Pre-bid building price forecasting accuracy: Price intensity theory

Gunner, John; Skitmore, Martin

Published in:
Engineering, Construction and Architectural Management

DOI:
10.1108/eb021117

PRE-BID BUILDING PRICE FORECASTING ACCURACY: PRICE INTENSITY THEORY

Dr John Gunner
Montville
Queensland
Australia

Prof Martin Skitmore
School of Construction Management and Property
Queensland University of Technology
Gardens Point
Brisbane 4001
Queensland
Australia

13 October 1998 (version 4)

PRE-BID BUILDING PRICE FORECASTING ACCURACY: PRICE INTENSITY THEORY

ABSTRACT: A theory of pre-bid building price forecasting accuracy is proposed based on the heuristic bias framework and with reference to the common practice of basing building price forecasts on the price per square metre of floor area, termed here as Price Intensity (PI). The main prediction of the theory, that high PI contracts will be underestimated and low PI contracts will be overestimated, is tested by a reanalysis of a set of Singapore data and in comparison with previous work.

Keywords: Price Intensity Theory, judgement bias, price forecasts, accuracy.

INTRODUCTION

There is a wealth of empirical studies aimed at identifying the causes of estimating bias (*eg.* Cheong, 1991; Flanagan and Norman, 1983; Gunner and Betts, 1990; Jupp, 1981; Lau, 1991; Morrison, 1984; Ogunlana and Thorpe, 1991; Skitmore, 1985, 1988; Skitmore *et al*, 1990; Thng, 1989). One of the most common findings of this work to date has been the seeming correlation between forecasting bias and the size of project, with the degree of bias reducing with increased project size in both absolute and percentage terms (*eg.* Flanagan and Norman, 1983; Morrison, 1984; Morrison and Stevens, 1980; Harvey, 1979; Gunner and Skitmore, 1998). Several other variables (see Gunner and Skitmore, 1998) have also been found to be correlated with bias, in addition to project size. Despite this, scant attention has been paid to the development of explanatory theories of these results (Skitmore, 1988; Skitmore *et al*, 1990; Gunner and Skitmore, 1998).

To address this deficiency, we start our analysis from a different point altogether, by reference to the judgement bias literature. This, together with the fact that it is common practice to base building price forecasts on the price per square metre of floor area, leads us to a theory based on Price Intensity. An attempt is then made to refute the PI theory in favour of the project size 'effect', and other likely variables, through a reanalysis of Gunner and Skitmore's (1998) Singapore data by linear regression. For the cases where the linear regression assumptions are not violated, the refutation does not succeed. Further attempts at refutation of the theory are also described through a reexamination of previous work. These attempted refutations also fail. With the lack of any available evidence to the contrary, PI theory is therefore proposed as offering a tenable, necessary and sufficient, explanation of pre-bid building price forecasting bias results to date.

PRICE INTENSITY THEORY

Judgement biases

Forecasting can be viewed as a choice amongst a range of discrete possibilities. In building price forecasting, forecasters are faced with a choice of values to apply to the various components of the forecast. This is so whether in the early stages of design, where the choice is the rate to apply at a broad brush level (eg. the functional price per bed for a hotel), or in the later stages of design, when more detailed estimates can be made, such as the price per unit area of a brick wall. Most often, forecasts are based on the price per unit of floor area (Fortune and Lees, 1996) and are continually refined as the design evolves. This unit price, commonly expressed in dollars per square metre, is termed here Price Intensity (PI). By this definition, contracts with a relatively high PI can be said to be relatively 'expensive' contracts and those with a relatively low PI are therefore relatively 'cheap' contracts[1].

Building price forecasting is uncertain and highly subjective, involving considerable judgement on the part of the forecaster. Judgement is necessary in selecting an appropriate ‘cue’ or rate (a

[1]Defining "expensive" and "cheap" in this way is by no means conventional as these terms have emotive connotations in common use, with "expensive" being thought of as overpriced and "cheap' as underpriced and probably of poor quality. For building contracts, this is confounded by the heterogeneous nature of the buildings involved. Here, the terms are used solely for clarity as mere labels for high and low PI values.

base price[2]) and adjusting it to meet the particular requirements of the building being designed. Such adjustments also include, but are not limited to, allowances for price inflation, currency movements on imported materials and the effect of different locations. Inevitably forecasters make errors in their judgements of the relevant price and the introduction of bias, in the form of systematic errors, is a common occurrence. Positively biased forecasts are systematic overestimates of the actual prices and negatively biased forecasts are systematic underestimates of the actual prices.

