34	-0.28	-0.27	-0.26	-0.13	-0.08	-0.05	-0.02
Ch. In Leverage	na	na	na	na	na	0.05	0.02	-0.004	0.000	-0.001	-0.01	-0.06	-0.02	-0.06	-0.06	-0.01
Ch. In CA	na	0.03	0.01	0.005	0.01	0.01	-0.01	-0.06	-0.02	-0.10	-0.17	-0.24	-0.10	-0.16	-0.06	0.01
Ch. In Gross margin	na	0.04	-0.02	-0.02	-0.02	0.004	-0.01	-0.01	-0.08	-0.03	-0.09	-0.08	-0.07	-0.05	-0.07	-0.001
Ch. In inv. turnover	na	na	na	na	na	0.004	0.000	-0.002	0.03	0.02	0.04	0.05	0.06	0.10	0.12	0.09
New equity	-0.04	-0.11	-0.03	-0.03	-0.01	-0.001	0.001	-0.01	-0.002	-0.004	-0.01	-0.01	-0.02	-0.08	-0.05	-0.02
Ch. In inv. to assets	na	-0.13	-0.06	-0.09	-0.07	0.000	-0.01	0.00	-0.002	0.01	0.04	0.03	0.002	0.005	0.004	-0.02
Ch. In inv. turnover	na	na	na	na	na	0.24	0.33	0.32	0.01	-0.02	-0.03	-0.02	-0.07	0.003	0.03	0.004
Ch. In capex to TA	na	Na	na	na	na	0.01	-0.01	0.01	0.01	0.002	-0.001	-0.01	-0.05	-0.07	-0.02	-0.10
Ch. In sales to inv.	na	0.24	-0.02	-0.01	-0.01	-0.05	-0.18	-0.03	-0.01	-0.01	0.001	0.01	0.01	0.000	-0.001	-0.02
ROE	-0.04	-0.15	-0.22	-0.21	-0.23	-0.07	-0.07	-0.08	-0.15	-0.17	-0.07	-0.10	-0.20	-0.06	-0.003	-0.01
Growth in sales	na	0.002	-0.01	-0.002	-0.01	-0.004	0.000	0.000	0.02	0.03	0.04	0.01	0.01	0.02	0.01	-0.01
Ch. in rec. to sales	na	0.01	-0.003	-0.01	-0.004	-0.06	-0.08	-0.03	0.001	-0.01	-0.02	-0.004	-0.01	-0.003	0.001	-0.07
Ch. In EPS	na	-0.03	-0.01	0.001	0.003	0.02	0.01	0.002	0.01	-0.003	-0.01	-0.001	-0.01	-0.06	-0.02	-0.04
Z score	0.27	0.03	0.02	0.03	0.07	0.11	0.44	0.06	-0.002	-0.03	-0.19	-0.46	-0.13	0.01	-0.003	0.01
Times int. covered	-0.05	0.00	0.02	0.00	-0.01	0.00	-0.02	-0.05	-0.003	0.03	0.003	0.005	0.000	-0.07	-0.05	0.02
Quick ratio	-0.83	-0.27	-0.40	-0.40	-0.43	-0.26	-0.20	-0.06	0.03	0.05	0.05	0.04	0.02	-0.03	-0.01	-0.002
DOL	na	-0.03	0.01	0.003	-0.002	0.000	-0.04	-0.10	-0.30	-0.11	-0.01	0.02	0.01	0.12	0.03	0.03
DFL.	na	-0.15	-0.15	-0.20	-0.09	-0.04	-0.01	0.001	0.05	0.002	0.004	0.003	-0.004	-0.01	0.002	-0.01
GMO qual.	-0.28	-0.13	-0.15	-0.11	-0.15	-0.14	-0.13	-0.09	-0.04	0.01	0.17	0.28	0.23	0.12	0.04	na
Vol. of ROE	0.24	-0.01	-0.01	-0.06	-0.19	-0.70	-0.65	-0.45	-0.25	-0.01	0.003	0.02	0.01	0.02	-0.002	na

