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The Accuracy of Valuations - Expectation and Reality

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Summary: The relationship between valuations and the subsequent sale price continues to be a matter of both theoretical and practical interest. This paper reports the analysis of over 700 property sales made during the 1974/90 period. Initial results imply an average under-valuation of 7% and a standard error of 18% across the sample. A number of techniques are applied to the data set using other variables such as the region, the type of property and the return from the market to explain the difference between the valuation and the subsequent sale price. The analysis reduces the unexplained error; the bias is fully accounted for and the standard error is reduced to 15.3%. This model finds that about 6% of valuations over-estimated the sale price by more than 20% and about 9% of the valuations under-estimated the sale prices by more than 20%. The results suggest that valuations are marginally more accurate than might be expected, both from consideration of theoretical considerations and from comparison with the equivalent valuation in equity markets.

1. Introduction

The debate about the relationship between valuation and subsequent market price has, since the provocative paper by Hagar and Lord (1985), been carried out in empirical and methodological terms (see for example Lizieri and Venmore-Rowland (1991) and Brown (1991)). The objective of this paper is to place the debate into a more theoretical context. By establishing a framework for the expected divergence of sales price and valuation some of the controversy will be seen to be resolved and future debate may then be channelled into more fruitful avenues for empirical work. In the following section we outline basic principles of market price behaviour and derive from a simple model the expected behaviour of the error between a valuation and the subsequent sale price some time later. In section 3, we review previous empirical research. This is followed by a simple analysis of the sample data set. We then consider the behaviour of the valuation error over time and follow this analysis by bootstrapping the regression model. Finally we compare the results of our analysis with research from other capital markets.

2. Theory of Market Price Behaviour.

Brown (1991) rightly draws the attention of property investors (and researchers) to the concept of market efficiency. Although investors in property might be reluctant to agree that market valuations may reflect information without bias, they might be more willing to accept the view that valuations move towards some sort of equilibrating level albeit with some drag or stickiness. Such behaviour can be modelled and indeed Ross and Zisler (1987) and Blundell and Ward (1987) independently devised models that set out to uncover the underlying market prices imposed by smoothed valuations.

The common feature of both approaches is the assumption that the underlying market prices are informationally efficient and react quickly to new information and new expectations on the part of investors. The research literature on the theory of efficient markets is voluminous and competent introductions to its concept can be found in almost any textbook on Investment Theory (see for example Elton and Gruber, 1987). Many of the accounts refer to the review of Fama (1970), as does Brown (1991) in Appendix 2B of his book.

As far as market efficiency is concerned, market prices are asserted to react quickly to all available information. One hypothesis which can be derived from the assumption is that successive market prices should themselves be uncorrelated as in the random walk[1] model for which

$$P_t = P_{t-1} + e_t \tag{1}$$

Researchers have tested different formulations of this model, commonly expressing it in log form where P_t is the natural logarithm of the security or market price at time t and e_t is the stochastic error term. This has the advantage that the model can also be expressed in return form[2]

$$R_t = e_t \tag{2}$$

where R_t is the continuously compounded return over the period t - 1, t.

The model expressed in (1) is non-stationary in that the price shows no tendency to revert to any long-term average. Indeed forecasting using past series of prices is seen by definition to be valueless since the optimal k-period ahead forecast is simply the most recently observed price. However what is germane to our view of the market price behaviour is that if we were to estimate the market price k-periods ahead, our best estimate would be today's price P_t but the accuracy of our estimate would depend crucially on the cumulative effects of the stochastic error e_t. In the most restrictive version of the efficient market model, the expected value of the error term is zero and the variance is constant over the entire period[3]. It is also assumed that the covariances of error terms in different periods are zero.

If we were to use the model for forecasting purposes the forecast of the market (log) price one period ahead (the price at t+1) would be to-days price P_t. But the model implies that the actual price will be given by $P_{t+1} = P_t + e_{t+1}$. Thus our forecast will differ from the actual price by the error term e_{t+1}. If our forecast is unbiased, the error for the one period-ahead forecast for model 1 will have an expected value of zero and an expected variance of $(\sigma_e)^2$.

For a forecast two periods ahead, the forecast will still be P_t but the actual price will be given by $P_t + e_{t+1} + e_{t+2}$. Our forecast will still be unbiased and will therefore have an expected value of zero but will have a variance given by the sum of the two error terms. Given our assumption of zero covariance between the error terms in different periods, the variance of the sum of two independent variables will be given by $2(\sigma_e)^2$.

For the two period-ahead forecasts, the variance will therefore be twice as large as the forecast variance for the one period-ahead forecast. By the same reasoning, the k-period ahead variance will be k times the individual period error variance (the standard deviation will therefore be $\sqrt{k}$ times the individual period error standard deviation).

Translating this concept into property we might initially assume that the valuation is an unbiased forecast of the current market price and that market prices (logs) behave in the form given by equation (1). If we define the difference between the valuation and the subsequent price as the forecast error, we would therefore expect that the variance of the error would increase in proportion to the time between the valuation and the date at which the sale price was agreed. In other words, if the standard deviation of annual returns on a particular class of properties is σ_A the standard deviation of the difference between valuation (log) and subsequent sale price (log) would be given by $\sigma = \sigma_A \sqrt{t}$ % where t is the interval in years between the valuation and the subsequent sale. Studies of the risk of the UK property market have produced various estimates of the annual standard deviation of returns, depending on the period chosen and the method chosen to estimate the 'true' or unsmoothed return distribution. Barkham and Geltner (1994) estimated a value of 18.6% for the annual standard deviation. In earlier studies of the sales/valuation relationship, the interval between valuation and sale has been chosen to be on average about nine months (that is, $t = 0.75$). Thus we might expect the standard deviation of the difference between valuation and sales price to be 18.6% x $\sqrt{.75}$ or about 16%.

3. Previous Empirical Research

There have been a number of papers that have reported the results of tests on valuation error. Papers include three (Lizieri and Venmore-Rowland (1991), Brown (1992) and Pratten (1992)) which have dealt with the methodological issues arising from the repression techniques commonly employed whilst others include Hutchison, MacGregor, Nanthakumaran, Adair and McGreal (1996), McAllister (1995) and Matysiak and Wang (1995).