Some possible root causes of bias when exercising judgement in the property/construction domain have been suggested by Raftery (1996). These relate to work in the field of judgement biases, which has identified "a number of heuristic principles that reduce the complex tasks of assessing probabilities and predicting values to simpler judgemental operations ... [but which] but sometimes lead to severe and systematic errors" (Tversky and Kahneman, 1982). As noted by Raftery (1996), three of the heuristic principles concern the biases that occur in the prediction of *values*. These comprise the (1) representativeness, (2) availability, and (3) adjustment and anchoring heuristics. Building price forecasts are also concerned with value in the sense that building contract prices represent the market value of the contracts. This suggests the three heuristics to be leading candidates for explaining biases in building price forecasts.

[2] In practice, this is usually the price of a similar building, although Beeston (1983) for example urges the use of the average of several building prices. This is discussed later in the paper.

Representativeness

In answering such questions as "What is the probability that object A belongs to class B?", if object A is highly representative of class B then people will judge that object A belongs to class B. This approach to the judgement of probability leads to serious errors, because an overemphasis on similarity, or representativeness, tends to preclude the consideration of several factors that should affect judgements of probability.

One of these factors is concerned with the prior probability of occurrence of an outcome or the weighting of differing sample sizes. As a result of the representative heuristic, this factor does not appear to be fully utilised in decision making - a phenomenon termed '*conservatism*' in the literature. Another factor occurs when people mistakenly attribute some systematic underlying mechanism to what are actually chance occurrences, perhaps because of small sample sizes. Another, termed *insensitivity to predicability* happens when people are called upon to make predictions of future value and then discount the fact that an inherently wide range of price makes certain prediction impossible. Yet another concerns the unwarranted confidence placed on predictions based upon high degrees of representativeness. A final factor concerns the lack of understanding that people have towards the occurrence of chance events about a mean, with the mean being treated as *the* value sought instead of a central tendency of a collection of possible values.

Availability

Availability is a useful clue for assessing frequency or probability, because instances of large classes are usually reached better and faster than instances of less frequent classes. It is, however, affected by factors other than frequency and probability and consequently leads to predictable biases.

Adjustment and Anchoring

Adjustment and anchoring together form a judgemental strategy that is highly dependent on information presented or available to a person. Once an initial figure is imprinted (anchored) in a person's mind, any adjustments made to that figure in the light of new information tend to be underestimated. Furthermore, availability and anchoring and adjustment strategies both depend heavily upon the initial point in the judgemental process: the information available.

Price Forecasting within the Heuristic Bias Framework

Likely examples abound in the context of building price forecasting. It is normal practice for a forecaster to select one or two similar previous past contracts for which prices are known (Beeston 1974, Skitmore, 1985) and with preference for contracts on which the forecaster has been personally involved (Skitmore, 1985; Skitmore *et al*, 1990). As Beeston has pointed out, bias could arise from this practice through misconceptions of chance in the selection of samples of inadequate size and the over-interpretation of findings based thereon. Price forecasters may have unfounded confidence when asserting that they are confident of accurately predicting prices for a particular type of building, even though they are aware of the wide range of likely prices which represent the differences within that building type. The price forecast for a particular building function may be heavily influenced by the number of similar projects for which the price forecaster has predicted values in the recent past. In addition, forecasting the price for meeting the requirements of a building performance specification for a highly technical, and singular, contract is a possible example of where "insensitivity to predicability" may occur due to lack of knowledge of the cues' effect on the building price.