Table 4

Posterior Probabilities For Each Variable Included In The US Models

Variable	1986	1987	1988	1989	1990	1991	1992	1993	1994	1995	1996	1997	1998	1999	2000	2001
ROA	0.63	0.71	0.59	0.84	0.95	0.86	0.66	0.99	0.99	0.94	0.95	0.98	0.84	0.70	0.41	0.35
Ch in ROA	na	0.33	0.22	0.21	0.17	0.13	0.16	0.15	0.18	0.27	0.21	0.18	0.26	0.12	0.13	0.20
Accrual	na	na	na	na	na	na	na	na	0.99	0.98	0.96	0.91	0.77	0.46	0.35	0.18
Ch. In Leverage	na	na	na	na	na	0.37	0.16	0.13	0.14	0.15	0.21	0.38	0.28	0.32	0.30	0.17
Ch. In CA	na	0.31	0.21	0.18	0.18	0.13	0.13	0.35	0.21	0.55	0.89	0.96	0.76	0.74	0.46	0.22
Ch. In Gross margin	na	0.35	0.22	0.20	0.19	0.13	0.14	0.14	0.43	0.34	0.54	0.54	0.54	0.38	0.38	0.14
Ch. In inv. turnover	na	na	na	na	na	0.22	0.11	0.13	0.23	0.24	0.34	0.33	0.42	0.49	0.57	0.66
New equity	0.26	0.48	0.36	0.26	0.15	0.11	0.10	0.13	0.13	0.16	0.22	0.16	0.29	0.38	0.33	0.21
Ch. In inv. to assets	na	0.57	0.50	0.56	0.52	0.21	0.14	0.13	0.12	0.18	0.35	0.26	0.17	0.11	0.11	0.23
Ch. In inv. turnover	na	na	na	na	na	0.85	0.93	0.98	0.37	0.22	0.27	0.18	0.43	0.16	0.20	0.14
Ch. In capex to TA	na	na	na	na	na	0.23	0.13	0.14	0.15	0.14	0.22	0.18	0.42	0.39	0.23	0.60
Ch. In sales to inv.	na	0.62	0.46	0.28	0.20	0.27	0.57	0.33	0.16	0.20	0.18	0.18	0.21	0.10	0.10	0.23
ROE	0.27	0.66	0.86	0.86	0.88	0.52	0.38	0.40	0.65	0.82	0.63	0.61	0.89	0.43	0.18	0.15
Growth in sales	na	0.29	0.20	0.15	0.16	0.12	0.10	0.12	0.22	0.26	0.36	0.16	0.19	0.18	0.13	0.15
Ch. in rec. to sales	na	0.27	0.19	0.17	0.15	0.34	0.34	0.23	0.14	0.17	0.24	0.14	0.20	0.12	0.11	0.49
Ch. In EPS	na	0.35	0.21	0.15	0.14	0.17	0.13	0.12	0.15	0.16	0.23	0.12	0.23	0.32	0.20	0.34
Z score	0.54	0.24	0.24	0.27	0.38	0.49	0.95	0.48	0.21	0.25	0.84	1.00	0.78	0.29	0.13	0.18
Times int. covered	0.28	0.38	0.24	0.17	0.16	0.12	0.15	0.30	0.13	0.28	0.17	0.13	0.18	0.32	0.30	0.21
Quick ratio	0.96	0.83	1.00	1.00	1.00	0.93	0.77	0.48	0.29	0.35	0.43	0.32	0.24	0.22	0.11	0.13
DOL	na	0.33	0.18	0.15	0.13	0.11	0.23	0.49	0.92	0.72	0.45	0.25	0.21	0.53	0.33	0.29
DFL.	na	0.61	0.75	0.87	0.64	0.41	0.15	0.12	0.33	0.14	0.20	0.12	0.16	0.14	0.11	0.14
GMO qual.	0.68	0.61	0.78	0.68	0.78	0.71	0.62	0.55	0.36	0.21	0.79	0.97	0.99	0.64	0.37	na
Vol. of ROE	0.49	0.29	0.21	0.37	0.71	1.00	0.99	0.98	0.88	0.40	0.19	0.18	0.21	0.15	0.10	na

