Identifying non-competitive bids in construction contract auctions

Skitmore, Martin

Published in:
Omega

DOI:
10.1016/S0305-0483(02)00057-9

IDENTIFYING NON-COMPETITIVE BIDS IN CONSTRUCTION CONTRACT AUCTIONS

Martin Skitmore
School of Construction Management and Property
Queensland University of Technology
Gardens Point
Brisbane Q4001
Australia

11 October 2001 (version 2)

IDENTIFYING NON-COMPETITIVE BIDS IN CONSTRUCTION CONTRACT AUCTIONS

Abstract: Construction contract auctions are characterised by (1) anticipated high outliers due to the presence of non-competitive bids, (2) very small samples and (3) uncertainty of the appropriate underlying density function model of the bids. This paper describes the simultaneous identification of high outliers and density function by systematically identifying and removing candidate (high) outliers and examining the composite goodness-of-fit of the resulting reduced samples with the normal and lognormal density functions. Six different identification strategies are tested empirically by application, both independently and in pooled form, to several sets of auction data gathered from around the world. The results indicate the normal density to be the most appropriate model and a multiple of the auction standard deviation to be the best identification strategy.

Keywords: Construction, contract, auctions, non-competitive bids, outliers, goodness-of-fit, small samples.

INTRODUCTION

The overwhelming majority of contracts for construction work are let by sealed-bid auctions, in which the criterion for award is the lowest bid (Merna and Smith, 1990). Increasingly, the participants (tenderers) of construction contract auctions, are chosen by the auctioneer (client, owner, principal, consultant) in advance of the auction. This is in order to restrict those tendering bids to the ones favoured by the auctioneer because of their known or conjectured ability to perform the work satisfactorily, as well as minimising the abortive tendering costs of those not so favoured. Preselection of tenderers in this way is fine when all the tenderers are keen to obtain the work and tender competitive bids. However, there are a variety of reasons why tenderers may prefer not to bid for a particular contract. These include full order books, the strength of the competition, low projected profit levels, cost of bidding and short period allowed for bid preparation. Rather than abstain in such situations, invited tenderers often bid anyway in order to stay in favour with the auctioneer by appearing to be interested in obtaining the contract. By their very nature, such bids are not intended to be competitive. They must also be inexpensive to produce and, to achieve their purpose, be undetectable by the auctioneer.

One means of achieving this is through what is known as ‘cover’ pricing, by which a competitor’s *bona fide* bid is used with the addition of a few percent to ensure non-competitiveness. Another possible means of non-competitive bidding is for tenderers to give detailed attention to desirable contracts only, the remaining bids being prepared in a more approximate manner with a risk allowance to cover unforeseen circumstances and for the less accurate method of estimating. Whichever method is used, the result is likely to be a suboptimal competition for the auctioneer, whose ignorance of the non-competitive nature of the bid precludes the possibility of selecting a replacement tenderer. It is clearly in the auctioneer’s interest, therefore, to be able to identify non-competitive bids for remedial action to be instigated.

None of the major international procurement agencies use formal methods for this identification process. Some arbitrary criteria are used by the local agencies, the Hong Kong Government, for example, deem all bids greater than 25% of the lowest bid to be non-competitive, with the guilty tenderers being rendered ineligible for future auctions.

The presence of non-competitive bids is also a complicating factor in competitor analysis and strategic bidding, where statistical models of bids are required. Here the task is to remove the non-competitive bids before modelling. The methods used by researchers to do this have been inconsistent and largely arbitrary. Some make adjustments intuitively (Pim, 1974; Southwell, 1971) while many make no adjustment at all (eg, Friedman, 1956; Gates, 1967; Johnston, 1978; Carr, 1982; Skitmore and Pemberton, 1994). Of the few objective methods used Franks (1970) simply excludes the upper 20 percent of bids; Morrison and Stevens (1980) exclude the highest two bids for each auction; and Whittaker's (1970) excludes all bids exceeding six times the average bid. The most sophisticated approach to date is by McCaffer (1976) in which outliers are identified, in the form of unexpectedly long tails, as a result of applying the Anderson-Darling test for distribution shape.

