Decomposing the Price-Earnings Ratio

Keith Anderson, ISMA Centre,

University of Reading

Chris Brooks♣, Cass Business School,

City of London

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♣ Corresponding author. Faculty of Finance, Cass Business School, City University, 106 Bunhill Row, London EC1Y 8TZ, UK. t: (+44) (0) 20 7040 5168; f: (+44) (0) 20 7040 8881;
e-mail C.Brooks@city.ac.uk .

Abstract

The price-earnings ratio is a widely used measure of the expected performance of companies, and it has almost invariably been calculated as the ratio of the current share price to the previous year's earnings. However, the P/E of a particular stock is partly determined by outside influences such as the year in which it is measured, the size of the company, and the sector in which the company operates. Examining all UK companies since 1975, we propose a modified price-earnings ratio that decomposes these influences. We then use a regression to weight the factors according to their power in predicting returns. The decomposed price-earnings ratio is able to double the gap in annual returns between the value and glamour deciles, and thus constitutes a useful tool for value fund managers and hedge funds.

1 Introduction

The price-earnings (P/E) effect has been widely documented since Nicholson (1960) showed that low companies having low P/E ratios on average subsequently yield higher returns than high P/E companies, and this difference is known as the value premium. A low price-earnings ratio is used as an indicator of the desirability of particular stocks for investment by many value/contrarian fund managers, and the P/E effect was a major theme in Dreman (1998). The value premium is mostly positive through time, and a large number of studies have confirmed its presence. While the continued existence of a value premium is puzzling for academics, a plausible explanation is that it provides compensation for the extra riskiness of value shares. However, the CAPM beta does not increase as the P/E decreases; if anything, it decreases (Basu, 1977), so the risk must reside in other measures. According to Dreman and Lufkin (1997), sector-specific effects are also unable to explain the value premium, and more complex multifactor models have similarly failed to rationalise the outperformance of value stocks (see, for example, Fuller *et al*., 1993). Others have proposed behavioural explanations (e.g., Lakonishok, Schleifer and Vishny, 1994), ascribing the extra returns from value shares to psychological factors affecting market participants.

However, the P/E as it is commonly used is the result of a network of influences, similar to the way in which a company's share price is influenced not only by idiosyncratic factors particular to that company, but also by movements in prices on market as a whole, and the sector in which the company operates. A large number of studies have examined the decomposition of stock returns into market-wide and sector influences, and in this paper we propose and show the usefulness of an analogous approach in deconstructing the P/E ratio. We identify four influences on a company's P/E, which are:

1) The **year**: the average market P/E varies year by year, as the overall level of investor confidence changes.

2) The **sector** in which the company operates. Average earnings in the computer services sector, for example, are growing faster than in the water supply sector. Companies in sectors that are growing faster in the long-term should warrant a higher P/E, so as correctly to discount the faster-growing future earnings stream.
3) The **size** of the company. There is a close positive relationship between a company's market capitalisation and the P/E accorded.
4) **Idiosyncratic** effects. Companies examined in the same year, operating in the same sector and of similar sizes nevertheless have different P/E's. Idiosyncratic effects, that do not affect any other company, account for this. Such effects could be the announcement of a large contract, whether the directors have recently bought or sold shares, or how warmly the company is recommended by analysts.

Using data for all UK stocks from 1975-2003, we take these four influences in turn, looking at the extent to which they affect the P/E, and how closely they are correlated with subsequent returns. We decompose the influences on each of our company/year data items, and we then run a regression to get a weight for each influence. Using these weights, we construct a new sort statistic for assigning companies to deciles, and we are able to double the difference in returns between the glamour and value deciles. Finally, we show, via a portfolio example, the practical effect of the new statistic on the values of the glamour and value deciles through time.

The remainder of this paper proceeds as follows. Section 2 describes our data sources, and the methodology we used in our calculations of P/E ratios and decile portfolio returns. Section 3 describes our results from decomposing the influences on the P/E, assigning suitable weights to them, and creating a more powerful weighted P/E statistic. Section 4 shows how the factor weightings are vitally affected by the bid-ask spread. In Section 5, we demonstrate the utility of the new statistic by comparing the fortunes of four sample portfolios. Section 6 concludes.

2 Data Sources and Methodology

Initially, we collated a list of companies from the London Business School's 'London Share Price Database' (LSPD) for the period 1975 to 2003. The LSPD holds data starting from 1955, but only a sample of one-third of companies is held until 1975. Thereafter, data for every UK listed company are held, so we took 1975 as our start date. We excluded two categories of companies from further analysis. These were financial sector companies, including investment trusts, and companies with more than one type of share - for instance, voting and non-voting shares. Apportioning the earnings between the different share types would be problematic.

Earnings data are available on LSPD, but only for the previous financial year. We therefore used Datastream, as this service is able to provide time series data on most of the statistics it covers, including earnings. A four-month gap is allowed between the year of earnings being studied, and portfolio formation, to ensure that all earnings data used would have been available at the time. We therefore requested, as at 1st May in each year 1975-2004, normalised earnings for the past eight years, the current price, and the returns index on that date and a year later, for each company.