Table 5

Return And Risk Associated With Alternative US Investment Strategies

Equally weighted Portfolio						
	Market	Value	Top25%	Bot25%	P>0.6	P<0.4
Return	13.76%	15.42%	17.30%	14.23%	19.34%	12.47%
Stand. Dev.	14.58%	17.85%	20.11%	26.79%	35.75%	20.43%
Beta	1.0	1.2	1.2	1.4	1.5	1.2
Market weighted portfolio						
	Market	Value	Top25%	Bot25%	P>0.6	P<0.4
Return.	13.34%	15.18%	17.62%	14.52%	20.74%	16.01%
Stand.dev.	13.59%	15.16	18.26%	29.09%	36.84%	18.24%
Beta	1.0	0.5	0.6	0.7	0.9	0.9

Table 6

Performance of Less Concentrated US Value Strategies

	Market	Value	Enhanced 80%+	80%+
Return (%pa)	13.7	15.4	16.1	15.9
Stand. dev. (%pa)	14.6	17.9	18.0	15.8
Beta	1.0	1.18	1.15	1.12

Table 7

Percentiles of Excess Return Distribution in the US

Percentile	5th	15th	25th	35th	50th	Mean	65th	75th	85th	95th
Value	-63.3	-38.9	-25.5	-16.1	-3.7	1.4	8.5	19.0	36.1	83.1
Top25%	-60.7	-36.5	-22.5	-13.2	-1.0	3.6	11.4	22.2	37.7	79.7
Bot25%	-74.9	-45.9	-29.3	-20.0	-4.8	1.9	12.6	26.5	48.3	92.8

Table 8

Size and Multiple Characteristics of US Value Stocks

Average book-to-market ratio			
Market	Value	Top 25% of Value	Bottom 25% of Value
0.55	0.98	0.95	0.95
Median size (' M.)			
Market	Value	Top 25% of Value	Bottom 25% of Value
493.9	189.5	279.0	146.2

Table 9

Return And Risk Associated With Alternative Investment Strategies: UK and Australia

UK portfolios				
	Market	Value	Top25%	Bot25%
Return	8.77%	9.16%	11.89%	2.32%
Stand. Dev.	11.96%	10.56%	12.84%	17.80%
Beta	1.0	0.7	0.8	1.3
Australian portfolios				
	Market	Value	Top25%	Bot25%
Return.	11.02%	10.66%	11.43%	4.33%
Stand.dev.	17.07%	19.48%	20.75%	24.78%
Beta	1.0	1.1	1.1	1.4