In short then, the analysts of the distribution of construction contract auction bids fall into two camps – those who prefer non-competitive bids to be included in their models and those who wish to exclude them from their models, by far the larger of which is the former group. What is undisputed is that non-competitive bids **DO** regularly occur. The cause of the differences between the two groups is, of course, not so much one of philosophy, but of the practical difficulties involved. Non-competitive bids are, by their very nature, designed to look competitive (to avoid detection by the auctioneer) even though they are not. The lack of objective tests to judge the performance of detection methods (data identifying which bids are **ACTUALLY** deliberately non-competitive is extremely scarce due to the associated legal and ethical issues involved).

To overcome these difficulties, the approach taken in this paper was to start with the assumption that there is an unknown underlying probability distribution from which competitive bids are drawn and that this will be revealed once the non-competitive bids are removed. For a single auction, this is simply a matter of successively removing the highest bids and applying a goodness-of-fit test to the remainder. Where there are many such auctions, a more powerful method is to apply a single composite goodness-of-fit test to the auction set. However, as the auctions are not homogeneous, this means that some strategy has to be devised for identifying candidate bid removals. Here, six such strategies are examined and tested empirically by application, both independently and in pooled form, to several sets of auction data gathered from around the world. The results indicate the normal density to be the most robust model and a multiple of the auction standard deviation to be the best identification strategy.

ANALYSIS AND IDENTIFICATION OF HIGH OUTLIERS

Density function

The textbook description of the compilation of competitive bids is that of the summation of the product of unit quantity and unit cost components followed by the application of a strategic mark-up multiplier in the form of a percentage addition. Researchers have sometimes treated the unit cost component as normally distributed (eg, Ranasinghe, 1994) but with little regard to the statistical nature of the unit quantities and mark-up values. Most commonly, the total bid price for each tenderer has been treated as a random variable from some well-known density function. Typically, these are the uniform (eg, Cauwelaert and Heynig, 1978; Fine and Hackemar, 1970; Grinyer and Whittaker, 1973; Whittaker, 1970), normal (Cauwelaert and Heynig, 1978; McCaffer, 1976; Mitchell, 1977; Morrison and Stevens, 1980; Skitmore 1986), lognormal (Brown, 1966; Klein, 1976; Skitmore, 1986; Weverbergh, 1982), weibull (Oren and Rothkopf, 1975) or just "positively skewed" (Beeston, 1974; McCaffer and Pettitt, 1976; Park, 1966). Often, the assumption of *iid* is made for each tenderer.

For construction contract auctions, the non-competitive bids are essentially contaminant observations as they are invariably produced by a different mechanism to that of competitive bids.

Outlier identification strategies

The arbitrary strategies described above reduce to special cases from four types of general strategies. These, together with two others considered to be appropriate, provided the six strategies to be tested. That is: (1) highest k bids, (2) highest n-m bids (where n is the number of bids in the auction), (3) bids higher than the average bid plus x_3 times the standard deviation, (4) bids x_4 times higher than the mean bid, (5) bids higher than x_5 times the lowest bid, and (6) the highest x_6% bids.

As far as the general statistical literature is concerned, Tietjen and Moore (1972) have produced a table of critical values for testing the hypothesis that there are up to k high outliers present in a normal sample. The test is, however, based on the assumption that k is known. The above general strategies were therefore used to decide the value of k for each auction and thence to apply Tietjen and Moore's (T&M) method to decide whether the k values are to be regarded as normal distribution outliers or not.

Goodness-of-fit tests

A battery of five composite goodness-of-fit statistics were applied, comprising the skewness (S), kurtosis (K), Geary's 'a' (G), studentised range (S-R) and Anderson-Darling's A^2 (A-D) statistics. Following McCaffer and Pettitt's (1976) analysis of similar data, the value of the statistics for each auction was calculated and its frequency distribution tested against the known distribution for the statistic for normal samples. This was done by counting the number of times the statistic fell into its probability deciles and using the chi-square test for uniformity of decile counts (after Skitmore, 1991). The small sample (n<25) S and A-D statistic decile points were obtained from those tabulated by Skitmore and Thomas (1993) and Pettitt (1975) respectively. The K, G and S-R decile points were generated by Monte Carlo simulation of 30,000 observations for each sample size (n=3(1)25). As is usual in goodness-of-fit tests in general, the term significance is used to denote that an observation is, or set of observations are, likely to be as assumed. Hence, by significance is meant that the probability of the assumption being correct is greater than 0.05.