What is known then of the process of building price forecasting suggests the heuristic bias framework may be appropriate. This implies that, because of 'conservatism' and regression, the price forecaster is likely to select a price which represents the middle, or average, of the range of possible values for an initial anchor but, due to the anchor effect, make insufficient adjustments in the light of further information. As suggested by Skitmore (1985) and Skitmore *et al*'s (1990) experimental work in early stage estimating and supported by Fortune and Lees' (1996) survey of common practice, forecasters take the price per square metre floor area, or Price Intensity (PI), of a comparable building as the starting point (anchor) cue for forecasting the price of a new building and then make adjustments to that value according to anticipated differences between the cue and the new building. According to the heuristic bias framework, such adjustments are likely to be insufficient, leading to a tendency to under estimate the price of expensive buildings and over estimate the price of less expensive ones.

The crucial aspect of this argument is that the under-adjustment will be in terms of PI. That it is accountable **only** in these terms may be an ambitious theoretical proposition, but certainly amenable to empirical examination. More formally, what is proposed is a PI theory that holds that **Price Intensity alone is both necessary and sufficient to account for systematic bias in building price forecasting**. Furthermore, if correct, PI theory should also apply equally at any stage of the design development process when building price forecasts are made, from early stage forecasts to those at the pre-bid stage.

REANALYSIS OF SINGAPORE DATA: MODELLING UNDERLYING FACTORS

Full details of the Singapore data, its analysis and comparison with previous empirical studies are described in Gunner and Skitmore (1998). In that study, a series of bivariate analyses for bias and consistency were used to model a wide range of independent variables thought to affect building price forecasting performance. Some independent variables were shown to be correlated or associated with bias and consistency. The result was to show that not only was that and previous analyses of similar data compatible and homogenous, but that a single underlying variable may exist - its identification being clouded by confounding effects of other variables in the analyses and hindered by the lack of a guiding theoretical framework.

PI theory predicts that Price Intensity is the one variable that is necessary and sufficient to account for any systematic bias involved. To test this theory rigorously, involves an exhaustive search among all other possible competing variables for a combination that performs better than Price Intensity. Multiple regression with backwards elimination of variables was attempted but ultimately failed due to the large number of independent variables present and insurmountable difficulties in building a model satisfying the assumptions required by the regression procedure. Forwards regression was then considered but rejected in favour of a search for an underlying variable of intuitive appeal, the latter being somewhat less arbitrary. The existence of the project size 'effect', referred to in the introduction to this paper, as a major rival to PI theory suggested a convenient starting point to the model building process.

A multiple regression model was therefore built from Gunner and Skitmore's (1999) data by entering independent variables representing both project size and Price Intensity as independent. This was subsequently followed by further regression analyses in which a variety of variables were entered to test for the existence of an underlying variable. PI theory predicts this underlying variable to be Price Intensity and will therefore be disconfirmed if either no underlying variable emerges or, if an underlying variable does emerge, it is not Price Intensity.

This analysis is described below.

Model

The approach adopted to test the PI theory was to work with the model:

$$y = ß_0 + ß_1 u + ß_2 v \qquad (1)$$

Where y is the dependent variable, u is an independent variables representing the possible underlying factor, v is an independent variable and $ß_0$, $ß_1$ and $ß_2$ are regression coefficients ($ß_0$ being the intercept).

If the hypothesis that there are no other variables of significance is not to be refuted, the regression coefficient for Price Intensity should always be significant whereas the coefficients for all other variables should never be significant.

Selection of Variables

As already mentioned, project size has been frequently expressed to be significant in affecting the accuracy of building price forecasts. Project size has been represented by the contract sum (*eg*. Harvey, 1979; Flanagan, 1980; Flanagan and Norman, 1983; Wilson *et al*, 1987; Skitmore, 1988); and contract period (Flanagan, 1980; Morrison and Stevens, 1980; Skitmore, 1988; Ogunlana and Thorpe, 1991; Skitmore *et al*, 1990). Similarly the Floor Area and number of Storeys Above Ground may be also considered as measures of 'size'.