Table 10

Proportion of Stocks Outperforming the Market

	US	UK	Australia
Value	44%	45%	40%
Top25%	48%	47%	44%
Bot25%	41%	39%	35%

Table 11

Size and multiple Characteristics of UK and Australian Value Stocks

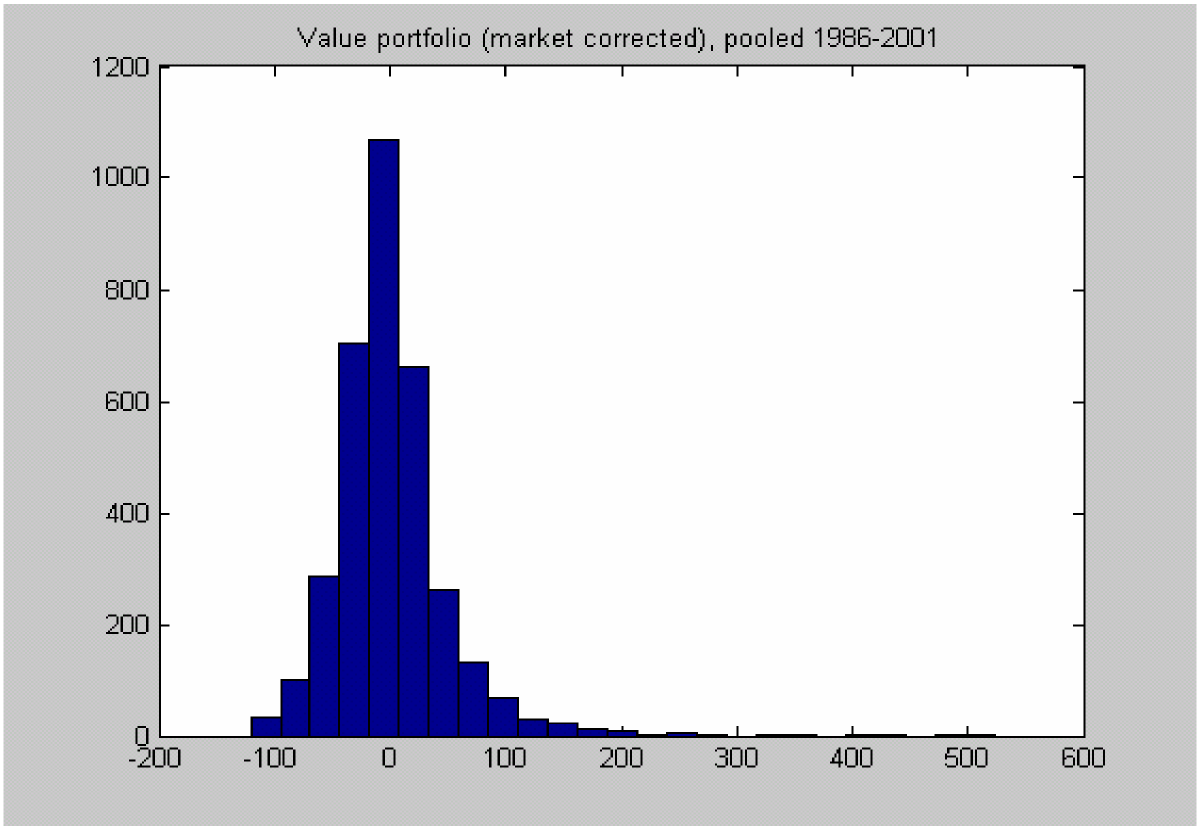
Average book-to-market ratio				
	Market	Value	Top25%	Bot25%
UK	0.82	2.08	1.14	2.00
Australia	0.65	0.93	0.97	0.93
Median size (’ M.)				
UK	140.14	39.30	70.17	36.07
Australia	456.92	325.98	460.97	318.31

Table 12

Performance of Less Concentrated Value Strategies: UK and Australia

UK				
	Market	Value	Enhanced 80%+	80%+
Return	9.06%	10.43%	10.99%	10.68%
Stand. Dev.	12.88%	10.17%	9.68%	9.05%
Beta	1.0	0.7	0.5	0.4
Australia				
	Market	Value	Enhanced 80%+	80%+
Return	11.02%	10.66%	12.02%	12.36%
Stand. Dev.	17.07%	19.48%	20.08%	20.28%
Beta	1.0	1.1	1.1	1.1

Figure 1
Histogram of Excess Returns Across All US Value Portfolios (1986 - 2001)
(% per annum)



