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ANALYSIS OF THE DISTRIBUTION OF THE NUMBER OF BIDDERS IN CONSTRUCTION CONTRACT AUCTIONS

Authors:

Ballesteros-Pérez, Pablo ^a ; González-Cruz, M^a Carmen ^b ...;
Fuentes-Bargues, Jose Luis ^c ; Martin Skitmore ^d

^a Assistant Professor of Construction Engineering and Management

Dpto. de Ingeniería y Gestión de la Construcción

Facultad de Ingeniería. Universidad de Talca

Camino los Niches, km 1. Curicó (Chile)

Email: pballesteros@utalca.cl; pablo.ballesteros.perez@gmail.com

Phone: (+56) 75 201733 Fax: (+56) 75 325958

Corresponding author

^b Associate Professor in Departamento de Proyectos de Ingeniería.

Escuela Técnica Superior de Ingenieros Industriales. Universitat Politècnica de València.

Camino de Vera s/n, 46022 Valencia, Spain

PhD. Industrial Engineering.

Phone: +34 963 879 866 (ext.:75654) Fax: +34 963 879 869 (ext.:79869).

E-mail: megonzal@dpi.upv.es

^c Lecturer in Departamento de Proyectos de Ingeniería.

Escuela Técnica Superior de Ingenieros Industriales. Universitat Politècnica de València.

Camino de Vera s/n, 46022 Valencia, Spain

PhD. Industrial Engineering.

Phone: +34 963 877 000 (ext.:85651) Fax: +34 963 879 869 (ext.:79869).

E-mail: jofuebar@dpi.upv.es

^d Professor of Construction Economics and Management

Room S711

School of Civil Engineering and the Built Environment

Queensland University of Technology

Gardens Point. Brisbane Q4001 Australia

Tel: +61 7 31381059 (w); +61 7 38933170 (A/H); 0450673028 (mob)

Email: rm.skitmore@qut.edu.au

<http://staff.qut.edu.au/staff/skitmore/>

Analysis of the distribution of the number of bidders in construction contract auctions

Abstract

The number of bidders, N , involved in a construction procurement auction is known to have an important effect on the value of the lowest bid and the mark up applied by bidders. In practice, for example, it is important for a bidder to have a good estimate of N when bidding for a current contract. One approach, instigated by Friedman in 1956, is to make such an estimate by statistical analysis and modelling. Since then, however, finding a suitable model for N has been an enduring problem for researchers and, despite intensive research activity in the subsequent thirty years little progress has been made - due principally to the absence of new ideas and perspectives. This paper resumes the debate by checking old assumptions, providing new evidence relating to concomitant variables and proposing a new model. In doing this and in order to assure universality, a novel approach is developed and tested by using a unique set of twelve construction tender databases from four continents. This shows the new model provides a significant advancement on previous versions. Several new research questions are also posed and other approaches identified for future study.

Keywords: *Modelling; Forecasting; Bidding; Tendering; International comparison, number of bidders.*

Introduction

An important consideration for bidders when preparing a serious construction tender proposal is the likely number and identity of the opponents to be faced. Studies of construction companies in the U.S. ([Ahmad & Minkarah, 1988](#)) and the UK ([Shash, 1993](#)), for example, have found this to be one of the three most important factors that conditions most bidding decisions. Clearly, any relevant information will be useful when making the decision to bid (d2b) and in strategically setting the bid price to increase the probability of winning the contract and making sufficient profit.

There is also strong evidence that some tender results, or at least their probability of occurring, have systematic differences depending on the number of bidders (N) involved. For example, high values of N tend to increase the correlation between the mean bid and the high and low bids in collective bid tender forecasting models ([Ballesteros-Pérez et al., 2012](#); [Shrestha & Pradhananga, 2010](#); [Skitmore, 1981b](#)) and the effect of the *winner's curse* ([Capen et al., 1971](#), [Skitmore, 2002](#)). N has also recently been shown to be proportional to the amplitude of the bid standard deviation ([Ballesteros-Pérez et al., 2015b](#)). Moreover, N plays an important role in combinatorial auctions, with high N increasing computational complexity when trying to find the best combination of winners ([Fukuta & Ito, 2007](#); [Sandholm, 2000](#)).

The traditional approach to anticipating N in practice is through personal experience of the past participation rate of bidders mostly in terms of project characteristics (e.g., owner, type and size) and nearby location ([Ballesteros-Pérez, et al., 2010](#); [Fu, 2004](#)). Attempts to forecast N more systematically by mathematic models have met with little success. The most popular of these have been to resort to a probabilistic approach by treating N as a statistical variable. [Friedman \(1956\)](#), for example, suggested that N might follow a Poisson distribution. To a lesser extent, similar approaches have been tried in forecasting the identity of bidders, or a group

of specific key competitors that might enter a future tender, but with even less success (Skitmore, 1986).

The debates in the early years became very intense at times, with studies proving and refuting different properties seemingly exhibited by N in specific contexts, countries or just according to the nature of the work involved. By the late 1980s, however, the controversies just stopped without a resolution as researchers gradually ran out of ideas and enthusiasm.

The purpose here is to revive this work by revisiting the major achievements made during the period 1956-1986, along with some untested later ideas and propose a new, improved, model to describe the statistical distribution of N . In doing this, a complete and varied set of twelve construction tender databases from around the world is analysed for the purpose of generalisation. The result is a critical view of past research while stimulating again a productive discussion on a subject that, as previously acknowledged, is of considerable importance from both owner and bidders' standpoint and strongly linked to other tender outcomes.

The paper is structured as follows. In the next section, a thorough but summarised literature review is provided. This is followed in *Materials and Methods* by an outline of the main features and countries of origin of the twelve databases and the subsequent research methodology. Next, the *Calculations* section tests the suitability of a variety of general statistical distributions for modelling N , the effect of contract size and the development of a composite two-distribution model for N . The *Results* section then provides a final comparison of the models, confirming the superiority of the new composite model. The *Discussion* and *Conclusions* sections summarise the work, posing several new research questions and identifying other paths for future study. The American term “(procurement or reverse) auction” and European “tender” are treated here as synonymous.