Circulated papers have included at best two papers by IPD, Drivers Jonas (1988), (1990)) which have a common methodology. A large sample of properties, drawn from the IPD Database, was selected and the sale price regressed against the valuation (both normalised by expressing in unit floor area). The results of the regressions are somewhat idiosyncratically reported in that they are presented only in diagrammatic form and are confined to presentations of "mismatch" and "unexplained variance". However in the Technical Appendix to the 1988 paper the following results were presented

Insert Table 1 here

The problem with these results is that they do not report any of the diagnostic tests which econometricians would conventionally expect. It is thus impossible to infer whether or not the results are significant and in particular whether there is any difference between the three sectors.

The lack of diagnostics in the IPD/Drivers Jonas papers was sharply criticised by Lizieri and Venmore-Rowland (1991). The criticism centred on three issues (a) the misleading emphasis on R^2 the coefficient of determination, (b) the ignoring of the effect of heteroscedasticity; (c) the lack of critical analysis on the relationship between the sale price/valuation error and the number of transactions. In the spirit of a rejoinder, Brown (1993) prefers to concentrate on a number of issues that he argues are neglected by Lizieri and Venmore-Rowland. In particular he discusses the need for prices to be compared with comparable valuations, specifically distinguishing between open market and special forced sales. However in his paper, the arguments advanced by Lizieri and Venmore-Rowland[4] are largely left on the table and researchers are left with a feeling that the earlier work has been devalued without knowing the extent of the distortions. Before we turn to the consideration of the econometric issues raised by Lizieri and Venmore-Rowland, we should refer readers to Pratten(1992) which discusses the issues of valuation accuracy in an authoritative paper for the Institute of Chartered Accountants. One of the useful contributions of Pratten's paper from our point of view is the brief discussion on the choices of model open to researchers when investigating the relationship between sales price and valuation. To some extent, we follow these models in extending the empirical work reviewed above.

4. Econometric Issues

The IPD/Drivers Jonas reports, as pointed out by Lizieri and Venmore-Rowland, contain almost no statistical information which would be expected if they had been submitted for publication in any rigorous (refereed) journal. The earlier paper by Brown covered work on a very small sample of properties. There is therefore a difference in the type of problem that arises in regarding the two studies. The problems of Brown's study stem from the small sample. The results could only be indicative at best and might be interpreted in the same way as a pilot study. Whilst it would have been preferable to carry out diagnostic tests for such problems as heteroscedasticity, the inferences which could have been drawn from the results would never have been more than indicative, even though readers might have seized upon the reported numbers in a desperate defence, against the external criticisms, of the valuers' skill.

The IPD/ Drivers Jonas study involved an altogether larger set of data and if, analysed efficiently and rigorously, would have been a significant academic contribution as well as a competent piece of marketing for the IPD database. One should not criticise a paper for failing to achieve aims that might not have been even considered by the authors. Nevertheless Lizieri and Venmore-Rowland are right when they criticise the heavy emphasis by IPD/ Drivers Jonas of the R^2 statistic as a measure of valuation accuracy. A more interesting number from the point of view of users of valuations is the standard error of estimate. However the reporting of the standard error might have problematical since it is less intuitive and might have been interpreted by the less sophisticated reader as being less supportive of the valuers' skill.

The second issue raised by Lizieri and Venmore-Rowland concerns heteroscedasticity. Heteroscedasticity is important because it influences the significance of the tests. If there is heteroscedasticity in a regression model, the estimates in the regression will not be biased but they will be inefficient and the standard errors of the estimators will also be biased.

The question of inefficiency is not very important for the IPD study simply because the sample was so large. The difference in the parameter estimates from those, which might have been apparent from a transformation designed to correct for heteroscedasticity, would probably have been negligible. However the bias in the standard errors of the estimated parameters is more important. In this particular study it is probably non-contentious to assume that if heteroscedasticity exists, it will be positively associated with the size of the variables, e.g. larger valued properties will also have the larger differences in sales price/valuations. This being so, it follows that the effect of bias is that the estimated standard errors are too small, thereby flattering the valuation accuracy. This would, as Lizieri and Venmore-Rowland point out, be particularly be troublesome for those larger or more valuable properties. It is a point not addressed by either the IPD study or the Brown papers but is taken up in our empirical work reported below.

A more recent paper by Matysiak and Wang(1994) resolves many of the econometric issues raised in the debate and applies bootstrapping techniques to derive confidence intervals for the valuations made over the period 1973 to 1991. The sample data for both studies was supplied from the same source. Although we have not replicated the methods used by Matysiak and Wang on our more comprehensive data set, our results in the main confirm the degree of accuracy that is exhibited by valuers. In particular we confirm that the relationship between valuation and subsequent sale price is directly related to the performance of the market around the time of the valuation. As found in Matysiak and Wang (1994), valuations are biased downward in a rising market and upwards in a falling market. Because we were able to identify the period in which the sale took place we can reduce some of this bias that appears in the valuation/sales data.

5. Empirical Analysis

The study used proprietary data drawn from the JLW PPAS database. It originally comprised 775 sales of properties between 1973 and 1990 that had been previously valued by over ten valuation groups. For each property, we had the sale price, the valuation made previously, the geographical location (by region), the sector (office, shop, industrial, miscellaneous) and the quarter in which the property was sold. The sales data are part of a large (more than £3 billion) private property database held within Jones Lang Wootton Fund Management. The same source also provided estimates of quarterly returns which were taken to indicate the state of the market as seen and known by those responsible for carrying out the valuation. Since these reported returns were available at the time to those carrying out the valuation, they are taken to be more representative of the perceived market return than other publicly available returns such as the JLW Index or the returns reflected in the Richard Ellis series.

Before analysing the data, checks were made to ensure that disposal costs were equally reflected in both value and sales data. The data were examined to eliminate any case in which there was any ambiguity about the instructions on valuation or the integrity of the reported sale price. Furthermore properties that were sold in the first nine months of the sample period were eliminated because of insufficient returns data. This preliminary analysis reduced the sample set from 775 to 747.

In order to reduce the probability that prior knowledge of agreed sales would have determined the valuation, the analysis used value penultimate to sale. These were mainly on a quarterly basis but annual valuations were used when the sale was completed between one and two quarters after the valuation. Thus the average gap between value used in the analysis and sales was around 4.5 months.