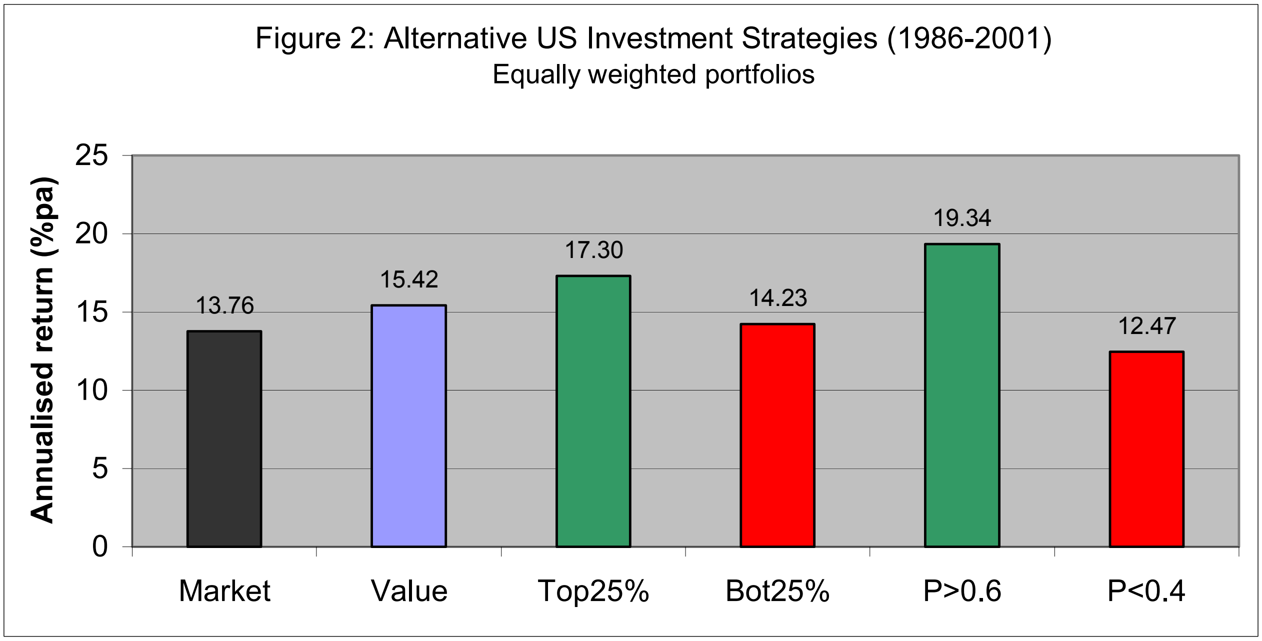


Figure 2: Alternative US Investment Strategies (1986-2001)
Equally weighted portfolios
Annualised return (%pa)
25
20
15
10
5
0
13.76
15.42
17.30
14.23
19.34
12.47
Market
Value
Top25%
Bot25%
P>0.6
P<0.4