Literature review

There have been several thorough reviews of the effect of N on auction results (e.g., [Dyer et al., 1989](#); [Levin and Ozdenoren, 2004](#); [Hu, 2011](#)) and these will not be recounted here. Instead, we are concerned with the statistical nature of N as a precursor to its potential prediction. It is well known in both practice and theory that N generally varies with the project type and size (e.g., [Azman, 2014](#); [Drew and Skitmore, 2006](#)), client and specific location ([Al-Arjani, 2002](#); [Benjamin, 1969](#)) and even with market conditions ([Ngai et al., 2002](#); [Skitmore, 1981a](#)).

Forecasting its value in advance, however, is more problematic, the earliest treatment being [Friedman \(1956\)](#), who suggested a variety of methods for estimating its expected value. One way is to use the often little information available about a company's competitors' intentions in combination with its managers' experience - an approach reiterated by [Rubey and Milner \(1966\)](#) with especial emphasis on the contract type and size involved.

Another suggestion is to exploit the statistical relationship between N and contract size (the complete budget to carry out the project) ([Friedman, 1956](#)), a reasonable enough assumption at that time of open tendering in the U.S., as larger projects are generally associated with larger (dollar) profits and therefore likely to attract more bidders. Empirical studies attempting this are quite limited and inconclusive, however. [Gates \(1967\)](#) and [Wade and Harris \(1976\)](#) have applied the method to U.S. data, producing generally weak predictive results. Other empirical U.S. research is even less supportive, finding no significant linear relationship between N and contract size, nor between contract size and the number of suppliers and subcontractors involved (e.g. [Sugrue, 1977](#)). [Skitmore's \(1986\)](#) analysis of UK construction auctions, however, where selective tendering is the norm, surprisingly found a weak to moderate correlation between N and contract size. A possible reason for the general lack of correlation in the U.S. suggested by [Park \(1966\)](#) is that the

relationship between N and contract size may be nonlinear. Although this has yet to be tested with U.S. data, Skitmore's (1986) UK analysis found the correlation to be certainly more apparent when contract size was transformed to a log scale.

The only other empirical approach to forecasting N is Skitmore's (1981b) study of several international tender datasets from different time periods, which identified an apparent relationship between N and market conditions. However, no mathematical model was developed for this. Today, the general conclusion is that using some measure of contract size will provide the best means of estimating N and certainly an advancement on considering it to be purely random (Ballesteros-Pérez & Skitmore, 2014), a view that has been dominant since Rickwood (1972).

For statistical applications involving N , besides estimating its expected value, it is important to be able to make some assumptions concerning its probability density function (pdf). In addition to bidding strategies, this has important ramifications in Auction and Game theory (Klemperer, 2004), driven by the different outcomes it produces on several types of auctions formats and under different types of valuations used by bidders of the auctioned items. Nevertheless, there is a long list of proposed candidates. These include the normal (Ballesteros-Pérez et al. 2013a, 2014), uniform (Ballesteros-Pérez et al. 2013b), gamma (Engelbrecht-Wiggans, 1980), Laplace (Ballesteros-Pérez et al. 2015a) and Weibull (Ballesteros-Pérez & Skitmore, 2014).

Of particular interest is the Poisson distribution, considered by Friedman (1956), as likely to “furnish a good fit” for N values, reasoning that similar individuals independently deciding whether or not to bid for a particular item is equivalent to N following the binomial distribution which, when the average of the number of bids is a small fraction of the total possible, is well approximated by the Poisson. This was later seemingly confirmed by Keller and Bor's (1978) empirical analysis of the bidding patterns of a significant number of similar construction contracts in which their results agreed with the Poisson distribution. In contrast, Skitmore's (1986)

empirical analysis of three sets of UK construction tenders found no significant fit with the Poisson ($N=51$, $\bar{x} = 6.2$, $sd=2.1$, $\chi^2_{(4)} = 20.7$; $N=218$, $\bar{x} = 5.7$, $sd=1.1$, $\chi^2_{(8)} = 16.4$; $N=373$, $\bar{x} = 5.1$, $sd=3.8$, $\chi^2_{(8)} = 31.4$). Meanwhile, others making use of, for example, U.S. Outer Continental Shelf Statistical summary of 1976 to 1978 oil tract auctions, found N might follow not only a distribution different from the Poisson but even bimodal distributions ([Engelbrecht-Wiggans, 1980](#)).

On being criticized by other researchers on theoretical grounds, Friedman then modified his original assertion to the distribution of the residuals of a regression between N and contract size ([Engelbrecht-Wiggans, Dougherty, & Lohrenz, 1986](#)). Others, however, have suggested the normal distribution to be a better option to reflect the random variability of such residuals – a point supported empirically by [Skitmore \(1986\)](#) for contract size with and without logarithmic transformation.

Since then, a compromise solution has been to consider the number of bidders as a purely stochastic variable in experimental settings ([McAfee & McMillan, 1987](#)) or as a fixed value in Game and Auction theory ([Harstad et al., 1990](#)), although quite surprisingly the Poisson model has endured since the very first and celebrated compilation of auction and bidding models from Stark and [Rothkopf \(1979\)](#) and [Engelbrecht-Wiggans \(1980\)](#) to modern and current online auctions ([Bajari & Hortacsu, 2003](#)).

A completely different approach to estimating N is to try to identify who the actual bidders might be. As with horse racing, where the same horses often race against each other, many contractors tend to prefer construction work of a certain type, size and location and therefore can be expected to bid against each other quite regularly. In the U.S., however, as [Morin and Clough \(1969\)](#) note, it is quite usual for the same bidder to submit proposals for different types of work. A contractor's decision to bid (d2b) is also limited by the number of contracts that can be managed

at any one time ([Skitmore, 1988](#)). Both of these factors lead to a situation where the same contractors bid less frequently against each other than might be otherwise imagined, making the prediction of their presence on a single auction a very difficult task in the absence of ‘inside’ information (which in itself is also difficult to obtain as being tantamount to collusion). An alternative is to simply “go and look”. Skitmore's (1987) research in the U.S., for example, identified several informal methods used by contractors to assess the state of opponents’ order book, including flying over their main compound to see the amount of machinery lying idle!