The correlation analyses of the Singapore data indicated that a number of variables were significantly correlated with contract sum and so this was chosen as a starting point for the analysis. The other 'size' variables, along with Price Intensity, that were significantly correlated with contract sum were (the correlation with contract sum variable is shown in parenthesis):

1 Price Intensity (r = 0.397)

2 Floor Area (r = 0.756)

3 Number of Storeys Above Ground (r = 0.848)

4 Contract Period (r = 0.567)

5 Number of Drawings (r = 0.359)

6 Number of Priced Items (r = 0.323)

That Price Intensity is significantly correlated with the Contract Sum indicates that 'expensive' buildings, on a Price Intensity ($/m2) basis, also tend to be expensive in terms of total price.

The dependent and independent variables used are described in detail in Gunner and Skitmore (1998). Unless otherwise mentioned, 'Gross Ratio'[3] was used as the dependent variable.

Testing for the Regression Assumptions

The independent variables were tested for multicollinearity using the Eigenvalue Test (see Gujarati, 1988:299). The residuals from all the regression analyses were then tested to ensure compliance with the basic assumptions inherent in linear regression, namely:

1 There is no auto correlation in the residuals.
2 The residuals are normally distributed.
3 The conditional variance of the residuals is homoscedastic.

Wherever possible, the most powerful statistical tests were applied strictly to each and every assumption. All hypothesis tests were applied at the conventional five percent level of significance.

[3] The 'Gross Ratio' variable is the pre-bid forecast divided by the awarded contract sum.

The residuals were tested for auto correlation using the Durbin Watson d statistic, for normality in their distribution by using the Kolmogorov-Smirnov test, for multicollinearity by the Eigenvalue Test (see Gujarati, 1988:299) and for homoscedasticity of variances by using the Lagrange Multiplier (see Maddala, 1992:233).

Results

Table 1 summarises the results of the regression analyses. This shows the variables included in the equations, their ß values (regression coefficients) to allow comparison of the relative contribution of each independent variable, the t-values and their associated probabilities and the results of the tests on the regression assumptions (yes=pass, no=fail).

None of the analyses failed to pass the auto correlation, distribution and multicollinearity tests. Of the eight analyses failing to satisfy the homoscedasticity assumption, seven produced chi-square values very slightly above the critical value of 3.841. Of these, five passed Levene's test for homoscedasticity leaving only two, Contract Work Type and Contract Period, as marginal. Based on a 5% confidence level and with twenty four independent variables it was expected that at least one of these marginal cases would be spurious. In view of this, and to avoid making unnecessary Type II errors, all the analyses except that involving Preliminaries % were taken to have passed the assumptions tests.

These results show that, in twenty two out of the twenty four analyses, Price Intensity was significant while the added variable was not significant. Of the two exceptions, one involved a 'near' result for Price Intensity (p=0.072) and the other failed to meet the homoscedasticity assumption.

The search for an alternative underlying variable was then widened to include a range of transformations and deflations. The Box and Cox methodology was used to transform the dependent (Gross Ratio) variable by various powers at 0.50 intervals through a range of -2.00 to +2.00. Square root, reciprocal and reciprocal square root deflators were also applied to the dependent variable and several independent variables. None of the transformations or deflators produced any evidence of the existence of a different underlying variable to Price Intensity.

Further tests on the PI model

The model

From the above, Price Intensity emerged as the only likely independent variable candidate as an underlying factor. The plot in Fig 1 provides a visual rendition of the data and model, the outer lines delineating the 5% confidence limits.

The Price Intensity model (Gross Ratio) is

$$R = 1.152 - 7.2(10^{-5})I$$

where R = Gross Ratio (price forecast ÷ awarded contract sum)

I = Price Intensity (rebased awarded contract sum ÷ floor area)

The model provides a good fit ($F=5.24$, $p<0.025$) and Price Intensity is highly significant ($t=24.80$, $p<0.000$) but has a high standard error of estimate (0.20) and explains only a relatively small part of the overall variation ($r^2=0.068$, adjusted $r^2=0.056$). The small value of the regression coefficient is mostly a reflection of the relatively small values of the Gross Ratio, with a mean value of 1.06 and a range between 0.63 and 2.40 (lower quartile 0.99 upper quartile 1.10), and the large values of the Price Intensity variable, with a mean of 1 279 and a range between 21 and 3 525 (lower quartile 790 upper quartile 1 672). It should also be noted that only 73 cases, out of the full sample 181 cases), were used to build the model observations due to data limitations caused by the absence of a price index for the older cases.