One simple representation of the relationship between the valuations and the subsequent sale price is to express the difference as a percentage of the original valuation. The distribution of this error is shown in Figure 1. The results would suggest that sale price of properties sold within the 1974 to 1990 period was on average nearly 7% higher than the valuation and that the standard deviation of the differences was slightly higher than 18%. This compares quite closely with the estimate derived from the Barkham and Geltner study referred to earlier. However it should be noted that the distribution is not symmetrical. Consider for example the proportion of errors that lie within the range ± 20%. The number of observations that are less than -0.2 is shown in the cumulative plot and indicates that approximately 4% of the errors are more negative than -0.2. An alternative expression is that 4% of the sales were effected at a price that was at least 20% lower than the valuation. On the right hand side of the distribution 85% of the errors were less than 0.2 - a result that implies about 15% of the sales took place at a price at least 20% higher than the valuation. The combined result suggests not only that nearly 20% of the sales differed by more than 20% from the valuations but that, during the period from which the sample was drawn, the valuations were on average underestimates of the sale prices. Of course this underestimation would be expected to be a function of the market performance. Since the period covered by this study, the relationship might well have changed in response to the market movements.

Insert Figure 1 here

An statistical representation of the histogram can be found by regressing the (log) Sale price against the (log) valuation.[5] The results are reported in Table 2 below. It should be noted that the data set is not a true time-series since in any one period, there will be multiple observations of valuation and associated sale.

Insert Table 2 here

Given an average (log) valuation of 12.886, the regression would imply the associated (log) sale price of 12.940 (that is, a difference of 5.27%) and would imply that the predicted sales price would rise more than proportionately for more valuable properties. The standard error of this regression is 15.90% and this can be inferred to be a crude estimate of the unreliability of the valuations in that it implies that even allowing for the modelled difference between valuation and sales price, the unexplained 'errors' are distributed with an overall standard deviation of nearly 16%. In other words, even if we can model the relationship between valuation and sale price, we would still have only two thirds of the sale prices coming within ±16% of the valuations.

Inspection of the distribution of the original valuations also revealed a huge difference in the size/value of the properties being valued. There were numerous observations of properties valued at less than £250,000 and at the other end of the scale a few properties worth many millions. This distribution is very common in analyses of economic cross-sectional data and is usually taken into account by transforming the values. If no transformation is carried out, subsequent analyses can be flawed because of the presence of heteroscedasticity in the errors of the model. To test/correct for heteroscedasticity, we used raw and log variables of. valuation and price of each property. We regressed (OLS) the sale price against the valuation and tested for heteroscedasticity using the Goldfield-Quandt and Breusch-Pagan tests. After applying the Box-Cox procedure (see Appendix A1), we concluded that a simple log transformation was sufficient to remove much of the heteroscedasticity and the remaining analysis (other than that using the Sales/Valuation Ratios) were carried out using only the logged variables. We present in Table A.1 in the Appendix, the results of the Box-Cox analysis. This analysis formally confirms the transformation used in the preliminary regression. The robustness of this transformation is confirmed in the analysis of Matysiak and Wang (op.cit.) who used a joint maximum likelihood estimation of a generalised Box-Cox transformation. They argue that joint estimation is preferable because it avoids potential bias but arrive at the same transformation as that used in this paper.

However, the transformation does not necessarily ensure that the errors of the regression are normally distributed. Although subsequent regression used the log transformations, we had to make additional adjustments in order to minimise the effect of non-normality in the model error terms. We bootstrapped the regression model since that technique would cope more appropriately with the asymmetrical distribution of residuals arising from the regression.

6. Behaviour of Valuation Error over time.

Even if we have dealt with the non-normality and asymmetrical issues, we have a further problem in analysing the data; the relationships between sales and valuations may change over time. To analyse this issue we analysed the data through time to see how the sales/valuation relationship changed in association with market movements. The simple analysis can be demonstrated by Figure 2 that plots the percentage difference between sale price and valuation and the series of quarterly returns (shown as a solid line). For each quarter the range of difference has been calculated and the results have been plotted in a minimum, average, maximum format.

Insert Figure 2 here

In Figure 2, the top line represents the quarterly return from the JLW internal index. The scale is given on the left-hand side of the figure. The lower lines represent a summary of the valuation errors as estimated in the quarter in which the sale was made. The lowest point of the Lowest-Mean-Highest line represents the largest negative error as a percentage of the valuation, that is the case where the sale price was the lowest in relation to the valuation.. The small horizontal line is the average error and the top of the line represents the case of the highest sale price relative to the valuation.

As can be seen, there is some cyclical behaviour of the sales/valuation ratio. In particular the 'boom' period of the late 1980s is reflected in the positive error (that is, the sale price tends to be greater than the valuation). This interpretation is supported by the rigorous tests carried out by Matysiak and Wang (1994). This would be consistent with the outcome that the valuations were biased at the time of sale by the process of the market movements between the time the valuation was made and the time at which the sale was agreed. We test this interpretation by examining by regression whether the valuation errors can be explained by a set of variables that might have conditioned the valuation process in a systemic manner. Because of the uncertainty about the information set on returns available to the valuers, the regression analysis included not only the return from the aggregate fund between the valuation and sale but also the returns in the four quarters prior to the sale quarter. Other variables included are dummy variables representing geographical areas (GLC, South East, East Anglia, other) and the sector (office, shop, industrial, mixed shop/office, other)[6]. The results of the regression are shown in Table 3. This regression suggests that many of the variables are statistically insignificant. To reduce the number of variables included in the regression, a series of tests were performed in which the groups of variables were tested for restricted values. The results are shown in Table 4.

Insert Tables 3 and 4 here

The results of these tests suggested that the sector variables were insignificant whereas the return variables are collectively clearly significant in explaining the valuation error. The geographical area variables were introduced because of the *a priori* argument that the national property market factor might differ in its influence from one sub-market to another. In the result, it can be seen that the two main sub-markets (GLC and South East) are indeed significantly different from the rest of the UK. The results of the tests for the significance of the return variables are not surprising. They suggest that the returns from the preceding quarters are sufficiently correlated that it is difficult to distinguish between the effect of any one quarter's return. Table 4 clearly shows that current and previous returns are important in explaining the valuation error but the information is insufficient to distinguish between the effect of the current (sale) quarter and the effect of the quarters before the sale quarter. The final test shown in Table 4 suggests that a regression that forces the coefficients on all the return variables to be equal cannot be rejected as being 'worse' than the regression in which all the return variables are allowed to have different coefficients. Accordingly in subsequent regressions, the return variables are combined in one variable that reflects the return from the property fund in the sale and preceding four quarters. The significance of this variable in the later regressions is confirmed but the interpretation is ambiguous. It could either imply that valuers were not reflecting the information from the property market within the year leading up to the valuation or it might merely reflect the collinear characteristics of the consecutive property market 'returns' .