The use of statistical methods is possible, with Wade and Harris (1976) for example suggesting to treat the identities of several bidders and their groups probabilistically, but there are difficulties in this, particularly involving the identities of those from whom the forecasting company does not have any information. This has led the tendering theory literature to classify the potential competitors as “key” and “strangers” ([Skitmore, 1986](#)).

Since 1986, however, there has been no further work in this area (Ballesteros-Pérez & Skitmore, 2014) and we will leave its consideration for a separate paper on the topic. Similarly, with the exception of additional studies such as by Athias and [Nuñez \(2009\)](#), [Skitmore \(2008\)](#) and [Costantino et al. \(2011\)](#) there has been no further empirical work concerning the statistical nature of N and therefore previous assumptions will not be considered further here.

Materials and Methods

Tender datasets

In order to make a thorough analysis of the distribution of N , a comprehensive and representative set of construction tender databases is needed. However, such databases are generally difficult to obtain because there are very few published in the regular scientific construction literature mostly due to their length. Therefore, an

intensive and detailed search was carried out and access was obtained to documents only available in printed form, mostly in MSc and PhD theses where the original bidding data was complete and unprocessed. This resulted in the collection of twelve databases - some in the original author's scanned form and others requiring a visit to the respective university repository.

The twelve databases contain construction bidding data from four continents: Europe (United Kingdom and Spain), America (United States), Asia (Hong Kong) and Oceania (Australia), all featuring different types of construction work from different time periods. Table 1 summarizes the most important aspects of each database.

For the sake of clarity, the tender databases are referred to by the numerical identifier stated in the column marked "ID".

< Insert Table 1 here >

In general, the sample described in Table 1 is considered sufficiently representative, since the twelve databases analysed encompass different works such as: buildings (housing, aeronautics, schools, hostels, police and fire stations), civil works (waste water treatment plants, railways) and services (specialized and general). All decades from the sixties until now are represented either completely or partially by at least one dataset and their sizes are large enough (from tens to hundreds of contracts) to carry out thorough statistical analyses. Furthermore, concerning the variable number of bidders, the databases range from low (mean N of around 5) to high (around 31) numbers of bidders, whose dispersion values are more or less scattered (see standard deviation column), have different levels of positive skewness (no dataset has negative skewness), as well as different levels of positive and negative kurtosis.

Finally, it is also noted that, among the twelve databases, the six from the United Kingdom and Australia used selective tendering, that is, the owner invites only certain bidders and therefore sets an upper-bound on the value of N . However, the

results obtained later seem to be very similar for both open and selective tendering processes.

Outline of Methodology

In the next two sections, several factors that either directly or indirectly affect N are identified from the twelve databases. First, the analysis begins with an extensive comparison of the goodness of fit of a range of common statistical distributions and an attempt to deduce why some distributions perform better than others. Next, the relationship between N and contract size is analysed in both natural and logarithmic scales, and studied to see how predictably the statistical mean, standard deviation, skewness and kurtosis vary when plotted against contract size, and some general behaviour patterns are provided. Finally, a new model for describing the statistical variation of N is presented along with the justification of its main assumptions - that both the frequency of contract sizes and that the population of potentially interested participating bidders are log-normally distributed. As is eventually demonstrated from the large variety of statistical curve shapes that can stem from this model and the thorough statistical distribution fit tests performed, the model represents a significant step forward in this topic. The next section is divided into three subsections describing these analyses in more detail.

Calculations

Comparison of goodness of fit of standard statistical distributions

Of the many statistical distributions proposed to date to model N (Poisson, normal, gamma, Weibull, Laplace, etc.) no clear single distribution has yet been found, with different studies making use of databases with different characteristics that are not always identified. To analyse the twelve databases, a χ^2 test is applied to every distribution, which are then ranked according to the number of times the sum of the

squared residuals are below the critical χ^2_{α} values (using three levels of significance $\alpha=1\%$, 5% and 10%) and the p-values. The more times the actual χ^2 values are below the critical χ^2_{α} values (from 0 to 3 on average), the lower is the p-value (from 0 to 1, on average) and hence the better fit of the distribution.

The range of distributions tested is basically restricted to the location-scale family, as the parameters that define these distributions have true physical meaning, improving the understanding of the underlying distribution involved. In addition, the gamma and Weibull distributions were also tested because of their prevalence in the literature. Of the location-scale distributions tested, seven symmetrical distributions (skewness=0) are of particular interest: the uniform (kurtosis close to -1.2), raised cosine (kurtosis close to -0.6), normal (kurtosis 0.0), logistic (kurtosis 1.2), hyperbolic secant (kurtosis 2.0), Laplace (kurtosis 3.0) and Cauchy (kurtosis undefined). These latter distributions are chosen to map in detail the level of kurtosis that might better fit the N distribution in terms of either platykurtic or leptokurtic behaviour. Asymmetrical forms of these seven distributions are also tested by transforming the N values into $\log N$ values (i.e., for testing against the log-uniform, log-raised cosine, log-normal, log-logistic, log-hyperbolic secant, log-Laplace and Log-Cauchy distributions) to map positive skewness with different kurtosis levels and, by using the N^2 values to test for negative asymmetries with different kurtoses (i.e., square-uniform, square-raised cosine, square-normal, square-logistic, square-hyperbolic secant, square-Laplace and square-Cauchy). Furthermore, the Poisson distribution is also tested with the natural, logarithmic and square N values. A flexible array of means and variances calculated by the method of moments are therefore tested using location-scale distributions and a representative grid of skewness and kurtosis levels tracked and checked, amounting to 24 combinations in all, plus the Weibull and gamma distributions, for each of the twelve databases. It is

also to be noted that, despite most distributions being continuous, a discretization of the X values (N values) is performed by obtaining the pdf $f(x=N)$, from the cumulative distribution function, $F(x=N)$, by the simple calculation: $f(x) = F(x+0.5) - F(x-0.5)$.

Table 2 and Figure 1 give the results for the four best distribution fits (normal, log-normal, logistic and log-logistic) together with the Poisson and the Laplace distributions.

< Insert Table 2 here >

< Insert Figure 1 here >

On average, the log-normal distribution produces the highest number of times the χ^2 values are below the critical three χ^2_α values and the lower p-value, although the normal, logistic and log-logistic are also quite close.