A common criticism of academic studies of stock returns is that the reported returns could not actually have been achieved in reality, due to the presence of very small companies or highly illiquid shares. In an attempt at least to avoid the worst examples, we excluded companies if the share mid-price was less than 5p, and we also excluded the lowest 5% of shares by market capitalisation in each year. We checked whether this removal of micro-cap and penny shares had a serious effect on returns. Penny shares and micro-caps did indeed contribute to returns, although this contribution was across all deciles, not just for value shares. Average returns were 1-1.5% higher when all companies are included, across all deciles and holding periods. An arbitrage strategy that is long in value companies and short in glamour companies would therefore be largely unaffected by the exclusion of very small companies and of penny shares. We also examine the impact of transactions costs, which are likely to be larger for small firms, in Section 4. A further criticism of many studies is that they do not deal appropriately with bankruptcies. Companies that failed during the year are flagged in the LSPD. In such cases, we set the RI manually to zero, as in Datastream it often becomes fixed at the last traded price. We assumed a 100% loss of the investment in that company in such cases.

3 P/E Decomposition

In this section, we isolate the various influences on the PE, then develop a model for putting them back together again in a new P/E statistic that more accurately reflects their power in predicting returns.

The P/E Ratio Through Time

Market average P/E's vary through time, as investor confidence waxes and wanes. We show average P/E's and average subsequent returns for each base year in Table 1. A major peak in P/E's can be observed in 1987, representing the run-up to the crash in October of that year. Average P/E's were fairly constant throughout the period 1995-2002. 2003 marked a major recent low for the average market P/E, as it reached a level last seen in the mid-1970's. However, note that the data were read as at 1st May 2003, only a few weeks into the market recovery of that year, so the average P/E for 2004 would be higher. The correlations between the market average P/E and subsequent returns are shown in the first row of Table 2. Compared to the other influences, the correlation is quite high, at 0.12 for the correlation of the market E/P to one-year returns.

Sector Effects on the P/E

Field G17 in the LSPD holds each company's FTSEA industrial classification. We calculated the average P/E for each sector with more than ten company/year returns. There were 151 of these, ranging from a P/E of 20.9 for Semiconductors, to 5.5 for Publishing. Note that these averages are for the sector across all years. In order to split the year effect from the sector and size effects, we must make the assumption that sector and size effects do not have their own year-dependent variation.

The correlation between sector E/P and subsequent returns is shown in the second row of Table 2. In this table, we examine holding periods from 1 to 8 years. In contrast to the year returns, the contribution of the sector to the E/P has a correlation that is small but usually negative, i.e. a higher sector E/P (lower P/E) means poorer returns. We assume that this is because, for example, the software sector with its average P/E of 17.1, as a whole really does give better returns on average than the water supply sector with its average P/E of 8.8, because software is growing more quickly in the long term, regardless of the returns on individual companies. Thus, the contribution of the sector has an opposite effect on the overall P/E, compared to that of the other effects. Therefore, it is desirable to negatively weight the influence of the sector P/E when constructing the modified P/E statistic. Using this, unloved companies from growth sectors will have a greater chance of being included in any value portfolio than they do with the traditional P/E. This is a useful result, for it suggests that while traditional value funds may comprise a mixture of stocks from value sectors and value stocks from glamour sectors, the latter are likely to produce higher returns.

Size Effects on the P/E

Larger companies usually command a higher P/E than smaller companies. Liquidity constraints suffered by large fund managers may account for a significant proportion of this premium since only the largest companies can offer the necessary liquidity in their shares if the fund manager is not to move the market price adversely. Managers of large funds therefore naturally gravitate towards investing in larger companies. Market capitalisations of companies vary hugely, but the distribution is skewed by the presence of a modest number of very large companies. A common approach to this issue is to rescale the market cap data by taking their logarithms. However, instead of taking logs, we took a more intuitively meaningful route and divided companies into categories. For each year, we divided companies into 20 categories by market value, and calculated the average P/E and average returns for each category. The results are shown in Table 3. Note that the P/E and returns quoted are averaged over all 29 years, but the category limits are specific to each base year, as the average capitalisation changes so much from year to year.

As the companies get larger, the P/E's increase but the returns fall: note the very high returns for categories 1 and 2 of 28%. However, this is for the smallest 10% of companies. In 2003, only companies with a market capitalisation of less than £7.6m fell into categories 1 and 2. Liquidity constraints on the shares of such companies would be a very real problem for even a small fund, and the wider bid-ask spread for small companies would further erode returns.

The close relationship between the size category and average P/E can more clearly be seen in Figure 1. There is a very high correlation of 0.82 between P/E and market size *category*, and this can clearly be seen here. Looking at the third row of Table 2, the 0.07 correlation of the size category of *individual* companies to one-year returns is larger than that of the industry, but smaller than that of the year average P/E.