The modified regression is shown in Table 5. In this regression, three new variables are included in order to indicate the confidence interval for the valuation errors of differently sized properties. The inclusion of these variables do not, it should be emphasised, influence the parameter estimates for the other variables. They are included to provide direct estimates of hypothetical predictions. As discussed in Maddala (1988, p 114 et seq.) this is achieved by including a dummy variable that is set to 0 for all observations except one, the (n+1)th. This observation is created by specifying the values of the explanatory variables required in the prediction and setting the value of the dependent variable as zero. In this application the values are chosen to reflect the valuation of small, medium and large valued properties, specifically, the values are chosen to indicate the 25th, 50th and 75th percentile valuation when ranked by value. The regression result thus indicates the predicted sale price and the associated standard error.

Insert Table 5 here

As can be seen from Table 5, the relationship between the valuation and the subsequent sales price is unbiased (i.e. the constant is insignificantly different from zero). There is no apparent effect of size once the effect of market movements are taken into account (the slope coefficient is insignificantly different from 1). Furthermore the accuracy of the valuation (as measured by the standard error of estimate) is 0.1531 which is consistent with that suggested by the earlier analysis. It should be borne in mind however, that the regression is defined in log terms so the standard error of the regression is not comparable with the standard deviation of the sales/valuation ratio. In order to make them comparable, we have to transform the standard error , viz.

$$\begin{aligned} \text{Variance} &= e^{\sigma^2}(e^{\sigma^2}-1) \\ \text{where } \sigma &= \text{standard error of estimate in regression} \end{aligned} \tag{3}$$

Using this transformation the prediction interval for the mean valuation error is found to be 15.58% in the sample. Similarly the confidence intervals for the different sized properties (as represented by the prediction dummy variables are given in Table 6 below.

Insert Table 6 here

One problem with the previous regression equations is that there is evidence that the residuals are not normally distributed. The skewness and excess kurtosis of the residual errors were calculated as 0.535 and 1.8006 respectively. These values are both significantly different from zero at any plausible levels of significance. Because of this, the regression estimates was analysed by use of the bootstrapping technique.

7. Bootstrapping

One approach that is advocated to overcome reservations about the inferences drawn from the regression is the use of bootstrapping. Although the technique is not widespread in the finance literature, it is being used increasingly. The principle of bootstrapping is very simple; it is to produce, by intensive computer methods, inferences about the results of regression or in fact any other estimating process used in statistics. To take a simple example, if we wished to estimate the standard error of the mean of a sample of 10 different valuations, we could conventionally calculate the standard deviation of the valuations and from that derive the standard error. The bootstrapping approach would be to consider a sample that might be drawn from the actual sample if every valuation had an equal probability of being chosen. Such a sample could be estimated by selecting 10 observations drawn at random (with replacement) from the original 10 valuations. This process would, if carried out once, would produce an estimated mean. The bootstrapping process therefore replicates this sampling procedure many times and records the distribution of the means produced. Then the standard error of the original estimated average valuation can be directly estimated since it is directly represented by the standard deviation of the empirical distribution of the means of each sample. The bootstrapping approach may use for simple statistics, such as the standard error, distributions that are formed by 200-300 iterations. In regression the number of iterations is commonly larger and in this paper 1000 iterations are carried out.

In regression bootstrapping there are two methods that are can be used to derive the random drawings from the original sample data. In this application in which the sample size is 747, the simplest is to execute the regression using OLS. We could then form 747 new observations of the dependent variable(sale price), each of which consists of the actual price to which is added an error term that is constructed by drawing at random (with replacement) from the first set of errors from the original regression. The OLS regression is then executed again. If the process is repeated 1000 times, we have 1000 estimated regression coefficients and from the distribution of these estimates we can infer the accuracy of the coefficients in the original regression. The second method is to bootstrap the original data sets, sampling from the original sale prices together with their associated dependent variables. Using the RATS software statistical package, this is slightly more cumbersome to program than the residual method. However, although the results are asymptotically equivalent to the residual approach, Efron and Tibshirani (1993) argue that it is more robust and makes fewer assumptions about the linearity of the relationship between the dependent and the independent variables[7]. In this study we tried both approaches and found little difference between the results. For the sake of robustness, the full bootstrapping method is reported here.

Insert Table 7 here

The results are summarised in Table 7. The column headed constant reveals the best estimate of the constant in the regression (in the row labelled "mean"). There is also evidence that the constant is not significantly different[8] from 0 because the 10th and 90th percentiles overlap zero. This is consistent with a significance test based on the standard error of the estimate (shown in the final row). The mean of the constant is clearly less than 2 standard errors away from zero[9]. As can be seen from Table 7, the valuations are unbiased in that the intercept is not significantly different from zero (the estimate for the 10% percentile is negative while the other estimates are positive) and the coefficient on the Value is close to 1. The other variables are also significantly different from zero (since their 10th and 90th percentiles do not overlap zero). They make some contribution in explaining the variability of the Sale price. With respect to the error in the specific-valued properties, the variability of the forecast error increases with the size/value of the property. The error will actually increase, the more outlying the predicted variable is from the other observations. In this case, because the distribution is highly skewed, the specified larger valued properties are further away from the mean observation than the specified small property.

We present in Figures 3 to 5, the distribution of the variation in valuations made on the three hypothetical specified properties, small, medium and large valued. The distributions plainly show the non-normal distribution of the errors. The information contained in the Figures is summarised in the following Table 8, which reveals the cumulative distribution of the valuation errors. In this table the errors or differences in valuations are expressed in percentage terms so, for example, the table reveals that for large valued properties, 9% of the valuations will undervalue by more than 20%, while 5% (100 - 95%) will over-value by at least 20%.

We would emphasise that this error is the unexplained error between valuation and the subsequent sale price. By reference to Figure 1, we have already shown that the crude error in valuations over the period resulted in an average bias of nearly 7% and that 19% of sales took place at prices that were more than ± 20% of the valuation. The results of the modelling and analysis are that we can (a) explain almost all the bias and (b) reduce the distribution of the error by reference to other variables.

The inferences that can be made about the other variables have to be considered carefully. To start with, the coefficient of the return variable suggests that if the accumulated return over the current and preceding four quarters has amounted to, say, 10%, the sale price will be about 4% higher than the valuation allowed for at the time of valuation[10]. The effect of a sale in either the GLC or the South East areas is similar; over the period, valuers persistently undervalued properties by about 3% in both of these areas. Whether this arose because of the distribution of sales throughout the period or whether it represents a secular increase in prices that was unrecognised by the valuers is unclear. But the recognition of both the return and the regional effects is sufficient to reduce the apparent bias in the valuations over the whole sample set. With this adjustment, Table 8 shows that for small properties, 15% of the properties are sold outside the range of valuation ±20% whilst for large properties, the equivalent proportion is 14%. This is substantially lower than the error revealed in the simple analysis in the earlier part of this paper. It also is less than the expected valuation error of 16%, derived from the Barkham and Geltner research.