These results are not very useful, however, as the fit is not good for any distribution, even the log-normal. That this may be due to the absence of another influencing factor is an issue taken up in the next section.

Improving accuracy by considering contract size

< Insert Table 3 here >

Table 3 gives the regression equations of N with contract size (in terms of the mean bid, B_m) for the twelve datasets. This indicates the existence of a weak correlation in most cases, irrespective of whether B_m is calculated from the natural or logarithmic bids. This may be due to two causes. First, there may be a large variation in N values obscuring an underlying correlation. Second, the distribution B_m observed in every database may not be uniform, so there is an uneven distribution of the N values on the X-axis.

To observe the variations in the N distribution values, one approach is to place the auctions in ascending order of log contract size (from lower to higher B_m) and

plot the first four moments (mean (μ), standard deviation (σ) skewness (γ) and kurtosis (κ)) of groups of N values as shown in Figure 2.

< Insert Figure 2 here >

As Newell and Hancock (1984) note, for practical purposes in statistical inference, estimates of γ and κ for sample sizes below 50 can indicate the underlying statistical distribution is normal when it is not. Therefore rolling groups of 50 N values are taken. That is, the moments of N values from the auctions ranked 1 to 50 are first recorded. Then the moments of N values from the auctions ranked 2 to 51 are recorded, and the process continued until reaching the last ordered auction. Four of the datasets do not contain sufficient auctions to do this and are therefore missing from Figure 2.

Even a window width of 50 auctions causes high oscillations in the γ and κ estimates. To clarify the situation, the rule of thumb of usual practice is followed in which only values outside the range of ± 1 are taken to be sufficient evidence to conclude the underlying distribution is either skewed or platy/leptokurtic.

As Figure 2 shows, when considered in terms of contract size, with very few exceptions the γ and κ estimates are quite close to zero. Figure 3 provides a first approximation why this might be the case. This contains several interesting features that need to be highlighted since it mirrors some aspects found in Figure 2.

< Insert Figure 3 here >

First, it is quite logical to think that, irrespective of the X axis (contract size) being represented in natural or logarithmic values, contract sizes that are very small or very large will fail to attract bidders, since bidders can make little profit in the former case, and no qualified bidder could submit a proposal in the latter case. This being the case, μ will increase initially from zero until it reaches a zone with relatively stable maximum N values, after which it will decrease asymptotically back to zero.

Second, it is expected that the σ curve will behave similarly. However, as Figure 2 shows, in almost all cases there seems to be a gap between the maximum μ and σ (identified as Δ). The reason for this is still to be researched.

Third, the γ and κ curves take on high values when the μ and σ curves are closer to zero. The reason is that when N is extremely low, the N distribution has to be as shown in the bottom left corner of Figure 3, which is remarkably asymmetrical and leptokurtic since the highest density and cumulative probability will remain between $0 \leq N \leq 1$. On the other hand, when the N curve has γ and κ close to zero, the distribution that models N can be assumed nearly normal. However, extremes of high γ and κ are rarely observed, since we can only have a glimpse of those atypical situations with very small and/or large contract sizes and, since they are quite scarce, it is difficult to accurately estimate the γ and κ values involved.

Nevertheless, Databases 4, 7 and 10 in Figure 2 seem to support the assumptions made above about γ and κ . On the other hand, when dissecting the variation in μ , σ , γ and κ along the contract size dimension, the curve modelling N (bottom half of Figure 3) for the rest of databases should be close to the normal distribution, as γ and κ are close to zero.

Model proposed

Hossein (1977) found contract size could be modelled by the exponential distributions, while a similar study by Skitmore (1986) however found the log-normal distribution to be more appropriate. Here, two distributions are checked for fit - the log-normal distribution and the Pareto distribution. The former because it has been found to outperform the exponential and the latter because it is closely related to the exponential distribution but has two parameters as has the log-normal. It is noted that both the Pareto and log-normal are alternative distributions for describing the distributions of sizes which abound in natural, physical, economic, and social

systems (Malevergne et al., 2011). Fat-tail distributions, such as the log-normal and the Pareto distribution have historically competed for describing with higher accuracy some generating processes and hard-to-distinguish tail properties (Malevergne et al., 2011), and this is the reason why both have been compared here.

The results in comparing both distributions are presented in Table 4, with a representation of the best log-normal distributions found in Figure 4. As noted from Table 4, the Kolmogorov-Smirnov tests indicate the log-normal distribution to generally provide the best fit, even when the datasets seem rather erratic – probably as a consequence of a tender dataset that did not include the complete range of tender sizes.

< Insert Table 4 here >

< Insert Figure 4 here >

On the other hand, a parallel theoretical debate has quite recently emerged concerning the use of a power-law distribution or a log-normal distribution to model firm size (Segarra & Teruel, 2012), as both appear to provide a close fit with real data. If we assume that the number of potentially interested bidders is a fraction or proportion of the population of companies found in a particular area and within a particular market, then the number of bidders should also follow a log-normal distribution with similar location (mean) and scale (variance) parameters, but differing on the Y-axis order of magnitude when representing absolute values, instead of frequency values. This is because the number of potentially interested bidders would be lower when representing the number of companies on the Y-axis compared to the total number of companies by size, but both should probably look quite similar when representing their pdfs, since they would then represent proportions. Therefore, a model is proposed that endeavours to take advantage of the log-normal distributions: (1) the distribution of contract size and (2) the distribution

of potentially interested bidders, both considered as log-normal, but with different location and scale parameters (μ_1 and σ_1^2 , and μ_2 and σ_2^2 , respectively).

What this model tries to represent is that, if there is a different number of bidders who might submit a bid for a future tender as a function of the contract size, and the number of contract size opportunities is known (both being variables well represented by different log-normal distributions), the calculation of the N distribution curve should be according to the representation of Figure 5.