A further regression was run with the Net Ratio as the dependent variable. This resulted in a similar equation but with the percentage explained still rather low at 6%.

Residuals diagnostics

The histogram of the residuals was inspected for any visual indication of abnormalities that might have not been detected by the Kolmogorov-Smirnov test. This indicated a trivially slight peaked distribution. The residuals were also plotted against each of the independent variables as a visual check against the Lagrange Multiplier test and no systematic features were observed to indicate undue heteroscedasticity. The plots did, however, indicate three outliers in excess of ±2.5 standard deviations from the mean. Two of these were demolition contracts and one a refurbishment contract. The possibility that, due to their specialised nature, these contracts may be more difficult to forecast was ruled out on the grounds that no outliers occurred with the other seven demolition contracts and thirteen refurbishment contracts included in the data. An OLS regression was run on the data excluding the three observations identified to establish whether these points were of significant influence on the model. The regression summary of the selected model without outliers (seventy observations) was then compared with that for the full model (seventy three observations). The results showed that both models are significant and that in both cases the Price Intensity variable remains a significant factor in the equation. Generally the 'selected' model is a better fit having a higher adjusted r^2 and smaller standard error. However the ß values of -0.262 and - 0.300 revealed a very small difference in the relative contribution to the prediction of the Gross Ratio. The coefficients were both negative, indicating that the slope of the regression line is consistent in direction. The actual values of the coefficients were -0.000072 for the full model and -0.000041 for the selected model, indicating a minimal influence of these three observations on the regression.

Missing variables

As the model includes only one significant variable, this raises the question of whether a relevant variable has been omitted from the model. In the absence of any alternative theories or immediate prospects of collecting additional data, it was only possible to look for a relevant omitted variable in the available data. Gujarati (1988:404) and Maddala (1992:63) describe statistical techniques but these require the existence of previous theory. Instead, an exhaustive approach was adopted to ensure that no such specification error had occurred. This involved the analysis of a series of models comprising three independent variables - (1) Price Intensity and (2 and 3) all possible paired combinations of the remaining 28 available independent. If Price

Intensity is the only significant variable then no other added variable should be significant of itself. A total of 506 regressions were conducted during this analysis and of those 146 were found to meet the assumptions of regression analysis. Of these 146 analyses, 115 (79%) showed Price Intensity to be the only significant variable in the equation. Of the remaining 31 analyses, the Price Intensity p value was between 0.051 and 0.060 in 25 cases and between 0.060 and 0.070 in 6 cases.

Functional Form

A number of different forms were fitted to the PI model in order to establish whether a better fit may be obtained. The criterion used to judge the best goodness of fit was the adjusted r^2. Apart from the more general functional forms of log, reciprocal, square root etc., polynomial functional forms were fitted to the data using OLS regression. None of the alternative functional forms was able to provide a higher adjusted r^2 than the linear model.

Post sample predictive power

The model was applied to six new cases that became available after the model was constructed. The results in Table 2 show that the predictions were greater than observed values of all the post sample observations. Four of the six observations were also negatively biased, ie. with a Gross Ratio below 1.00. Overall bias in both data sets is positive but the proportion of observations with a negative bias in the within sample data set is 30%. On this basis it is possible that the small number of post sample observations are not entirely representative of the population and may not be facilitating reasonable comparisons.

Theoretical Consistency

The model has a negative slope, with the trend line intersecting the neutral point (Gross Ratio=1.0) approximately two-thirds along the Price Intensity axis (Fig 1). The practical outcome of this is, as predicted by PI theory, that cheap contracts tend to be over-estimated to a greater degree than expensive contracts. This negative trend corresponds with results of previous research in regard to the 'size' variables of Contract Sum and Floor Area (eg. Harvey, 1979; Morrison and Stevens, 1980; Flanagan and Norman, 1983; Morrison, 1984; Skitmore, 1988) which showed that, as the value of the independent variable increased, bias in the price forecast decreased. However, the Price Intensity variable, though correlated, is not a measure of 'size' in itself.