8. Evidence from Other Markets

We have found that valuation errors of the range found in this study are consistent with the variation of valuation error over time. However, one can also put the results in perspective by comparing them with comparable studies in other markets. One can for example look to the stock market for *a priori* estimates of the likely difference between valuation and subsequent sale price. In the market for equities, a comparable situation exists when share issues are made for the first time. At this stage, a company has to be valued by reference to comparable entities. Usually the valuers (or share issuers) will evaluate the likely earnings per share of the new company and, on the basis of the "quality" of the previous history as well as the future prospects of the profit of company, will estimate a likely P/E ratio to arrive at an estimate of the market price on the day of the issue. Of course the P/E ratio is simply another term for the YP used in property valuation and the "quality" of earnings is comparable to the many factors used by valuers in assessing the risk premium for a specific property. The big difference between the two exercises in share issues and property market valuation is the time lag between the valuation and sale. In the stock market this delay will rarely be greater than six weeks and will often be little more than one week.

The stock market would be regarded as being relatively volatile when compared with the property market so it might be thought that the shorter time between valuation and market price would be compensated by the greater uncertainty in market movements.

Research carried out by Levis (1992) reveals that, as might be expected, the difference between the initial value or issue price and the subsequent market price represented by the quoted market price for the share at the end of the first day's trading, on average reveals a conservative bias, i.e. the market price is higher. The mean bias on a sample of 712 competing ordinary share issues over the period 1980-1988 was 14.3%. However, more interestingly from the perspective of the property researcher, the standard deviation of the difference was 20.9% over the whole period. This is considerably higher than the error in valuation revealed in the present study.

9. Conclusions

By using a large sample of properties with the date of sales identified within a specific quarter over the period 1973 to 1990, we have been able to analyse the effects of market movements on the sales valuation relationship. We have also made some attempt to compensate for the more common econometric problems that might have been expected to distort the results of regressions in this type of data.

By reflecting on the results that might be expected from this analysis, on the basis of the stochastic behaviour of property market 'returns', we are able to form a priori expectations of the scale of the valuation errors. By modelling the functional form of the sale/valuation relationship and by including additional significant variables, we are able to construct a parsimonious model which suggests that valuations are relatively more accurate than might be expected and that valuers are unbiased once market movements and proxy factors covering geographical sub-sectors are taken into account.

The results are consistent with the findings of Matysiak and Wang (1994), who found that a simple classification of market states explained the subsequent valuation bias. However, the finding in this paper that the returns of the JLW Fund property index in the period before the valuation also affected the difference between valuation and subsequent sale price indicates that the valuers might not have incorporated the information to which they would have access. This result would partly explain why Matysiak and Wang (1994) found persistent bias in the market performance classifications around the time of valuation. It would suggest that valuers have scope to reduce the bias in their valuations by being more sensitive to recent market reports and behaviour.

Appendix - The Box Cox Routine

The Box-Cox procedure is designed to identify a transformation of the raw data that will make the model more nearly linear. It is particularly helpful when the distribution of the data is skewed but can also be useful when the distributions appear to be hetereoscedastic and non-normal. A simple transformation might be $f(x) = x^2$ or $f(x) = \sqrt{x}$. The Box-Cox function provides a general transformation that includes both of these examples as well as the transformation f(x) = log(x). It can be applied to a single variable, or to several variables independently or, as in this application, to the Price/Value variables jointly. The routine maximises the log-likelihood of the Box-Cox function given below with the unknown parameter **λ**.

$$\%BOXCOX(x,\lambda) = \begin{cases} \dfrac{x^{\lambda} - 1}{\lambda} & \text{if } \lambda \neq 0 \\ \log(x) & \text{if } \lambda = 0 \end{cases}$$

When for example, $\lambda = 2$, the function effectively transforms the variable x into the squared function x^2.

The Box-Cox function can be used either in a search/grid mode in which different values of λ are tried and the function which minimises the residual variance is chosen or in a maximum likelihood function approach in which the likelihood function of the regression equation is given by

$$L = (\lambda - 1)\sum_i \log Y_i - \frac{n\log(2\pi)}{2} - \frac{n\log(\sigma^2)}{2} - \frac{1}{2\sigma^2}\sum_i \left[\frac{Y^{\lambda} - 1}{\lambda} - \alpha - \beta\frac{X_i^{\lambda} - 1}{\lambda}\right]^2$$

where α and β are the regression coefficients.

One problem with the approach is that it simultaneously yields a functional form and approximates the disturbances to be more nearly normal. It has been shown[11] that the estimated λ would be biased in the direction required for the transformed variable to be more nearly homoscedastic. In particular, if the regression equation is linear but hetereoscedastic, the estimate of λ is biased towards zero.

Some confidence that this bias is not significant is found by expressing the equation in two starting forms, the first in which the variables are expressed in their original form and the second in which the variables are logged. It can be seen that apart from the first regression that involves raw sale prices and valuations, the estimates are close to each other. The transformed functions do have higher standard error of estimates higher than the untransformed series. However, it is interesting that in the last two rows, only the standard errors of estimates are affected. In both cases the likelihood function is maximised when the function is expressed in log form. In the first case the value of λ is 0 whilst in the second it is 1. We also take comfort that the procedure arrives at the same functional form as that found by Matysiak and Wong(1994) using more flexible procedures so in this application our approach does not seem to cause any great difficulty.

Table A.1 Regression Results with Box-Cox Transformations

Regressand	Constant	Slope	Lambda	R^2	Std.Error of estimate
Sale Price	15182 (25454)	1.090 (0.007)	-	0.965	658376
Sale Price (Transformed)	-0.072298 (0.053)	1.0105 (0.053)	0.0057 (0.0084)	0.988	0.190
Log Sale Price	-0.0682 (0.0513)	1.0102 (0.0040)	-	0.988	0.177
Log Sale Price (Transformed)	-0.0684 (0.056)	1.0106 (0.0040)	1.0943 (0.11)	0.988	0.225

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[1] Of course the random walk model is a specific and highly constrained form of stochastic behaviour implied by efficient markets. In this paper we use the model in order to clarify the association of variability over time and cross-sectional variability.