< Insert Figure 5 here >

In particular, Figure 5 represents how, in order to calculate the probabilities associated to every possible value of N (N_i from 0 to $+\infty$), it is only required to add up the two probability bands in the distribution of contract sizes (log-normal whose location and scale parameters are μ_1 and σ_1) that are delimited by the two pairs of X values from the distribution of the number of interested bidders (log-normal whose location and scale parameters are μ_2 and σ_2) whose respective Y values correspond to that specific $N_i \pm 0.5$. For instance, in Figure 5 we want to calculate the probabilities of finding $N_i=4$ in a database. Despite the number of bidders N_i being natural numbers, we need to assume that the number of interested bidders distribution will correspond to a band of Y values between 4.5 and 5.5 (as represented on the right Y axis). Those two Y values each correspond to another two different X values by horizontal intersection first, and then by vertical intersection, in the same log-normal distribution describing the number of interested bidders. But once these four X values are identified, they also define the vertical probability bands within the log-normal distribution of contract sizes that, on being summated, will result in the probability of finding $N_i=4$ in the database.

Generally speaking, Figure 5 highlights that the final N distribution is affected by the number of bidders that would submit a bid if there was an occasion to do so as well as by the number of times each contract size occurs. In other words if, for each

possible N value it is known that there are a fixed number of interested bidders (by means of curve 2, and ± 0.5 to discretized the distribution), and if the frequency of that range of contract sizes is calculated (by means of curve 1), then the same frequency will be equivalent to the number of times that that N will be found in the final N distribution.

Concerning the five parameters to be estimated in the model (μ_1 , σ_1 , μ_2 , σ_2 and N_{max}), the mean and standard deviation of the distribution of contract sizes (parameters μ_1 and σ_1) can be directly obtained by calculating the first and second moments from the series of all tender B_m (bid average) values found in a database; N_{max} can be set to the maximum N_i value found in the database (or slightly above); whereas the mean and standard deviation of the distribution of the number of interested bidders (parameters μ_2 and σ_2) cannot be directly estimated (unless extensive and time-consuming field research is carried out for estimating the distribution of nearby firm sizes with potential interest in the type of works contained in the database under study). Therefore, it is recommended that, when looking for the best combination of parameter values, μ_1 , σ_1 and N_{max} are calculated as suggested above, while parameters μ_2 and σ_2 are set according to a simple two-variable numerical optimization approach for providing the best overall distribution fit. In this connection, according to the multiple combinations of these five parameter values, the broad range of mathematical shapes that this model distribution can take is represented in Figure 6.

< Insert Figure 6 here >

As can be seen, the model is able to provide a number of statistical curve shapes changing the γ from positive to negative, or reaching higher levels of κ near the $N=0$ and N_{max} values. For the sake of simplicity however, the most common cases are identified and framed in the thick line on the top rows of Figure 6. This distribution is checked and compared against previous distributions in the next section.

Results

Comparison of standard statistical distributions considering contract size

In summary, Table 2 gives the best results for a complete comparison of several statistical distributions irrespective of contract size. However, Figure 3 suggests that, within a certain range of contract sizes, N is quite close to a normal distribution. It is also apparent that working with narrower intervals of contract sizes also leads normal-like distributions for N , this being the case with the three central images depicted on the top row of Figure 6, where narrow contract size intervals have necessarily quite small variance values from the distribution of contract size opportunities ($\sigma^2_1 \rightarrow 0$) when compared to the variance of the number of potentially interested bidders (σ^2_2), forcing $\sigma^2_1 \ll \sigma^2_2$.

To examine this further, the Table 2 analysis is repeated but with non-rolling groups of contract sizes as shown in Table 5.

< Insert Table 5 here >

As can be seen, the best pdf for N is now the normal distribution with both indicators (the number of times the χ^2 values are below the critical χ^2_α values, and the p-values) significantly improved. However, this improvement also applies to all the other distributions tested, since the two indicators are approximately between 30% and 60% better on average for all of them when compared with the results in Table 2. It is shown, therefore, although the best approximation of N is the normal distribution, the log-normal, logistic and log-logistic are not far behind.

Model validation

To test the new five parameter ($\mu_1, \sigma_1, \mu_2, \sigma_2$ and N_{max}) model, it is first effectively reduced to a two-parameter model by forcing μ_1 and σ_1 to take on the values of the

actual (log-normal) contract size distributions represented in Figure 4 (that were directly obtained by the method of moments) and having the N_{max} values vary within a nearby range to the actual maximum N values observed in the twelve databases, leaving the only remaining parameters μ_2 and σ_2 to be estimated. This is done by a simple two-dimensional optimization process to find the values that minimize the actual χ^2 values. The results are shown in Table 6 and the model curves illustrated in Figure 7.

< Insert Table 6 here >

< Insert Figure 7 here >

As can be seen, the model outperforms all the distributions tested so far, even when taking narrower intervals of contract size (although the improvements are only around 10% in this latter case). However, both approaches have different aims: the model only provides a better explanation of the distribution of N , while breaking down the series of N values by more compact contract sizes only reduces the amount of randomness when trying to describe the unexplained variation of N .

Summary

Many distributions have been compared in this study by means of multiple chi-square tests performed on twelve databases. Therefore, in order to highlight potential differences between the performance of these statistical distributions, it is convenient to summarise the results in a single ranking table.

This is the aim of Table 7, which presents the average and standard deviation results (the latter not presented earlier to avoid confusion with other variables involved) of the number of times the sum of the squared residuals are below the critical $\chi^2\alpha$ values (from 3 –good fit- to 0 –bad fit-) and the p-values (from 0 –perfect fit- to 1 –worst fit-). Table 7 distributions have been ordered in descending order of the average p-values but, as can be seen, some distributions nearly tie when taking

into account both the $\chi^2\alpha$ and p values simultaneously (distributions ranked as 3rd and 8th).

< Insert Table 7 here >

The consequence of a lower p-value is directly indicative of a loss of accuracy when modelling the actual distribution of the N values, and this table shows how the new model outperforms (on average) other common distributions. However, it is noted that the standard deviation values obtained, even without the need for carrying out ANOVA tests, denote potential overlaps in the means of the p-values, particularly among the top-ranked distributions. Fortunately, the $\chi^2\alpha$ has zero variance for the new model, which indicates that the model has provided, without exception, what may be considered a reasonable approximation in the twelve databases. This is not the case with the other models.

Further discussion of Table 7 is provided in the next section.