Datasets

Table 1 summarises the eight datasets analysed. Each of the datasets 1-6 comprise the values of all the bids entered for each contract auction, standardised to the first quarter 1980 sterling equivalent by the relevant price indexes and exchange rate series'. Datasets 7-8 comprise the raw, unstandardised, values. Tests were carried out on the individual and pooled datasets by means of specially written Fortran programs. The result of the individual dataset producing the worst result (termed here as the 'worst-case' result) was recorded together with the results for the pooled set.

Data set	Source	Type	Period	No of auctions	Average no. bidders	Average low-bid	Average Std Devn	Average cv
1	Skitmore (1986)	London building contracts	1981-2	51	6.24	1.58m	82k	5.52
2	Skitmore (1986)	London building contracts	1976-7	373	5.13	0.81m	47k	6.35
3	Brown (1986)	USA Govt agency building contracts	1976-84	64	6.73	1.41m	122k	19.14
4	Runeson (1987)	Australian PWD contracts	1972-82	152	8.66	1.51m	103k	6.98
5	Runeson (1987)	Australian PWD specialist contracts	1972-82	161	6.27	0.21m	29k	16.21
6	Skitmore (1981)	UK building contracts	1969-78	272	6.14	0.81m	48k	6.03
7	Skitmore (1986)	North England PWD building contracts	1979-82	218	5.67	0.14m	11k	11.99
8	Shaffer & Micheau (1971)	USA building contracts	1965-9	50	4.70	0.91m	67k	7.30
All				*1341*	*6.06*	*0.77m*	*51k*	*9.07*

Table 1: Data sets

RESULTS

Tables 2 and 3 summarise the results of the tests based on the lognormal and normal models respectively. These show the cut-off values for each of the six methods, for both unadjusted (u) and Tietjen and Moore's (T&M) adjustment, together with the number of outliers identified and removed (shown in parenthesis) for each of the five goodness-of-fit tests and recording both the worst case (w) results and the results of pooling the data (p). For example, Table 2 shows the skewness (S) test on highest k bids removed for each auction (method 1) to be best satisfied at k=3, Tietjen and Moore (T&M) adjusted, for the pooled (p) datasets – this resulting in a total of 307 bids removed. For both the unadjusted and T&M adjusted versions of method 1, however, no value of k satisfied the S test for all the individual datasets (w). Similarly, the unadjusted version of method 1 produced no value of k that would satisfy the S test for the pooled datasets. Table 2 also shows that G(w) and S-R tests were satisfied entirely by the original data, ie., no outliers at all were identified. The same S-R result also occurred for the tests based on the normal model (Table 3).

Discussion

The cut-off values shown in Table 2 and 3 are the values that produce the minimum number of removed bids commensurate with satisfying the goodness-of-fit test (at the conventional 5% level). This is for the obvious reason that any number of bids removed above the minimum number cannot qualify as outliers by definition as their retention would not have caused the goodness-of-fit test to fail. By similar reasoning, the relative power of the tests can be judged for each method, with the test that is the hardest to satisfy being the most powerful. Thus for method

1 based on the lognormal model (Table 2) the S test is clearly the most powerful for the unadjusted (u) data, for both the pooled and worst-case results, as it is the only test to have failed with all values of *k*. For the method 1 T&M results, all the tests on the pooled datasets are satisfied, in which case the test producing the largest number of outliers, ie., the S test, is the most powerful. For the worst-case method 1 T&M results, the S, K and A-D tests all fail at all values of *k* and are therefore indistinguishable in terms of power. On this basis, then, it is possible to summarise the results of the relatively most powerful (RMP) tests. These are shown in Table 4. Here, the first point of interest is that none of the six methods can produce a cut-off value, in either unadjusted or T&M adjusted form, to satisfy the RMP lognormal tests for all the individual datasets. That some of the pooled data lognormal RMP tests are satisfied suggests that there is some degree of heterogeneity between the datasets, which suggests that pooling is not likely to be appropriate with these data. The results of the normal RMP tests, however, are somewhat different in that all the T&M adjusted results fail. Thus, a process of elimination leaves us left with the unadjusted normal RMP tests. The successful of these are methods 2-6 for the pooled datasets and method 2,3 5 and 6 for the worst-case results. Now we are in a position to decide which is the best **method** for that will be the one that produces the **least** number of outliers as the method producing the least number of outliers is clearly the most efficient in their detection. For both the pooled dataset and worst-case results, this is method 3, with 419 and 558 outliers respectively. Referring to Table 3, the cut-off values for these results are x_3=1.58 and 1.47 for the S and G test respectively.