[2] If P_t = the natural log of the Security Price (S_t), then $P_t - P_{t-1} = \log_e (S_t/S_{t-1}) = \log_e(1+r_t)$. But the continuously compounded return $R_t = \log_e (1+r_t)$. Therefore we can see equation (2) follows from (1).

[3] The random walk model chosen here has the advantage of intuitional simplicity. In the more general versions of the efficient market model, the return generating process has simply to be a 'fair' game. This would still imply that the information set available at any time would be fully incorporated in the price at that time and that there would therefore be no serial correlation in the error term in equation (1).

[4] Lizieri and Venmore-Rowland (1993) provide a further note to the discussion.

[5] If we take the ratio of sale price to valuation and assume that different properties should exhibit similar ratios, we are implicitly assuming that the proportionate differences are likely to be more similar that the absolute differences - a reasonable assumption given the large variation in the size and value of properties in the sample. Therefore in regression terms, we can find the equivalent relationship by regressing the log sale price against the log value.

[6] If the total number of categories reflected in the dummy variables is n, the regression includes n-1 dummy variables. Thus the intercept reported includes the effect of the areas/sectors not specified by the dummy variables. The coefficients on the dummy variables therefore indicate the marginal effect of the sector/region.

[7] See Efron and Tibshirani (1993), pp 113 -116 for a useful discussion on this issue.

[8] To estimate the standard errors of the bootstrapped results, we followed the percentile method of Stine (1985) and Efron (1987)

[9] One should remember the finding that the parameter distribution is not symmetrical; the standard error-based inference would be expected to be unreliable. However in this case, the results are unaffected sufficiently to lead to this result.

[10] The returns are not measured in percentages, therefore the coefficients in the regression have to be multiplied by 100 to equate their effects with the other variables.

[11] MacKinnon J G, White H and Davidson R, "Tests for Model Specification in the Presence of Alternative Hypotheses: Some Further Results", Journal of Econometrics, 21, January 1983, pp 53-70

Table 1: IPD Drivers Jonas (1988) Regressions 1982-1988

Sector	**Regression**	**R^2**	**Average Lag in months**
Industrials	S = 0.0774 + 0.978V	0.994	9.7
Offices	S = - 0.526 + 1.139V	0.894	9.8
Retails	S = 6.368 +1.060V	0.930	9.7
Overall	S = 3.56 + 1.061V	0.934	9.7

where S = Log(Sale price) and V = Log(Value), each normalised on a unit area

Table 2: Regression of (Log) Sales against (Log) Valuations

Variable	**Coefficient**	**Std.Error**
Constant	-0.095**	0.048
(Log) Valuation	1.0116**	0.004

Note: ** indicates that the coefficients are significantly different from 0 at the 5% level. In addition the coefficient of 1.0116 is significantly different from 1.00 at the 5% level.

Table 3 : Regression of (Log) Sales against (Log) Valuations plus other explanatory variables.

Variable	**Coefficient**	**Std.Error**
Constant	-0.0133	0.0554
(log) Valuation	1.0009**	0.0041
Shop	0.0243	0.0231
Office	0.0074	0.0241
Industrial	0.0168	0.0233
Mixed	0.0280	0.0391
South East	0.0271**	0.0140
GLC	0.0305**	0.0147
East Anglia	-0.0029	0.0347
Return Quarter (-4) (t04)	0.0022	0.0033
Return Quarter (-3) (t03)	0.0048	0.0044
Return Quarter (-2) (t02)	-0.0001	0.0045
Return Quarter (-1) (t01)	0.0055	0.0044
Return Quarter (0) (t00)	0.0073**	0.0037

Note: R^2 = 0.991, Standard Error = 0.1534. ** signified parameter estimates are significant at the 5% level. The results of the Breusch-Pagan Test (1.81, significance=0.62) and the Goldfield-Quandt test (F(245,247) =0.857, significance = 0.88) suggest that heteroscedasticity is not significant.

Table 4: Hypothesis tests for regression parameter estimates

Variables	Hypothesis	Result
Shops, Offices, Industrial, Misc.	= 0	F(4,733) = 0.477 pvalue=0.752 Null Accepted
All return variables (t04 to t00)	= 0	F(5,733)= 12.43, pvalue= 0.000 Null Rejected
All past return variables (t04 to t01)	equal	F(3,733) = 0.202, pvalue= 0.894 Null Accepted
All return Variables (t04 to t00)	equal	F(4,733) = 1.0165, pvalue= 0.398 Null Accepted

Table 5: Regression between (Log) Sales and (Log) Valuations plus modified explanatory variables.

Variable	**Coefficient**	**Std.Error**
Constant	0.0264	0.0490
Log value	0.9994**	0.0039
Accum. Returns	0.0038**	0.0005
GLC	0.0287**	0.0140
SEAST	0.0286**	0.0137
Small	11.9291**	0.15335
Medium	12.9584**	0.15334
Large	13.9528**	0.15345

Note: R^2 = 0.993, Standard Error 1 = 0.1531. ** signified parameter estimates are significant at the 5% level.

Table 6.: **Transformed Standard Errors**

Prediction	**Transformed**	**Standard Error**
Small (11.929)	£151,610	15.6%
Medium (12.9584)	£424,390	15.6%
Large (13.9528)	£1.147,160	15.7%

Table 7: Bootstrapped Regression Summary

Percentile	Constant	Value	Accumulated Returns	GLC	S.East	Prediction Small	Prediction Medium	Prediction Large
90%	0.089	1.005	0.004	0.047	0.047	12.12	13.18	14.19
Mean	**0.021**	**1.000****	**0.004****	**0.029****	**0.028****	**11.95**	**13.01**	**13.98**
10%	- 0.040	0.994	0.003	0.012	0.010	11.73	12.78	13.74
Std.Error	0.049	0.004	0.001	0.013	0.014	0.144	0.147	0.158

Note: The standard errors are the standard deviations of the bootstrapped coefficients

Table 8: Distribution of Errors in Valuations

(Bootstrapped)

Cumulative Distribution of Percentage Valuation Error			
	Small	**Medium**	**Large**
-20	9	7	9
-10	23	23	22
0	48	48	46
10	80	80	81
20	94	94	95

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Figure 1: Distribution of Sales/Valuation Errors