Discussion

From the results obtained in the previous sections, it is clear that the contract size distribution within each database is close to log-normal and strongly conditions N . The direct comparison of many statistical distributions (partially shown in Table 1 and Figure 1, as well as in Table 7) is also expected to be biased towards the log-normal distribution. However, as also observed in Tables 5 and 7, the normal distribution naturally presents an acceptable fit (closely followed by the log-normal) when the contract size effect is considered. Therefore, as with many other such goodness-of-fit studies, there is an intermediate situation in which it is difficult to distinguish between the suitability of the normal and log-normal distributions. In addition, the logistic and log-logistic distributions are also good candidates, since they are quite similar in shape to the normal and log-normal distributions respectively, although slightly more leptokurtic. This fact is also frequently

observed, since the juxtaposed effect of mixing the normal and log-normal distributions slightly increases the kurtosis coefficient.

In summary therefore, in delimiting the potential values of N for a future tender, removing the effect of contract size by using only recent past tenders with a similar contract size or calculating the mean, standard deviation, skewness and kurtosis as in Figure 2, is preferable to directly modelling the whole dataset values of N without allowing for contract size. On the other hand, as Tables 6 and 7 show, the new model provides a better fit than the many other statistical distributions examined, although its superiority is not decisive, as indicated by the small differences and high standard deviation between p-values in Tables 5, 6 and 7. In addition, the model assumes the log-normal distribution representing the expected value of the number of interested bidders as fixed, when this curve Y values must necessarily evidence variability since, for instance, it seems counter intuitive to state that the number of potentially interested bidders for a given contract size is constant, but variable as well.

Conclusions

Knowing the statistical distribution of the number of bidders, N , for a construction contract is important in real-life bidding because it conditions the decision to bid and how to set the final bid price so as to increase the probability of winning, but also in tendering theory since it affects many related outcomes, such as the correlation between the mean and lowest bids or the dispersion of the bid values, which are key assumptions of many collective bid tender forecasting models. However, little progress has been made despite the many studies from 1956 to 1986 except that there are other variables that seem to condition or have a significant correlation with N . Not all of these have been explained in conjunction with measuring their possible interactions.

In this study, a unique set of twelve construction and services tender databases from four continents are used for a thorough comparison of many candidate statistical distributions with the primary aim of determining which are the most accurate and in what conditions.

The univariate results show the log-normal distribution to be the best fit, while the normal distribution provides the best fit when contract size is taken into account. These are basic but important outcomes, since many bidding practitioners and researchers tend to use the normal distribution without distinction when modelling the distribution of bidders, while it is shown here that this distribution is only the most accurate when contracts of similar nature of work and economic size are used. If these conditions are not fulfilled, then the log-normal distribution is the most accurate.

Next, the expected variation of the N distribution mean, standard deviation, skewness and kurtosis as a function of contract size is analysed in both natural and logarithmic scales. The four moments are studied to see how predictably they vary when plotted against contract size and some interesting general behaviour patterns are provided. For example, most construction tenders operate within a band of contract sizes that have low levels of skewness and kurtosis, allowing the use normal-like distributions with barely loss of accuracy. However, this situation is no longer valid for extremely high or low contract values, since contractors will usually have less previous experience with such contracts, when the distribution of N becomes strongly positive skewed and peaked.

Finally, a new model for describing N is presented along with the justification of its main assumptions - that both the frequency of contract sizes and that the population of potentially interested participating bidders are log-normally distributed. As is demonstrated from the large variety of statistical curve shapes that can stem from this model and the thorough statistical distribution fit tests performed,

the model results are significantly more accurate in modelling the variations in N than the other alternatives considered for all 12 datasets examined, including the ubiquitous normal distribution which is used in similar studies.

Despite this, however, it is felt that there is still room for further improvement. For instance, research in forecasting the identity of future bidders may, paradoxically, shed further light on the issue. There are also new questions concerning differences in contract size (value) that exist between the maximum expectation and variance of N when represented as a function of contract size. An additional question is how to replace the deterministic number of potentially interested bidders in the model by a distribution with a random component.

The result is a critical view of past research while stimulating again a productive discussion on a subject that, as previously acknowledged, is of considerable importance from both owner and bidders' standpoint and strongly linked to tender outcomes beyond the construction context.

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<i>ID</i>	<i>Database Alias</i>	<i>Description</i>	<i>Tender method</i>
1	UK51	Building-related tenders within the London area with one bidder in common and cover prices	Selective
2	UK272	Construction industry Building Cost Information Service report	Selective
3	UK218	Civil engineering work tenders from the North of England	Selective
4	UK373	Building-related tenders within the London area	Selective
5	US64	Building-related tenders from the US National Aeronautics and Space Administration	Open
6	US50	Building-related tenders from the US	Open
7	HK199	Tenders of buildings for education, police, firemen and hostels in Hong Kong	Open
8	HK261	Tenders from the Hong Kong Administrative Service Department	Open
9	AU152	General contractors' civil engineering works and housing in New South Wales, Australia	Selective
10	AU161	Specialised contractors' civil engineering works and housing in New South Wales, Australia	Selective
11	SP45	Waste Water Treatment Plants and Sewage lines in Catalonia region, Spain	Open
12	SP114	Spanish High-speed Railway Infrastructure Manager (ADIF) tenders	Open

<i>ID</i>	<i>Number of auctions</i>	<i>Period</i>	<i>Mean (μ)</i>	<i>Std. Dev. (σ)</i>	<i>Skewness (γ)</i>	<i>Kurtosis (κ)</i>	<i>Source</i>
1	51	1981-1982	6.235	1.464	0.250	0.241	(Skitmore and Pemberton, 1994)
2	272	1969-1979	6.140	1.786	0.265	1.009	(Skitmore, 1981b)
3	218	1979-1982	5.665	2.260	0.497	0.994	(Skitmore, 1986)
4	373	1976-1977	5.134	1.944	0.124	-0.580	(Skitmore, 1986)
5	64	1976-1984	6.734	3.108	1.756	4.763	(Brown, 1986)
6	50	1965-1969	4.680	1.834	0.558	-0.260	(Shaffer and Micheau, 1971)
7	199	1981-1990	12.724	6.262	0.696	0.497	(Drew, 1995)
8	261	1991-1996	13.663	7.279	0.654	-0.498	(Fu, 2004)
9	152	1972-1982	8.651	3.987	0.685	-0.060	(Runeson, 1987)
10	161	1972-1982	6.273	2.877	1.595	3.531	(Runeson, 1987)
11	45	2007-2008	14.133	11.108	1.496	1.706	(Ballesteros-Pérez et al. , 2012)
12	114	2008-2014	31.974	12.082	0.414	-0.345	(Fuentes-Bargues et al. , 2015)