			Method					
			1	2	3	4	5	6
lognormal	u	p	-	-	S(146)	A-D(329)	A-D(782)	-
		w	-	-	-	-	-	-
	T&M	p	S(307)	-	S(244)	-	S(225)	S(335)
		w	-	-	-	-	-	-
normal	u	p	-	A-D(4184)	**S(419)**	S(486)	A-D(1097)	S(1288)
		w	-	S(2069)	**G(558)**	-	G(2204)	S(3946)
	T&M	p	-	-	-	-	-	-
		w	-	-	-	-	-	-

Table 4: Summary of relatively most powerful tests

CONCLUSIONS

The purpose of the analysis and identification of construction contract auction outliers is essentially to provide better, or at least alternative, models for the identification of non-competitive bids and bidders. This is to possibly minimise their frequency, improve auctioneers and tenderers analysis and prediction of competitive behaviour, and analysis and prediction of changing distribution parameters[1]. Once identified, the aim is therefore to omit the outliers and treat the reduced sample either as a new or censored sample.

The nature of construction contract auctions is such that high outliers are anticipated on most occasions and their identification and accommodation is of both theoretical and practical interest. The absence of any theory that predicts the true underlying density function precludes any simple treatment – the type of function being an empirical issue in its own right. In addition, that there are small sample sizes involved means the analysis has to be concerned with behaviour of multiple, rather than single, samples. The approach adopted, therefore, was to attempt to simultaneously identify outliers and function type by first removing candidate (high) outliers and then examining the goodness-of-fit of the resulting reduced samples. Furthermore, with multiple small size auctions, it is necessary for the proposition of candidate outliers to be made strategically by formulae, as visual inspection of many auctions is literally impossible. Four of these strategies were found in the domain literature, with two obvious extra alternatives added.

Applying a battery of tests to eight sets of construction contract auction data gathered from around the world, results were obtained for both lognormal and normal distributions, unadjusted and T&M adjusted, and pooled and unpooled data. The relatively most powerful tests were then identified, which led to the rejection of the lognormal model and acceptance of the normal model with method 3 being the most efficient outlier identification method with cut-off values of x_3=1.58 and 1.47 for the pooled and worst-case results respectively. In order words, construction contract auctioneers are advised to treat bids over 1.47 times the standard deviation above the mean value of the bids as being non-competitive.

Whilst there is universal acceptance that construction contract auction data is positively skewed, there is equal acceptance of the regular occurrence of non-competitive bids in the form of high outliers. Nowhere has it been suggested that, once the high outliers are removed, the remaining data will continue to be skewed in this way. The results of the empirical analyses described here supports the view that the distributions are intrinsically normal, with the addition of non-competitive bids in the form of high outliers being responsible for the subsequent positively skewed appearance. This being the case, it is easy enough to construct a theoretical supporting argument on the grounds that, as none of the bidders can be sure of the market price of the contract under auction, the bids they enter are homogeneously genuine unbiased estimates of that market price and therefore, collectively, normally distributed.

ACKNOWLEDGEMENTS

The author is indebted to Prof Tony Pettitt for guidance in locating background reading on outlier tests, and the Universities of Auckland, Hong Kong Polytechnic and Lae New Guinea for the provision of study facilities to carry out the early stages of the work. Thanks also go to Goran Runeson and Joseph Brown for the provision of data.

[1] Particularly in response to market conditions (after Johnston, 1978; Skitmore, 1981; Rowlinson and Raftery, 1997) and construction contract characteristics (after Skitmore, 1981).

REFERENCES

Beeston, D.T., 1974, One statistician's view of estimating, Cost Study No 3, Royal Institution of Chartered Surveyors Building Cost Information Service.

Brown, J.A., 1986, Personal communication.

Brown, K.C., 1966 A theoretical and statistical study of decision making under uncertainty - a competitive bidding for leases of offshore petroleum tracts, PhD dissertation, Southern Methodist University, Dallas.

Carr, R.I., 1982, General bidding model, *Journal of the Construction Division, Proceedings of the American Society of Civil Engineers*, **108** (CO4), 639-50.