A Model for Deconstructing the Influences on the P/E

We have now assessed the strengths of the identifiable influences on the P/E. Unlike the other influences, the idiosyncratic part of the E/P (termed IdioEP) cannot be independently observed: it is merely that part of the overall E/P that is unexplained by the year, market value and industry factors. We assumed a multiplicative arrangement of the influences, so that

$$\frac{ActualEP_i}{AverageEP} = \frac{YearEP_i}{AverageEP} \times \frac{SizeEP_i}{AverageEP} \times \frac{SectorEP_i}{AverageEP} \times \frac{IdioEP_i}{AverageEP} \quad (1)$$

where the average E/P is the average over all companies and years. Note that is not a regression equation, and there is no error term: IdioEP is simply a way of relating what would be expected for the E/P, given the year, company size and industry, to what has been observed. Thus, for a company with uniformly average characteristics, the actual, year, market cap and sector E/P terms (each including the denominator) would be unity, so the idiosyncratic E/P term would be unity also. On the other hand, a company with a low observed E/P (high P/E) with average year, market cap and sector E/P's would be assigned a low idiosyncratic E/P, and this term would make it less attractive as an investment according to the E/P statistic developed below.

Rearranging (1), we calculate the idiosyncratic E/P for each company/year return as

$$IdioEP_i = \frac{ActualEP_i \times AverageEP^3}{YearEP_i \times SizeEP_i \times SectorEP_i} \quad (2)$$

As can be seen in the final row of Table 2, the idiosyncratic E/P has a positive correlation of 0.025 with one-year returns, so its influence is in the same direction as the year and market cap E/P's, but its correlation is somewhat weaker than that of the market value E/P. Figure 1 summarises the various influences on the price-earnings ratio, showing that overall, low P/E ratios lead to high returns, while returns are likely to be high if the P/E that year is uncharacteristically low. Returns are also likely to be superior for high P/E sectors, for small firms (that typically have lower P/E ratios), and if the idiosyncratic P/E is low. Having calculated all four influences on the P/E, we can now show the correlations between the different influences, in Table 4. The influences all have very little correlation with each other, which should mean that there is no problem of multicollinearity in the subsequent regressions.

We now combine the four influences in the model

$$Rtn01_i = \beta_0 + \beta_1 YearEP_i + \beta_2 SizeEP_i + \beta_3 SectorEP_i + \beta_4 IdioEP_i + u_i \quad (3)$$

where $Rtn01_i$ is the 1-year return for firm-year i, the β terms are parameters to be estimated, and u_i is a disturbance term. Here we are trying to predict one-year returns by giving weights to the four decomposed influences on the P/E that we have just revealed. Note that there are 16,000 company/year returns and 16,000 different IdioEP values, but only 29 different

YearEP's, 20 different SizeEP's and 151 different SectorEP's. The idiosyncratic contribution to the E/P turns the E/P that one would expect to observe, given the year, industry and size, into the E/P actually observed.

A linear regression of this model results in the following estimated coefficients and standard errors:

$$\underset{}{Rtn01=}\ \underset{(0.0269)}{0.7725}\ \underset{(0.1051)}{+2.4918}\ YearEP\ \underset{(0.2305)}{+2.2362}\ SizeEP\ \underset{(0.1636)}{-0.3526}\ SectorEP\ \underset{(0.0348)}{+0.1406}\ IdioEP \tag{4}$$

All coefficients are significant at the 0.1% level, except for the sector term, which has a *p*-value of 0.03. Of the E/P variables included in the regression, the year E/P is roughly as useful in predicting returns as the market capitalisation (size) category E/P, but these two dominate the other two factors. The industry classification E/P is the only predictor variable to have a negative coefficient, as foreshadowed earlier by its negative correlation with returns.

The effect of the weights is to make it more likely that small companies, which on average have a higher E/P (low P/E) will be selected as part of the value decile. Companies from faster-growing sectors that usually have a low E/P (high P/E) are also more likely to be selected. We now offer a couple of examples to illustrate the differences that our approach would make to the selected portfolios. Stanley Gibbons appears in the 2003 value decile. Based on the traditional P/E, the company appears in decile 4, but its size (market cap category 2) propels it into the value decile. Stanley Gibbons shares tripled in value between 1st May 2003 and 1st May 2004. At the other end of the value-glamour scale, Imperial Tobacco is the least attractive company on the whole UK market in 2003 using the decomposed P/E, yet when using the traditional P/E it falls into decile 3. It is very large (market cap category 20), the Tobacco sector has a lower than average sector P/E of 9.5, but the company's overall P/E of 15.3 results in a high idiosyncratic P/E of 13.6. All three factors count against it in the new weighting system. In 2003-4 total returns on Imperial Tobacco shares were 25%, compared to the overall market gain of 55%.

Do the regression weights allow us to achieve a P/E statistic with a higher resolution between the glamour and value deciles? We calculated a sort statistic for each company/year return, that is the weighted average of its decomposed E/P influences, where the weights are as shown in (4). The sort statistic is

$$EP_i = \frac{\beta_0 + \beta_1 YearEP_i + \beta_2 SizeEP_i + \beta_3 SectorEP_i + \beta_4 IdioEP_i}{\sum_{j=1}^{4} \beta_j} \tag{5}$$

where EP_i is the new statistic for company/year *i*, and the right-hand side of the equation is a weighted average of the four decomposed influences on the E/P, divided by the sum of the weights. The new sort statistic can be understood as meaning that a company is most likely to be included in the value decile if it is small and operates in a sector that usually has high P/E's, but has a low idiosyncratic P/E[1]. We use the sort statistic to assign companies to deciles, with the results shown in column 1 of Table 5. In order to gauge the relative effects of each part of the E/P, columns 2 to 4 of Table 5 also show the returns by decile when sorting by each of the component E/P's alone. For comparison, the results for the traditional P/E are shown in column 5.