Of more relevance in assessing theoretical consistency would be other findings in relation to the Price Intensity variable. The only instance of this is in Skitmore *et al*'s (1990) experimental work with early stage building price forecasters. Although their research was essentially aimed at identifying the bias-affecting characteristics of forecasters, a few project related variables, including Price Intensity, were also examined. Encouragingly, their analysis also found a significant, negative, regression coefficient for Price Intensity. However, with only a small number of contracts (fifteen) available for analysis, they were reluctant to conclude that this result was anything more than "indicative".

GENERALISATION OF PI THEORY

Compliance with previous findings

The literature review revealed that a considerable number of independent variables had been found, or speculated, to be of significant effect on the building price forecast errors. Gunner and Skitmore (1998) tested the significance on many of these in a series of bivariate analyses conducted on a sample of Singapore data that is "representative of the industry at large" world-wide. The result of this was to show that theirs and all the comparable larger studies in this field are in general agreement with each other. Table 3 lists all the variables involved in terms of both bias and consistency. The analyses described in this paper indicated that, of these, all except three variables (the results of which are inconclusive due to failure to meet the multiple regression assumptions) were confounded with Price Intensity, *ie.* although significant in bivariate analysis, they ceased to be significant once the effects of Price Intensity was removed.

By extension, this finding could equally apply to previous work had those researchers sought out confounding effects with the Price Intensity variable. It has to be concluded therefore that PI theory is not disconfirmed, as the lack of investigation into confounding effects by previous researchers has resulted in no counter evidence being available.

CONCLUSIONS

This paper introduced a new theory of building price forecasting accuracy. Based primarily upon the work of Tversky and Kahneman, this states that low price intense buildings, in terms of contract price per square metre floor area, will tend to be overestimated more than high price intense buildings.

Previous work using bivariate analysis was shown to support the results of this work, where those findings were based upon relatively robust analyses. Tests of the theory did not reveal sufficient evidence for its rejection as, after partialling out the effect of all other independent variables, Price Intensity was the underlying factor associated with systematic bias in building price forecasts. In addition, it was also shown that adjusting for Price Intensity, being homoscedastic, removes any trends associated with changes in the consistency of forecasts.

The results of this work were generalised beyond the source of data for this study to suggest that the PI theory is generally applicable to all pre-bid forecasts. It was also noted that PI theory should also apply equally at any stage of the design development process when building price forecasts are made, from early stage forecasts to those at the pre-bid stage.

ACKNOWLEDGMENTS

The authors gratefully acknowledge the time, help and guidance of Winston Hauw and Lai Meng Seng of Rider Hunt Levett and Bailey, Singapore, and Martin Betts and David Skinner of the University of Salford, UK.

REFERENCES

Beeston, D.T., 1974, *One statistician's view of estimating*, *Cost Study F3*, London: Building Cost Information Service.

Beeston, D.T., 1983, Statistical models for building price data, E&FN Spon, ISBN 0 419 12270 2.

Cheong, P.F., 1991, Accuracy in design stage cost estimating, MSc dissertation: National University of Singapore.

Flanagan, R., 1980, Tender price and time prediction for construction works, PhD thesis, University of Aston in Birmingham.

Flanagan, R., Norman, G., 1983, The accuracy and monitoring of quantity surveyors' price forecasts in building work, *Construction Management and Economics*, **1**(2) 157-80.

Fortune, C., Lees, M., 1996, The relative performance of new and traditional cost models in strategic advice for clients, *RICS Research Paper Series*, **2**(2), The Royal Institution of Chartered Surveyors, 12 Great George Street, London SW1P 3AD, ISBN 0 85406 767 1.

Gujarati, D.N., 1988, *Basic econometrics*, 2nd ed, McGraw Hill.

Gunner, J., Betts, M., 1990, Price forecasting performance by design team consultants in the pacific rim, *Value in Building Economics and Construction Management CIB W-55/65 Symposium Sydney*, 3, 302-12.

Gunner, J., Skitmore, R.M., 1998, Comparative analysis of pre-bid forecasting of building prices based on Singapore data. *Construction Management and Economics* (in press).

Harvey, J.R., 1979, Competitive bidding on Canadian public construction contracts: stochastic analysis for optimisation, PhD thesis, School of Business Administration, University of Western Ontario.