Cauwelaert F V, Heynig E 1978 Correction of bidding errors; the Belgian solution, *Journal of the Construction Division*, American Society of Civil Engineers **105**(CO1): 13-23.

Fine, B., Hackemar, G., 1970, Estimating and bidding strategy, *Building Technology and Management* Sep: 8-9

Franks, J., 1970, An exercise in cost (price?) estimating, *Building*, 12 Jun 133-4.

Friedman, L, 1956, A competitive bidding strategy, *Operations Research* **1**(4): 104-12.

Gates, M., 1967, Bidding strategies and probabilities, *Journal of the Construction Division, Proceedings of the American Society of Civil Engineers*, **93** (CO1), 75-107.

Grinyer, P.H., Whittaker, J.D., 1973, Managerial judgement in a competitive bidding model, *Operational Research Quarterly* **24**(2): 181-191

Johnston, R.H., 1978, Optimisation of the selective competitive tendering system by the construction client, Transport and Road Laboratory Report 855 DOG, UK.

Klein, J.D., 1976, Joint ventures and bidding for offshore oil, in Amihud Y (ed), *Bidding and auctioning for procurement and allocation*, New York University Press.

McCaffer, R., 1976, Contractor's bidding behaviour and tender price prediction, PhD thesis, Loughborough University of Technology.

McCaffer, R., Pettitt, A.N., 1976, Distribution of bids for buildings and roads contracts, *Operational Research Quarterly*, **27**(4i) 835-43.

Merna, A., Smith, N.J., Bid evaluation for UK public sector construction contracts, *Proc Inst Civ Engrs* Pt **1** Feb 91-105.

Mitchell, M.S., 1977, The probability of being the lowest bidder, *Applied Statistics* **2**(2): 191-94.

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

Oren, S. S., Rothkopf, M.H., 1975, Optimal bidding in sequential auctions, *Operations Research* **23**(6)

Park, W.R., 1966, *The strategy of contracting for a profit*, Prentice-Hall.

Pettitt, A.N., 1975, Small sample percentage points of the Anderson-Darling statistic for testing normality. Math Res no 71 Dept of Mathematics, Loughborough University of Technology.

Pim, J.C., 1974, Competitive tendering and bidding strategy, *National Builder*, **55** (11) pp. 541-545, **56** (2) pp. 56-57, **56** (10) pp.361-365, **57** (3) pp. 68-70.

Ranasinghe, 1994, Quantification and management of uncertainty in activity duration networks, *Construction Management and Economics* **12**(1) 15-29.

Rowlinson, S., Raftery, J., 1997, Price stability and the business cycle: UK construction bidding patterns 1970-91, *Construction Management and Economics* **15** 5-18.

Runeson, K G (1987) Analysis of building price estimates, MSc thesis, School of Building, University of New South Wales.

Shaffer, L.R., Micheau, T.W., 1971, Bidding with competitive strategy models. Journal of the Construction Division, Proceedings of the American Society of Civil Engineers 97(CO1) Jul 113-26.

Skitmore, R.M., 1981, Bidding dispersion - an investigation into a method of measuring the accuracy of building cost estimates, MSc thesis, University of Salford.

Skitmore, R.M., 1986, A model for the construction project selection and bidding decision, PhD. thesis, Department of Civil Engineering, University of Salford.

Skitmore, R.M., 1991, The contract bidder homogeneity assumption: an empirical analysis, *Construction Management and Economics* **9**(5) 403-29.

Skitmore, R.M., Pemberton, J., 1994, A multivariate approach to contract bidding mark-up strategies, *J Opl Res Soc*, **45**(11) 1263-72.

Skitmore, R.M., Thomas, R., 1993, Percentage points of $\sqrt{b_1}$ for small normal samples, The University of Salford, ISBN 0 9519060 5 42.

Southwell, J., 1971, Building cost forecasting, selected papers on the systematic approach to forecasting building costs, presented to the Quantity Surveyors (Research and Information) Committee, Royal Institution of Chartered Surveyors. London.

Tietjen, G.L., Moore, R.H., 1972, Some Grubbs-type statistics for the detection of several outliers, *Technometrics* **14** 583-97.