The market capitalisation factor has the largest effect on the E/P of the three influences, providing a D10-D1 resolution of 13%. (This is however reduced if transactions costs are taken into account; see Section 4). The industry factor gives a resolution of only around 5%, but it works in the opposite direction to the other two factors. Putting all three together using the weights suggested by the linear regression, with the industry factor given the appropriate negative weight, results in a remarkably powerful statistic: the resolution of the undifferentiated statistic is multiplied two-and-a-half times to 15.4%, and a value decile is identified that has average one-year returns of 28.6%.

4 The Effect of the Bid-Ask Spread

In Section 3, the returns were calculated using mid-mid prices, i.e. not taking account of the bid-ask spread. However, it is well known that smaller companies' shares suffer from much wider bid-ask spreads than those of larger companies, and the major contribution to the 15.4% difference between the value and glamour deciles returns in Section 3 is because the value decile consists of a higher proportion of small companies, and the glamour decile of large

[1] Note that in fact, the intercept and year factor do not need to be included when calculating the modified EP statistic since we are sorting within each year separately, and the constant will adjust each modified EP by the same amount, leaving the rank ordering of firms unaffected.

companies, than would be the case if the traditional E/P were used. Is the difference in decile returns much reduced if bid-ask spreads are taken into account?[2]

Bid and ask prices were first recorded on Datastream in 1987, and for the majority of companies are only available from 1991. Where the actual bid-ask spread was available for that company on that day, we used it, calculating the returns after allowing for costs due to the bid-ask spread as

$$Rtn01Sprd = \frac{P_0}{PA_0} \times \frac{P_1}{P_0} \times \frac{PB_1}{P_1} \qquad (6)$$

where P_n is the mid-price at time *n*, PA_n is the ask price at time *n*, and PB_n is the buy price at time *n*. The first fraction in (6) represents the notional loss when buying, the second fraction is the mid-mid return as used in Section 3, and the third fraction is the notional loss when selling. To cater for companies for which bid and ask prices were not available, we calculated the average bid-ask spread for each market value category. The results can be seen in Figure 3. The spreads vary monotonically from over 10% for the smallest 5% of companies, to 1.15% for the largest 5%. This will clearly have a major impact on any strategy based largely on investing in small rather than large companies, such as we developed in Section 3. Where companies' bid-ask spreads were not available, we employed the average bid-ask spread for that size category for calculating returns. Where a share remains in the decile portfolio for more than one year, we applied no spread on selling if a company would remain in the same decile next year, and applied no buying spread if the company had already been in the same decile portfolio the previous year.

Since the returns have now changed, we re-ran the linear regression from Section 3, using returns after spread costs as the new dependent variable, which gave the following coefficients and standard errors:

Rtn01=	0.9056	+2.3916	YearEP	+0.5157	SizeEP	-0.3383	SectorEP	+0.1235	IdioEP
	(0.0257)	(0.1004)		(0.2204)		(0.1564)		(0.0332)	

(7)

All coefficients are significant at the 0.1% level, except for SizeEP and SectorEP with *p*-values of 0.02 and 0.03 respectively. The company size E/P influence has lost three-quarters of its predictive power now that we are allowing for the effect of bid-ask spreads on returns.

[2] In the UK, a tax known as stamp duty of 0.5% must be paid on all share purchases; we do not include this in our calculations.

The effect of spread costs on decile returns can be seen in Table 6. The weighting scheme from Section 3, developed using mid-mid returns, suffers a major reduction in its resolution, from 15.4% to 9.4%. This is due to its heavy reliance on the size effect, so that the value decile, full of small companies, is much more seriously affected by the bid-ask spread than the glamour decile. The new weighting scheme, with its lesser weight on market cap, shows a higher resolution of 10.49%, double that of the traditional P/E, and moreover the returns for the value decile are now much less reliant on the size of the company. The value decile's average market value category of 5.64 corresponds to a market capitalisation of £16.2m in 2003, compared to a market value category of 2.21 (£5.7m) for the value decile using Section 3 weights, and this would present much less of a liquidity problem for a large investor.

It is important to note that the D10-D1 figure in Table 6 is literally just that, and does not represent the returns that would actually be available from an arbitrage strategy that is long in the value decile and short in the glamour decile. The larger the glamour portfolio spread costs are, the wider the D10-D1 figure is, whereas in reality spreads should be a cost to the arbitrageur on both sides of the arbitrage trade. The effect of spreads on the glamour portfolio returns are 4.07%, 0.85% and 1.39% for the traditional P/E, the Section 3 weights and the Section 4 weights respectively. Doubling these and subtracting them from the D10-D1 figures gives realisable arbitrage returns of –2.89%, 7.7% and 7.71%. This result shows that after allowing for reasonable transactions costs in the appropriate way, arbitrage rules based on the traditional P/E ratio will actually lose money, whereas the new statistic still yields positive returns.