Hogarth, R.M., 1987, *Judgement and Choice*, 2nd ed, Wiley.

Jupp Mansfield & Partners, 1981, Reliability of detailed cost data for estimating during detailed design, (unpublished), Oct.

Lau H.M., 1991, Public sector estimating accuracy, MSc dissertation, National University of Singapore.

Maddala, G.S., 1992, *Introduction to economics*, 2nd ed, Simon and Schuster.

Morrison, N., 1984, The accuracy of quantity surveyors' cost estimating, *Construction Management and Economics*, **2**(1) 57-75.

Morrison, N., Stevens, S., 1980, *Construction cost data base*, 2nd annual report of research project by Department of Construction Management, University of Reading, for Property Services Agency, Directorate of Quantity Surveying Services, DOE.

Ogunlana, S., Thorpe, A., 1991, Factors affecting the accuracy of cost estimates: developing correct associations, *Building and Environment*, **26**(2) 77-86.

Raftery, J., 1996, Quasi-rational behaviour in the property and construction market, *Proceedings*, 7th Int Symp, The International Council for Building Research Studies and Documentation CIB W-55, 4-7 Sep, M Katavic (ed), Faculty of Civil Engineering, University of Zagreb, Kaciceva, Croatia, ISBN 953 96245 2 5, 469-85.

Skitmore, R.M., 1985, *The influence of professional expertise in construction price forecasts*, Salford: The University of Salford, ISBN 0 901025 09 7.

Skitmore, R.M., 1988, Factors affecting accuracy of engineers Estimates, *Cost Engineering*, **30**(10), 16-23.

Skitmore, R.M., Stradling, S.G., Tuohy, A.P., Mkwezalamba, H., 1990, *The accuracy of construction price forecasts: a study of quantity surveyors' performance in early stage estimating*, Salford: The University of Salford, ISBN 0 901025 12 7.

Thng, 1989, Estimating accuracy at public sector - housing development board, MSc dissertation, National University of Singapore.

Tversky, A., Kahneman, D., 1982, Judgement under uncertainty: heuristics and biases, in *Judgement under Uncertainty: Heuristics and Biases*, D Kahneman, P Slovic and A Tversky (eds), Cambridge University Press, 3-20.

Wilson, O.D., Sharpe, K., Kenley, R., 1987, Estimates given and tenders received, *Construction Management and Economics* **5**(3).

CAPTIONS:

Table 1: Summary of results of analyses

Table 2: Post sample predictive power

Table 3: Summary of significant variables and confounding effects

Fig 1: Price Intensity and Gross Ratio

Table 1 Summary of results of analyses

	Variables	*ß*	*t*	*P*	Assumptions
1	PI	-0.274	-2.368	0.021	Yes
	Sector	-0.097	-0.841	0.403	
2	PI	-0.262	-2.271	0.026	Yes
	Procurement Basis	0.042	0.367	0.715	
3	PI	-0.262	-2.272	0.026	Yes
	Contract Conditions	0.001	0.010	0.992	
4	PI	-0.276	-2.379	0.020	Yes
	Commercially Negotiated	-0.095	-0.820	0.415	
5	PI	-0.258	-2.229	0.029	Yes
	Tender Price Index %	0.044	0.378	0.707	
6	PI	-0.262	-2.275	0.026	Yes
	Fluctuations Paid	-0.021	-0.183	0.855	
7	PI	-0.261	-2.084	0.041	Yes
	Local Architect	-0.003	-0.025	0.980	
8	PI	-0.248	-1.565	0.050	Yes
	Local Contractor	-0.043	-0.337	0.737	
9	PI	-0.261	-2.161	0.034	Yes
	Number of Bidders	0.016	0.133	0.895	
10	PI	-0.260	-2.250	0.027	Yes
	Floor Area	-0.025	-0.218	0.828	
11	PI	-0.254	-2.043	0.045	Yes
	Storeys Above Ground	-0.027	-0.218	0.828	
12	PI	-0.263	-2.286	0.025	Yes
	Number of Drawings	-0.055	-0.479	0.633	
13	PI	-0.263	-2.279	0.026	Yes
	Number of Priced Items	-0.021	-0.181	0.857	
14	PI	-0.321	-2.216	0.032	Yes
	Number of Prior Forecasts	-0.216	-1.490	0.144	
15	PI	-0.265	-2.108	0.039	Yes
	Contract Sum	0.007	0.059	0.953	
16	PI	-0.266	-2.312	0.024	Yes
	Price Forecaster	0.077	0.675	0.502	
17	PI	-0.253	-2.212	0.030	No (χ^2=4.088)
	Contract Work Type	0.133	1.162	0.249	
18	PI	-0.256	-2.270	0.026	No (χ^2= 5.110)
	Builder's Experience	0.208	1.846	0.069	
19	PI	-0.285	-2.229	0.029	No (χ^2= 4.526)
	Market Conditions	0 129	1.108	0.272	
20	PI	-0.277	-2.300	0.024	No (χ^2= 3.869)
	Good/Bad Years	0.051	0.424	0.673	
21	PI	-0.274	-2.367	0.021	No (χ^2= 3.869)
	Residential/Others	0.094	0.809	0.421	
22	PI	-0.298	-2.464	0.016	No (χ^2= 4.161)
	Commercial/Others	-0.113	-0.032	0.354	
23	PI	-0.223	-1.829	0.072	No (χ^2= 3.976)
	Contract Period	-0.132	-1.078	0.285	
24	PI	-0.292	-2.661	0.010	No (χ^2=12.264)
	Preliminaries %	0.312	2.848	0.006	

Table 2 Post sample predictive power

	Value ($/m^2)	Observed	Predicted
1	699	I .07	1.10
2	941	0.78	1.08
3	966	1.04	1.08
4	978	0.88	1.08
5	1124	0.93	1.07
6	1688	0.96	1.03
Mean	1194	1.02	1.07

Table 3. Summary of significant variable and confounding effects

	Independent variable	Bias	Consistency	Confounding variable
1	Commercially Negotiated	x	√	Yes
2	Contract Conditions	√	x	Yes
3	Contract Period	√	√	–
4	Contract Sum	√	√	Yes
5	Contract Work Type	√	√	–
6	Floor Area	x	√	Yes
7	Fluctuations	x	√	Yes
8	Good/Bad Years	x	√	Yes
9	Locality of Architect	√	x	Yes
10	Locality of Contractor	x	√	Yes
11	Market Conditions Index	x	√	Yes
12	Number of Bidders	√	x	Yes
13	Number of Priced Items	x	√	Yes
14	Number of Prior Forecasts	√	√	Yes
15	Preliminaries %	x	√	–
16	Price Forecaster	x	√	Yes
17	Procurement Basis	√	√	Yes
18	Sector	x	√	Yes
	Price Intensity	√	x	Not applicable

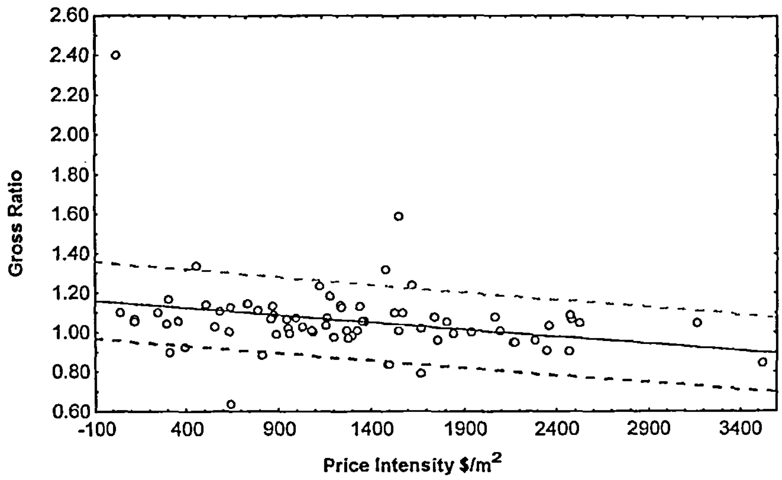

Figure 1 Price Intensity (PI) and Gross Ratio.