Table 1. Description of the twelve construction tender databases analysed

ID	Database alias	Critical χ^2 α values			Poisson			Normal			
		$\chi^2_{\alpha=0.01}$	$\chi^2_{\alpha=0.05}$	$\chi^2_{\alpha=0.10}$	χ^2	$\chi^2 < \chi^2_{\alpha?}$	p-value	χ^2	$\chi^2 < \chi^2_{\alpha?}$	p-value	
1	UK51	18.475	14.067	12.017	30.188	0	1.000	8.736	3	0.728	
2	UK272	21.666	16.919	14.684	57.384	0	1.000	11.061	3	0.728	
3	UK218	21.666	16.919	14.684	16.017	2	0.933	10.136	3	0.660	
4	UK373	21.666	16.919	14.684	31.082	0	1.000	17.886	1	0.963	
5	US64	23.209	18.307	15.987	14.736	3	0.858	18.793	1	0.957	
6	US50	18.475	14.067	12.017	2.077	3	0.045	3.801	3	0.198	
7	HK199	48.278	41.337	37.916	10169.1	0	1.000	49.274	0	0.992	
8	HK261	49.588	42.557	39.087	4602.7	0	1.000	88.747	0	1.000	
9	AU152	30.578	24.996	22.307	78.525	0	1.000	23.064	2	0.917	
10	AU161	27.688	22.362	19.812	79.735	0	1.000	109.893	0	1.000	
11	SP45	34.805	28.869	25.989	1131.92	0	1.000	26.107	2	0.903	
12	SP114	57.342	49.802	46.059	3079.7	0	1.000	54.931	1	0.983	
				avg.	0.667	0.903	avg.	<u>1.583</u>	<u>0.836</u>		

ID	LogNormal			Logistic			LogLogistic			Laplace					
	χ^2	$\chi^2 < \chi^2_{\alpha?}$	p-value	χ^2	$\chi^2 < \chi^2_{\alpha?}$	p-value	χ^2	$\chi^2 < \chi^2_{\alpha?}$	p-value	χ^2	$\chi^2 < \chi^2_{\alpha?}$	p-value			
1	8.951	3	0.744	7.755	3	0.645	7.650	3	0.636	7.022	3	0.573			
2	47.767	0	1.000	10.488	3	0.688	34.870	0	1.000	24.233	0	0.996			
3	50.246	0	1.000	10.160	3	0.662	48.580	0	1.000	20.475	1	0.985			
4	72.666	0	1.000	30.904	0	1.000	82.635	0	1.000	55.608	0	1.000			
5	6.932	3	0.268	15.441	3	0.883	5.708	3	0.161	11.483	3	0.679			
6	1.755	3	0.028	4.194	3	0.243	2.399	3	0.066	244.245	0	1.000			
7	45.495	1	0.980	47.163	1	0.987	49.564	0	0.993	56.750	0	0.999			
8	46.083	1	0.977	109.201	0	1.000	68.904	0	1.000	123.869	0	1.000			
9	16.593	3	0.656	25.550	1	0.957	21.134	3	0.867	28.882	1	0.983			
10	4.721	3	0.019	39.731	0	1.000	3.101	3	0.002	30.176	0	0.996			
11	10.88	3	0.100	26.545	2	0.912	12.467	3	0.178	18.354	3	0.567			
12	55.818	1	0.986	63.802	0	0.998	63.864	0	0.998	87.614	0	1.000			
				avg.	<u>1.750</u>	<u>0.647</u>	avg.	<u>1.583</u>	<u>0.831</u>	avg.	<u>1.500</u>	<u>0.658</u>	avg.	0.917	0.898

Table 2. Chi-square tests for checking the Poisson, Normal, LogNormal, Logistic, LogLogistic and Laplace distribution fit for N

ID	Database alias	Optimal regression curves			
		$X=B_m$ (natural scale) & $Y=N$	R^2	$X=B_m$ (log scale) & $Y=N$	R^2
1	UK51	$Y=-6E-14X^2+7E-07X+5.4185$	0.109	$Y = 0.2649X^2-7.0073X+52.236$	0.101
2	UK272	$Y= 1.7382X^{0.1001}$	0.115	$Y= -0.1737X^2+4.8162X-26.52$	0.146
3	UK218	$Y=0.7977LN(X)-3.0126$	0.253	$Y= 0.7977X-3.0126$	0.253
4	UK373	$Y=0.372X^{0.2034}$	0.253	$Y=0.0063X^{2.6271}$	0.270
5	US64	$Y=-0.282LN(X)+10.534$	0.018	$Y=0.0941X^2-2.8759X+28.2$	0.024
6	US50	$Y=-1E-13X^2+8E-07X+4.233$	0.038	$Y=-0.1128X^2+3.2137X-17.948$	0.041
7	HK199	$Y=-5E-16X^2+1E-08X+12.917$	0.012	$Y=-0.9458X^2+30.389X-230.2$	0.052
8	HK261	$Y=-7E-09X+14.658$	0.035	$Y=-0.9451X^2+34.254X-295.73$	0.035
9	AU152	$Y=1.6998X^{0.1095}$	0.067	$Y=0.1297X^{1.5581}$	0.070
10	AU161	$Y=5.5924EXP(1E-07X)$	0.009	$Y=0.3815X^2-9.0763X+59.735$	0.070
11	SP45	$Y=-2E-13X^2+4E-06X+5.5083$	0.374	$Y=1.0237X^2-24.343X+151.48$	0.297
12	SP114	$Y=-2E-15X^2+9E-08X+33.465$	0.147	$Y=-3.8248X^2+125.47X-990.14$	0.235
avg.			0.119	avg. 0.133	

Table 3. Regression results between variables Contract size (via Mean bid, B_m) and Number of bidders (N)