Can the superior returns from the value decile be explained as a fair return for having taken on extra risk? The Sharpe ratios when using the new linear regression weights are shown in Figure 4. We calculated the Sharpe ratios of the portfolios as the excess return of the portfolio over the risk-free rate, divided by the standard deviation, using the three-month Treasury bill rate as the proxy for the risk-free rate. Although the variability of returns is somewhat higher for the low P/E deciles, the standard deviation does not rise as quickly as the returns, so that the Sharpe ratios for the low P/E deciles are much higher. The Sharpe ratio of the value decile is almost four times that of the glamour decile. If one expects returns over the risk-free rate to be proportional to the variability of returns, then the low P/E decile seems to represent very good value[3].

5 Portfolio Illustration

This example shows in a more concrete manner the extra return that can be obtained by decomposing the P/E. We calculated the performances of the value and glamour deciles identified using the weights arrived at through the linear regression developed above, and compared them to the returns for the deciles calculated using the traditional P/E, in which the influences of year average E/P, size E/P and industry E/P had not yet been differentiated. All portfolios use annual rebalancing. Table 7 shows the percentage returns and portfolio values for the glamour and value deciles for the two sort statistics. Since the decomposition weights were based on returns after spread effects (i.e. net of transactions costs), the values in Table 7 are also calculated on this basis.

For the value decile, *average* returns are 2.5% better for the new statistic than for the traditional E/P, and for the glamour decile, average returns are 2.74% worse. The impact of this is that the new value decile portfolio ends up being worth almost double the old value decile based on a 30-year investment horizon. The modified E/P statistic also provides a more consistent profile of positive returns, yielding only 7 years where the long-value-short-glamour arbitrage portfolio lost money. If the traditional E/P were used to assign companies, the number of years where the arbitrage strategy would lose money is raised to 13.

6 Conclusions

Although the P/E effect was first documented almost fifty years ago, and it is well-known that non company-specific influences affect individual company P/E's, as far as we are aware we are the first to investigate whether accounting for these various influences can deliver a P/E effect of greater value in predicting returns. Using data for all UK companies from 1975-2003, we imposed a model of performance attribution onto the P/E ratio. We identified the influences on a company's P/E as the annual market-wide P/E, the sector, the company size,

[3] These results can fairly be criticised as suffering from a look-ahead bias, in that the regression weights could only have been known in May 2004, but we use them to calculate annual returns for the whole dataset from 1975. We used a rolling ten-year sub-sample to check whether the results would be affected by the use of trailing windows of historical data to calculate the regression weights. We found that the returns are slightly degraded, but since the impact is not marked, to avoid repetition we do not report these results.

and idiosyncratic influences. We isolated the power of each of these effects. Company size has a high correlation with the P/E and with subsequent returns, so it is apportioned a higher importance in the final statistic than the other factors. The industry classification has a decidedly moderate predictive power for returns, but its effect upon the P/E is in the opposite direction compared to the other factors. Reversing the direction of the sector influence on the P/E so that it produces better company sorts is, we feel, an important innovation of this paper.

Having isolated these influences, we developed a model that provides weights for them, so that company size is weighted more heavily than the others, and the industry factor is assigned its appropriate negative weight. However, the weighting for company size E/P is very much dependent on whether bid-ask spreads are taken into account, and it loses three-quarters of its predictive value if returns are calculated after transactions costs. We found that the new statistic using these weights was considerably better than the traditional P/E in predicting future returns. Using the optimum weightings suggested by the linear regression, we doubled the average annual difference in returns between the glamour and value deciles from 5.25% to 10.5%.

The higher returns for the value decile cannot be explained as payment for greater risk (at least in the sense of the Sharpe ratio), and the factor weights are reasonably robust whichever sub-period of returns is chosen. Our portfolio illustration shows that the value and glamour deciles chosen using the new weighted P/E bracket the value and glamour deciles chosen using the traditional P/E, and the new value portfolio comfortably outperforms the old by 2.4% annually. These results should be of interest even to managers of large funds, since the value decile after spreads are taken into account is much less dependent on the size of the company than if spreads are ignored. Future work in this area could involve replicating this result for the much larger US markets. Additionally, our list of influences on the P/E is likely not exhaustive: gearing, for example, may be a further significant explanatory variable, since of two otherwise identical companies, the one with higher gearing will merit a lower P/E.

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Table 1: Market average P/E's and subsequent 1-year returns for each year, 1975-2003

Year	Average P/E	Return	Year	Average P/E	Return	Year	Average P/E	Return
1975	5.62	34.92%	**1985**	13.60	44.27%	**1995**	12.95	30.98%
1976	6.80	22.39%	**1986**	14.94	46.38%	**1996**	14.35	7.36%
1977	6.27	52.67%	**1987**	16.91	6.95%	**1997**	13.92	16.60%
1978	7.43	55.92%	**1988**	13.37	22.83%	**1998**	13.28	-3.48%
1979	9.27	-3.65%	**1989**	12.98	-16.90%	**1999**	11.42	24.74%
1980	7.50	33.29%	**1990**	8.90	0.63%	**2000**	11.44	7.87%
1981	11.16	8.07%	**1991**	9.39	8.46%	**2001**	12.18	1.30%
1982	12.34	40.32%	**1992**	11.44	16.83%	**2002**	12.70	-20.10%
1983	15.27	35.85%	**1993**	12.45	31.48%	**2003**	8.41	55.29%
1984	15.35	21.07%	**1994**	17.72	-2.34%			