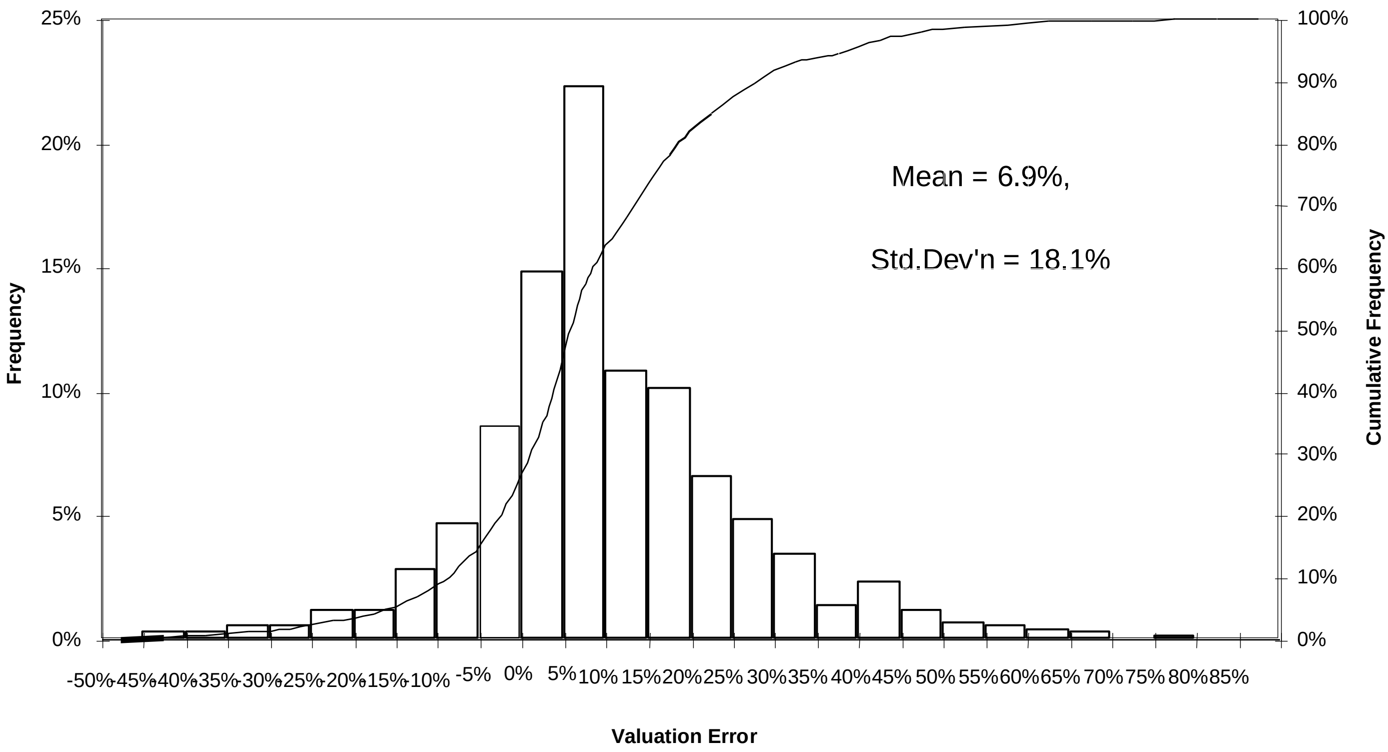

Figure 2: (High, Average, Low) Valuation Error
Also JLW Fund Quarterly Return 1974- 1990

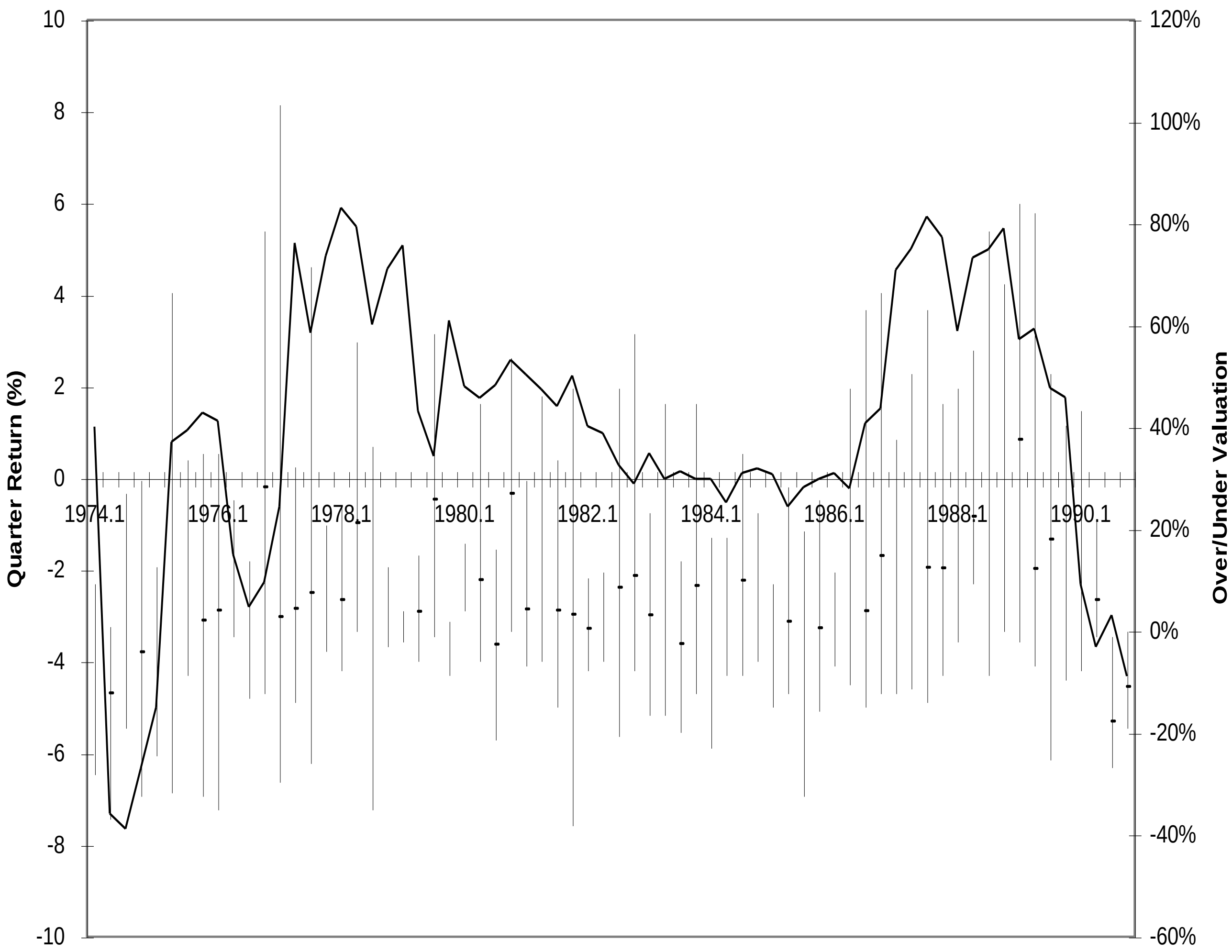

Figure 3: Distribution of Percentage Forecast Errors for Valuation of Small-Value Properties