Weverbergh, M., 1982, Competitive bidding: estimating the joint distribution of bids, Working paper 82-79, Dec, Centrum voor Bedrijfseconomie en Bedrijfseconometrie Universiteit Antwerpen - USFIA.

Whittaker, J.D., 1970, A study of competitive bidding with particular reference to the construction industry, PhD thesis, City University, London.

Test			Method 1 (k) u	1 (k) T&M	2 (m) u	2 (m) T&M	3 (x_3) u	3 (x_3) T&M	4 (x_4) u	4 (x_4) T&M	5 (x_5) u	5 (x_5) T&M	6 (x_6) u	6 (x_6) T&M
Test	S	p	-	**3(307)**	7(819)	-	**1.91(146)**	**0.51(244)**	1.191(261)	-	1.320(626)	**1.128(225)**	-	**67(335)**
		w	-	-	7(819)	-	-	-	-	-	-	-	-	-
	K	p	1(977)	1(103)	11(182)	10(74)	2.69(14)	2.69(14)	1.590(26)	1.590(16)	1.886(86)	1.886(21)	1(991)	1(103)
		w	4(2534)	-	-	-	0.95(1191)	-	1.080(857)	-	1.155(149)	-	14(1264)	-
	G	p	1(1138)	1(115)	16(23)	11(50)	2.46(23)	2.82(9)	1.594(25)	1.570(18)	2.097(54)	1.854(27)	1(1154)	1(115)
		w	0(0)	0(0)	21(0)	21(0)	All(0)	All(0)	All(0)	All(0)	All(0)	All(0)	All(0)	All(0)
	S-R	p	0(0)	0(0)	21(0)	21(0)	All(0)	All(0)	All(0)	All(0)	All(0)	All(0)	All(0)	All(0)
		w	0(0)	0(0)	21(0)	21(0)	All(0)	All(0)	All(0)	All(0)	All(0)	All(0)	All(0)	All(0)
	A-D	p	5(3662)	1(115)	3(4184)	6(197)	2.17(65)	2.17(42)	**1.166(329)**	1.250(58)	**1.275(782)**	1.382(83)	16(1558)	1(115)
		w	1(1138)	1(115)	6(1298)	13(26)	2.82(9)	2.82(9)	1.014(2654)	1.286(43)	1.394(439)	1.459(65)	51(2865)	1(115)

Table 2: Lognormal model

			Method											
			1 (k)		2 (m)		3 (x_3)		4 (x_4)		5 (x_5)		6 (x_6)	
			u	T&M	u	T&M	u	T&M	u	T&M	u	T&M	u	T&M
Test	S	p	-	-	5(2069)	-	1.58(419)	-	**1.127(486)**	-	1.244(940)	-	**6(1288)**	-
		w	-	-	**5(2069)**	-	1.68(309)	0.45(346)	-	-	1.188(1360)	-	**80(3946)**	-
	K	p	1(977)	1(140)	5(2069)	7(205)	2.19(60)	2.20(47)	1.313(104)	1.321(59)	1.324(516)	1.421(99)	1(991)	1(140)
		w	1(977)	-	**5(2069)**	-	1.62(381)	-	1.168(293)	-	1.304(568)	-	1(991)	-
	G	p	1(1138)	1(155)	11(182)	10(95)	2.46(23)	2.46(23)	1.542(35)	1.462(31)	1.806(112)	1.641(66)	1(1154)	1(155)
		w	1(1138)	2(313)	8(819)	-	**1.47(558)**	1.26(203)	1.138(425)	1.075(264)	**1.122(2204)**	1.112(346)	1(1154)	20(228)
	S-R	p	0(0)	0(0)	21(0)	20(0)	All(0)	All(0)	All(0)	All(0)	All(0)	All(0)	0(0)	0(0)
		w	0(0)	0(0)	21(0)	20(0)	All(0)	All(0)	All(0)	All(0)	All(0)	All(0)	0(0)	0(0)
	A-D	p	4(3365)	1(155)	**3(4184)**	5(333)	**1.90(149)**	1.88(106)	1.160(345)	1.189(114)	**1.219(1097)**	1.275(176)	5(1260)	1(155)
		w	3(2886)	2(313)	6(1298)	5(333)	1.59(409)	1.17(213)	1.098(752)	1.039(339)	1.301(683)	1.104(350)	7(1309)	15(200)

Table 3: Normal model