Table 2: Correlations between the different influences on the P/E and subsequent 1-8 year returns, 1975-2003

	1-Year	2-Year	3-Year	4-Year	5-Year	6-Year	7-Year	8-Year
YearEP	0.1166	0.1171	0.1479	0.1737	0.1472	0.1923	0.2232	0.2670
SectorEP	0.0071	0.0012	-0.0065	-0.0189	-0.0326	-0.0340	-0.0356	-0.0356
SizeEP	0.0745	0.0931	0.0931	0.0855	0.0821	0.0748	0.0676	0.0658
IdioEP	0.0248	0.0326	0.0364	0.0424	0.0448	0.0478	0.0529	0.0529

Table 3: Average P/E's and returns, 1975-2003, categorised by market capitalisation

Market Cap Category	Avg P/E	Return	Market Cap Category	Avg P/E	Return
1 (smallest)	8.18	27.88%	**11**	11.26	19.37%
2	8.51	28.44%	**12**	11.54	18.38%
3	9.01	24.58%	**13**	12.05	17.91%
4	9.42	21.40%	**14**	12.01	17.50%
5	8.91	21.49%	**15**	12.36	18.64%
6	10.01	18.35%	**16**	12.68	19.84%
7	9.87	19.47%	**17**	12.80	15.12%
8	10.31	18.33%	**18**	12.17	17.38%
9	10.59	20.80%	**19**	12.53	16.89%
10	10.82	18.67%	**20 (largest)**	13.68	16.05%

Table 4: Correlations between P/E influences

	SizeEP	SectorEP	IdioEP
YearEP	-0.0014	0.1624	-0.0753
SizeEP		0.1338	-0.1678
SectorEP			-0.1606

Table 5: E/P deconstruction model returns, 1975-2003

	1 Linear Regression	2 SizeEP alone	3 SectorEP alone	4 IdioEP alone	5 Traditional P/E
Weights assigned					
SizeEP	2.2362	1	0	0	-
SectorEP	-0.3526	0	1	0	-
IdioEP	0.1406	0	0	1	-
One-year returns					
High P/E	13.17%	15.48%	24.42%	18.08%	17.83%
Decile 2	16.74%	18.19%	22.54%	20.36%	19.89%
Decile 3	17.50%	17.92%	19.59%	17.06%	18.40%
Decile 4	17.76%	17.68%	20.34%	18.41%	16.90%
Decile 5	19.87%	18.99%	19.39%	18.55%	18.39%
Decile 6	20.15%	20.24%	18.00%	20.12%	18.79%
Decile 7	19.86%	19.01%	20.14%	19.00%	21.62%
Decile 8	21.86%	21.80%	17.90%	21.51%	20.89%
Decile 9	24.53%	22.84%	19.47%	21.99%	22.89%
Low P/E	28.59%	28.48%	18.61%	24.93%	24.39%
D10 – D1	15.42%	12.99%	-5.81%	6.85%	6.56%

Notes: Each column shows first the weights used to construct the sort statistic, then the decile returns resulting from assigning companies to deciles using that sort statistic. Column 1 shows the returns when using the linear regression weights. Columns 2 to 4 show the returns when sorting by each E/P influence on its own, so as to indicate the relative effectiveness of each influence as a predictor of returns. Column 5 shows the returns when using the traditional P/E, which has not been decomposed into the different influences.

Table 6: The effect of bid-ask spreads on returns, 1975-2003.

	Traditional P/E		Weights from Rtn01 regression		Weights from Rtn01Sprd regression	
	Returns after spread	**Average Size Category**	**Returns after spread**	**Average Size Category**	**Returns after spread**	**Average Size Category**
Weights assigned						
SizeEP	-	-	2.2362	-	0.5157	-
SectorEP	-	-	-0.3526	-	-0.3383	-
IdioEP	-	-	0.1406	-	0.1235	-
One-year returns						
High P/E	13.76%	9.45	12.32%	17.40	11.02%	14.11
Decile 2	16.15%	11.61	15.25%	16.48	13.71%	13.06
Decile 3	14.82%	12.06	15.69%	15.68	13.94%	12.53
Decile 4	13.45%	12.21	15.68%	14.38	14.96%	12.53
Decile 5	14.78%	11.97	17.19%	12.06	14.10%	11.54
Decile 6	14.97%	11.48	16.79%	9.68	16.62%	10.82
Decile 7	17.45%	10.80	15.78%	7.71	17.46%	9.69
Decile 8	16.40%	9.87	16.63%	5.62	18.02%	8.25
Decile 9	18.10%	8.77	18.30%	3.81	20.69%	6.87
Low P/E	19.01%	6.83	21.72%	2.21	21.51%	5.64
D10 – D1	5.25%	-	9.40%	-	10.49%	-

Notes: We show the decile returns after allowing for the bid-ask spread, and each decile's average market value category, using three different P/E ratios to assign companies to deciles: the traditional P/E, the decomposed P/E with a heavy weighting on SizeEP as suggested by the linear regression on one-year bid-bid returns, and the decomposed P/E with a lower weighting on SizeEP, as suggested by the linear regression on one-year returns after taking into account bid-ask spreads.