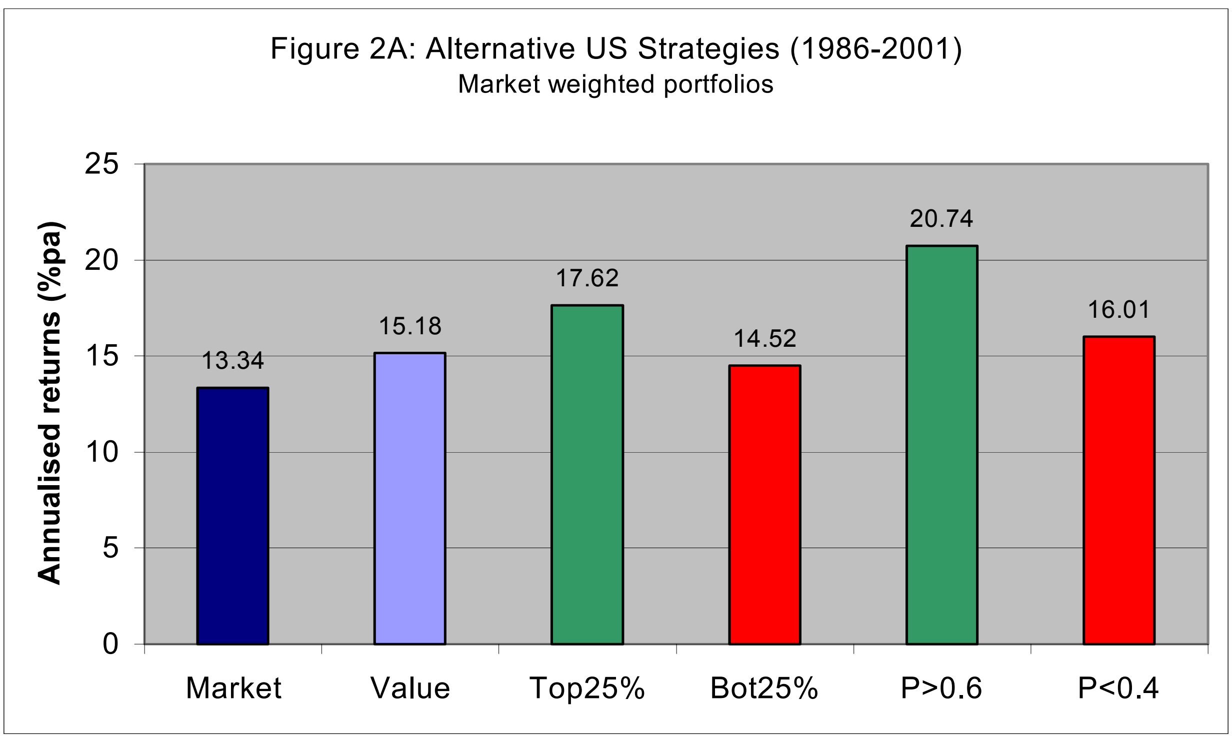


Figure 2A: Alternative US Strategies (1986-2001)
Market weighted portfolios
Annualised returns (%pa)
25
20
15
10
5
0
13.34
15.18
17.62
14.52
20.74
16.01
Market
Value
Top25%
Bot25%
P>0.6
P<0.4