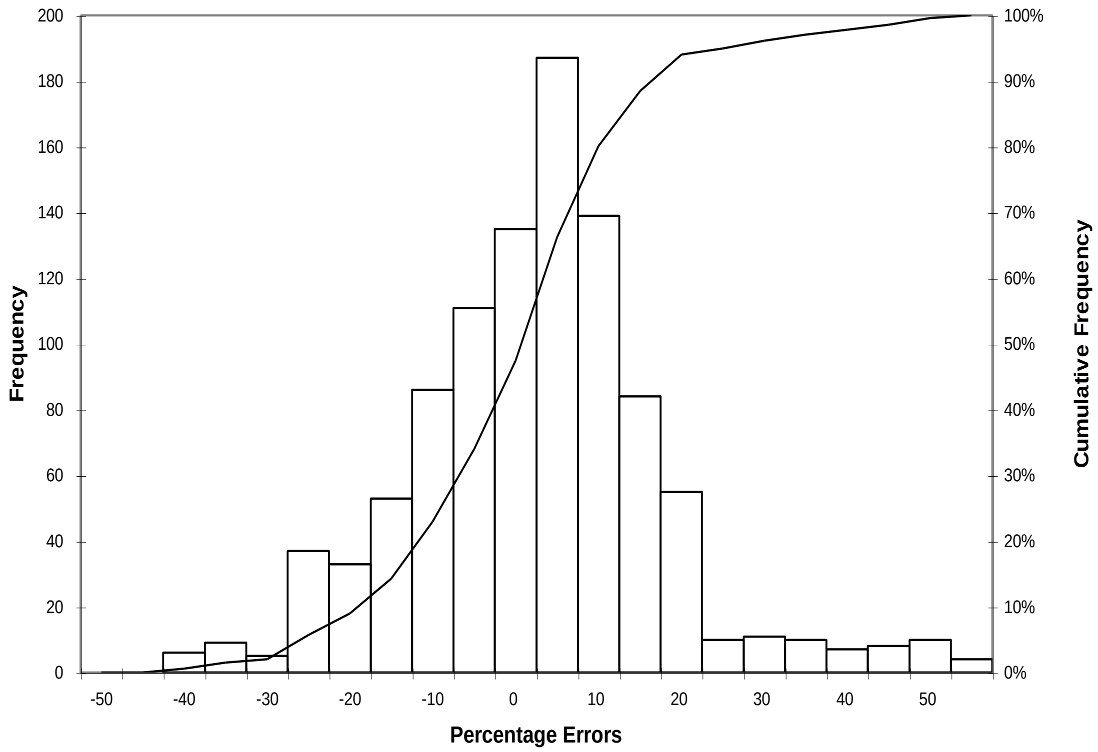

Figure 4: Distribution of Percentage Forecast Errors for Medium-Value Properties

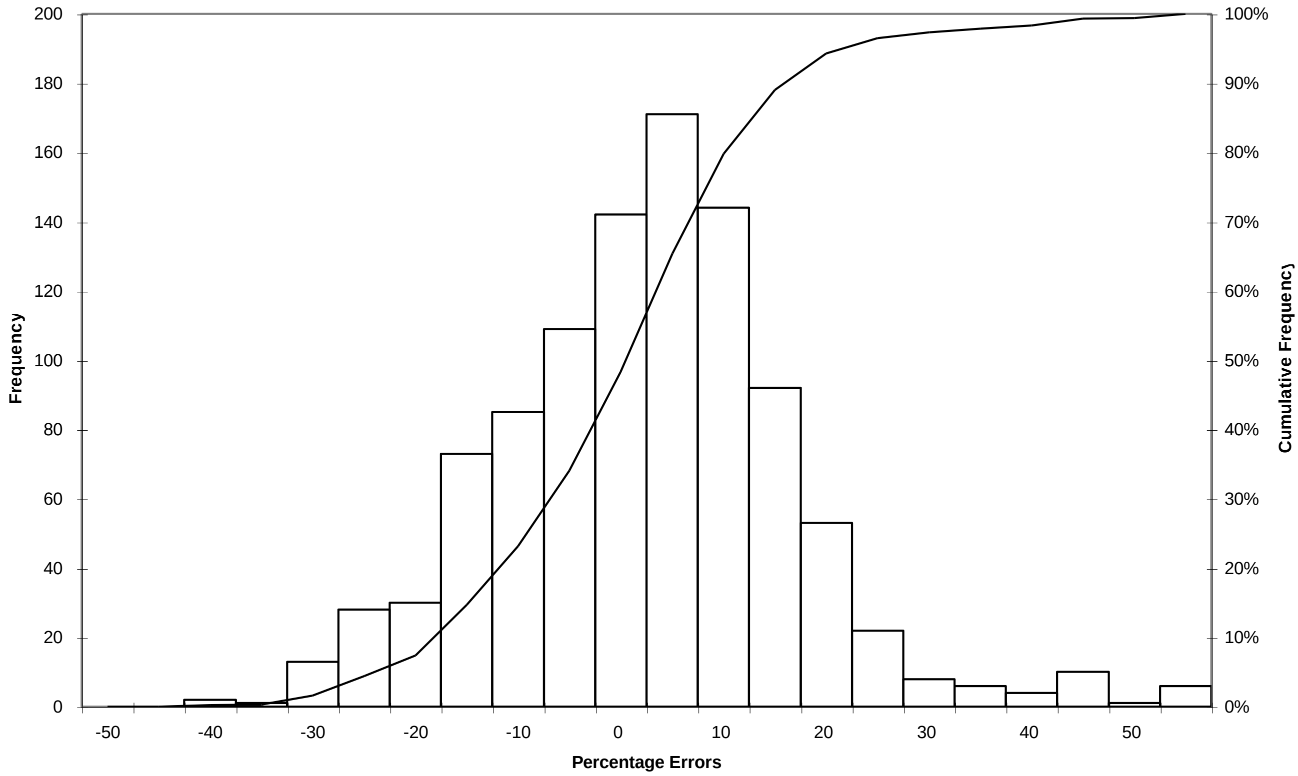

Figure 5: Distribution of Percentage Forecast Errors for Valuation of Large-Value Properties