Table 7: Portfolio values and percentage returns for the glamour and value deciles from the E/P decomposition linear regression and from the traditional undifferentiated E/P, 1975-2003

	Decomposed E/P				Traditional E/P			
	Value Decile Value	**Value Decile %**	**Glamour Decile Value**	**Glamour Decile %**	**Value Decile Value**	**Value Decile %**	**Glamour Decile Value**	**Glamour Decile %**
1975	£1,000	31.46%	£1,000	29.20%	£1,000	34.97%	£1,000	9.05%
1976	£1,315	26.38%	£1,292	18.07%	£1,350	26.86%	£1,090	23.32%
1977	£1,661	67.63%	£1,526	32.23%	£1,712	57.85%	£1,345	43.20%
1978	£2,785	73.21%	£2,017	31.47%	£2,703	63.70%	£1,926	44.95%
1979	£4,824	2.15%	£2,652	-10.31%	£4,424	-12.86%	£2,791	5.92%
1980	£4,927	32.38%	£2,378	28.24%	£3,855	32.96%	£2,957	19.63%
1981	£6,523	6.46%	£3,050	-4.70%	£5,126	10.58%	£3,537	-3.84%
1982	£6,944	46.01%	£2,907	29.45%	£5,668	38.36%	£3,401	28.45%
1983	£10,139	42.30%	£3,763	26.61%	£7,843	43.77%	£4,369	37.81%
1984	£14,428	20.64%	£4,764	16.25%	£11,275	22.75%	£6,021	8.78%
1985	£17,405	52.57%	£5,538	37.63%	£13,841	60.77%	£6,549	21.81%
1986	£26,554	50.90%	£7,621	37.14%	£22,252	49.25%	£7,977	54.61%
1987	£40,071	9.29%	£10,452	-2.25%	£33,211	12.96%	£12,334	3.83%
1988	£43,792	19.65%	£10,217	16.99%	£37,514	27.80%	£12,806	20.60%
1989	£52,397	-17.97%	£11,953	-14.93%	£47,944	-26.78%	£15,443	-21.23%
1990	£42,982	-16.40%	£10,168	-7.78%	£35,104	-12.42%	£12,164	-22.13%
1991	£35,931	-6.25%	£9,377	2.74%	£30,743	-9.50%	£9,472	-15.19%
1992	£33,687	25.84%	£9,634	9.34%	£27,824	9.95%	£8,034	11.67%
1993	£42,393	40.97%	£10,534	22.82%	£30,591	31.65%	£8,971	32.19%
1994	£59,762	7.13%	£12,938	-9.15%	£40,274	1.90%	£11,859	-14.42%
1995	£64,024	28.80%	£11,754	22.84%	£41,038	14.11%	£10,148	36.99%
1996	£82,463	-3.76%	£14,438	-0.73%	£46,830	-1.30%	£13,902	11.11%
1997	£79,360	7.03%	£14,332	11.54%	£46,223	10.08%	£15,446	12.45%
1998	£84,937	-3.33%	£15,986	1.45%	£50,881	-12.29%	£17,369	-7.44%
1999	£82,106	28.49%	£16,218	8.02%	£44,626	19.07%	£16,076	82.60%
2000	£105,499	17.42%	£17,519	-14.69%	£53,136	23.54%	£29,355	-30.75%
2001	£123,875	-1.86%	£14,944	-10.59%	£65,643	3.18%	£20,328	-34.31%
2002	£121,571	-25.77%	£13,361	-22.75%	£67,730	-21.15%	£13,354	-32.28%
2003	£90,239	62.32%	£10,321	35.38%	£53,404	51.50%	£9,043	71.60%
2004	£146,475		£13,973		£80,904		£15,517	