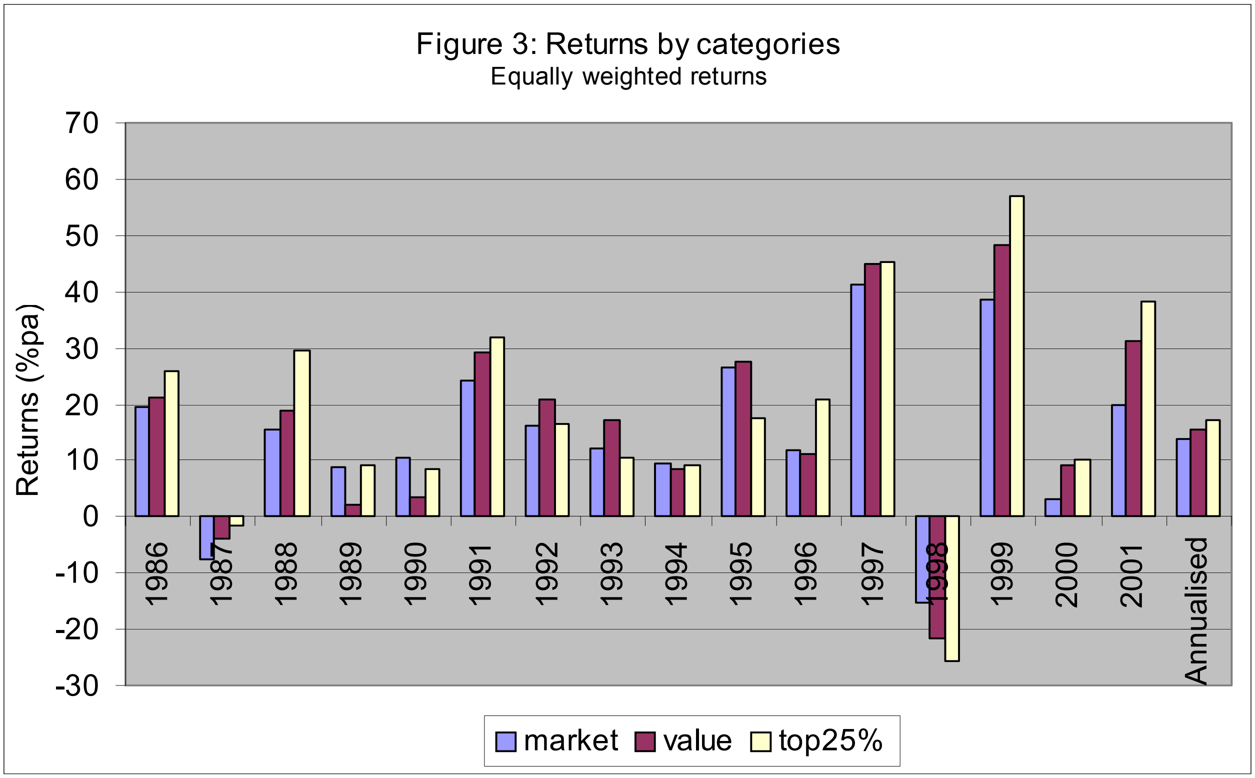


Figure 3: Returns by categories
Equally weighted returns
Returns (%pa)
70
60
50
40
30
20
10
0
-10
-20
-30
1986
1987
1988
1989
1990
1991
1992
1993
1994
1995
1996
1997
1998
1999
2000
2001
Annualised
market
value
top25%

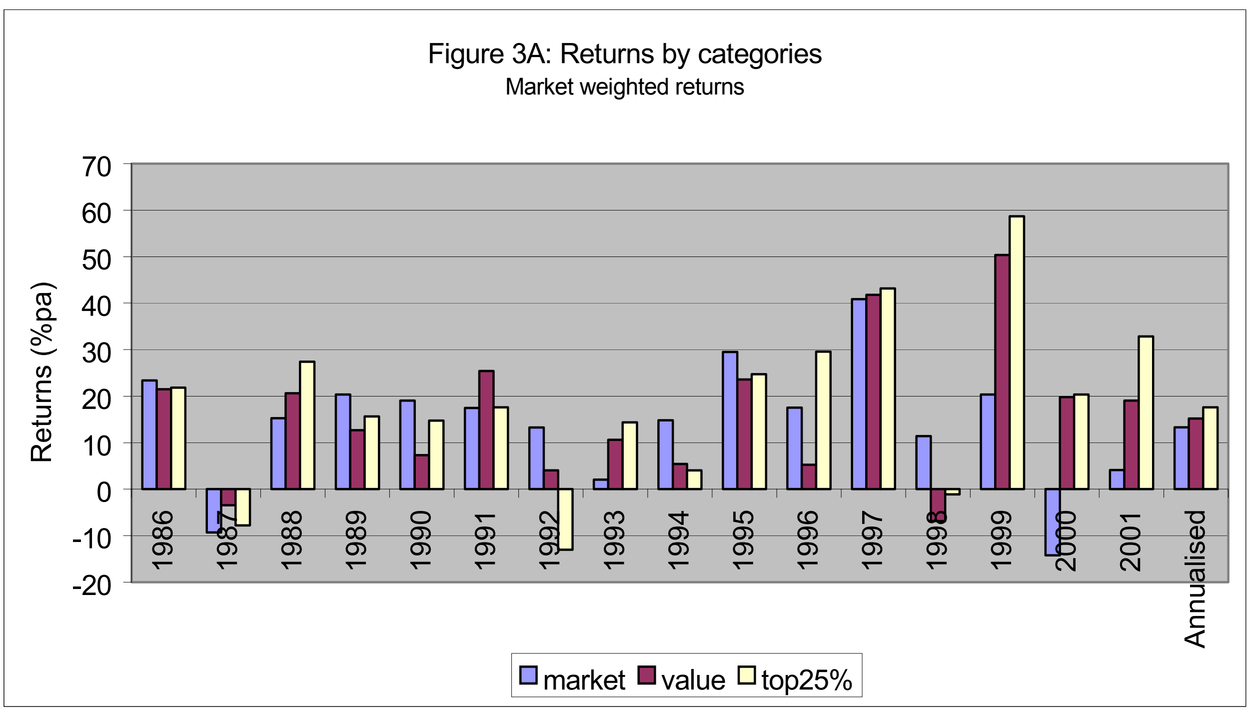


Figure 3A: Returns by categories
Market weighted returns
Returns (%pa)
70
60
50
40
30
20
10
0
-10
-20
1986
1987
1988
1989
1990
1991
1992
1993
1994
1995
1996
1997
1998
1999
2000
2001
Annualised
market
value
top25%

Figure 4
Histogram of Excess Returns of Value and Enhanced Value Portfolios (1986-2001)
(% per annum)