Figure 1: Average P/E's by market capitalisation category, 1975-2003

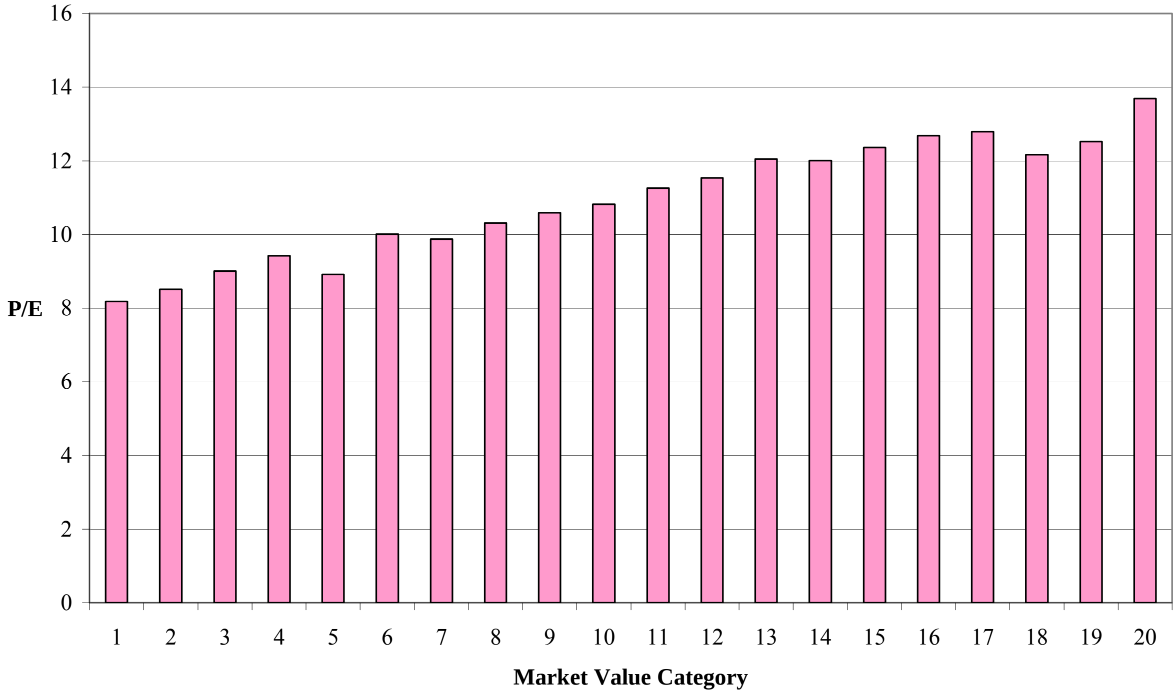

Figure 2: Influences on the P/E ratio

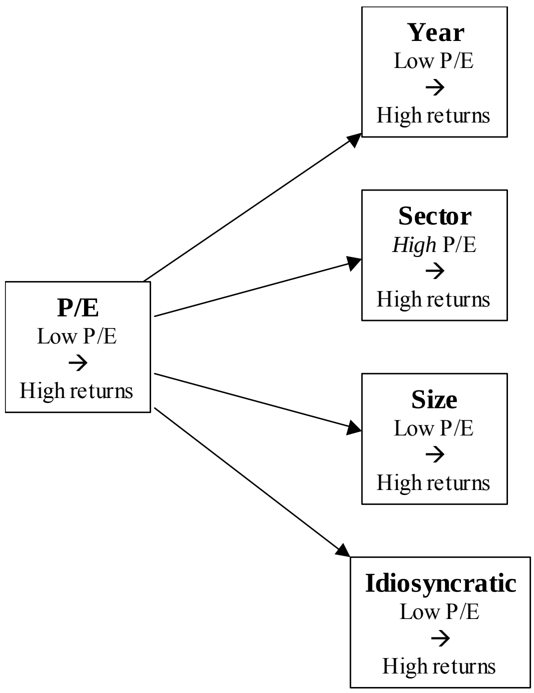

Figure 3: Bid-offer spreads by market capitalisation category, all UK companies 1987-2003

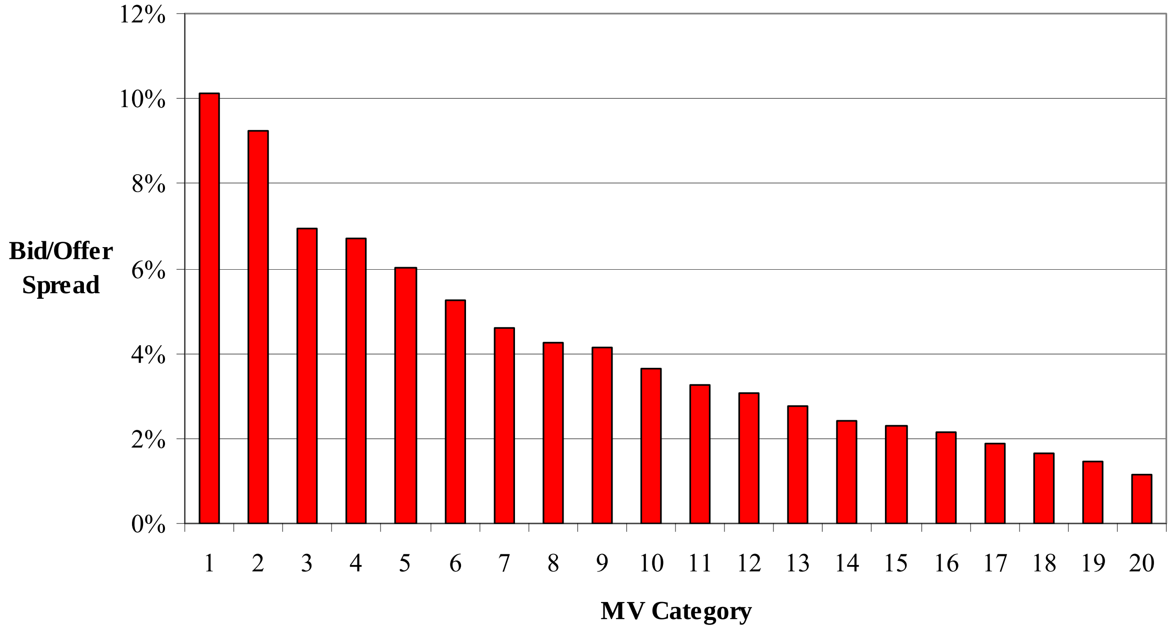

Figure 4: Sharpe ratios of one-year returns when assigning companies to deciles using E/P decomposition linear regression weights, 1975-2003.