ID	Database		Lognormal					
	alias	D	$D\alpha=0.01$	$D\alpha=0.05$	$D\alpha=0.10$	$D < D\alpha=0.01?$	$D < D\alpha=0.05?$	$D < D\alpha=0.10?$
1	UK51	0.074	0.143	0.123	0.113	Yes	Yes	Yes
2	UK272	0.039	0.063	0.054	0.050	Yes	Yes	Yes
3	UK218	0.051	0.070	0.060	0.055	Yes	Yes	Yes
4	UK373	0.022	0.053	0.046	0.042	Yes	Yes	Yes
5	US64	0.081	0.128	0.111	0.101	Yes	Yes	Yes
6	US50	0.077	0.144	0.125	0.114	Yes	Yes	Yes
7	HK199	0.032	0.073	0.063	0.058	Yes	Yes	Yes
8	HK261	0.060	0.064	0.055	0.051	Yes	<u>No</u>	<u>No</u>
9	AU152	0.070	0.084	0.072	0.066	Yes	Yes	<u>No</u>
10	AU161	0.050	0.081	0.070	0.064	Yes	Yes	Yes
11	SP45	0.060	0.152	0.131	0.120	Yes	Yes	Yes
12	SP114	0.094	0.096	0.083	0.076	Yes	<u>No</u>	<u>No</u>

ID	Database		Pareto					
	alias	D	$D\alpha=0.01$	$D\alpha=0.05$	$D\alpha=0.10$	$D < D\alpha=0.01?$	$D < D\alpha=0.05?$	$D < D\alpha=0.10?$
1	UK51	0.088	0.224	0.187	0.168	Yes	Yes	Yes
2	UK272	0.261	0.098	0.082	0.074	<u>No</u>	<u>No</u>	<u>No</u>
3	UK218	0.101	0.109	0.091	0.082	Yes	<u>No</u>	<u>No</u>
4	UK373	0.129	0.084	0.070	0.063	<u>No</u>	<u>No</u>	<u>No</u>
5	US64	0.074	0.200	0.167	0.150	Yes	Yes	Yes
6	US50	0.140	0.226	0.188	0.170	Yes	Yes	Yes
7	HK199	0.200	0.114	0.095	0.086	<u>No</u>	<u>No</u>	<u>No</u>
8	HK261	0.080	0.100	0.083	0.075	Yes	Yes	<u>No</u>
9	AU152	0.118	0.131	0.109	0.098	Yes	<u>No</u>	<u>No</u>
10	AU161	0.122	0.127	0.106	0.095	Yes	<u>No</u>	<u>No</u>
11	SP45	0.133	0.238	0.198	0.179	Yes	Yes	Yes
12	SP114	0.158	0.151	0.126	0.113	<u>No</u>	<u>No</u>	<u>No</u>

Table 4. Kolmogorov-Smirnov tests for checking the LogNormal and Pareto distributions fitting to the distribution of Contract size opportunities

ID	Database <i>alias</i>	LogNormal (Contract size)		LogNormal (Number of interested bidders)			Critical χ^2 α values			Model distribution		
		μ_1 (log)	σ_1 (log)	μ_2 (log)	σ_2 (log)	N_{max}	$\chi^2_{\alpha=0.01}$	$\chi^2_{\alpha=0.05}$	$\chi^2_{\alpha=0.10}$	χ^2	$\chi^2 < \chi^2_{\alpha}?$	p-value
1	UK51	13.937	0.852	17.143	3.305	10	18.475	14.067	12.017	3.803	3	0.198
2	UK272	12.122	0.932	14.731	2.925	9	21.666	16.919	14.684	8.768	3	0.541
3	UK218	10.788	1.357	13.910	3.023	9	21.666	16.919	14.684	10.056	3	0.654
4	UK373	12.457	1.032	15.287	2.565	9	21.666	16.919	14.684	11.819	3	0.776
5	US64	13.336	1.393	17.543	3.452	13	23.209	18.307	15.987	6.808	3	0.257
6	US50	14.125	0.488	15.507	1.167	9	18.475	14.067	12.017	1.403	3	0.015
7	HK199	16.157	1.158	20.490	2.986	35	48.278	41.337	37.916	27.320	3	0.499
8	HK261	18.130	1.023	15.085	2.143	33	49.588	42.557	39.087	31.237	3	0.646
9	AU152	13.813	1.251	18.115	3.078	21	30.578	24.996	22.307	13.386	3	0.428
10	AU161	11.701	1.128	15.219	3.078	11	27.688	22.362	19.812	8.098	3	0.163
11	SP45	14.297	1.274	18.592	2.674	40	34.805	28.869	25.989	12.213	3	0.164
12	SP114	17.054	1.185	20.097	2.991	51	57.342	49.802	46.059	42.942	3	0.832
avg.										3.000	0.431	

Table 6. Chi-square tests for checking the model distribution fitting to the Number of Bidders

Rank	Distribution	Average values		Std. Deviation values	
		$\chi^2 < \chi^2_{\alpha}$?	p-value	$\chi^2 < \chi^2_{\alpha}$?	p-value
1	New model proposed (with two-LogNormals)	3.000	0.431	0.000	0.269
2	Normal (discriminating by contract size)	2.830	0.492	0.509	0.327
3	LogNormal (discriminating by contract size)	2.623	0.508	0.860	0.335
3	Logistic (discriminating by contract size)	2.811	0.520	0.622	0.328
3	Loglogistic (discriminating by contract size)	2.660	0.535	0.758	0.336
6	Laplace (discriminating by contract size)	2.528	0.589	0.953	0.311
7	LogNormal (without discriminating by contract size)	1.750	0.647	1.357	0.420
8	LogLogistic (without discriminating by contract size)	1.500	0.658	1.567	0.426
8	Poisson (discriminating by contract size)	1.679	0.745	1.384	0.330
10	Logistic (without discriminating by contract size)	1.583	0.831	1.379	0.232
11	Normal (without discriminating by contract size)	1.583	0.836	1.240	0.234
12	Laplace (without discriminating by contract size)	0.917	0.898	1.311	0.178
13	Poisson (without discriminating by contract size)	0.667	0.903	1.231	0.274

Table 7. Ranking of distributions analysed for modelling the Number of bidders as a function of the chi-square test results

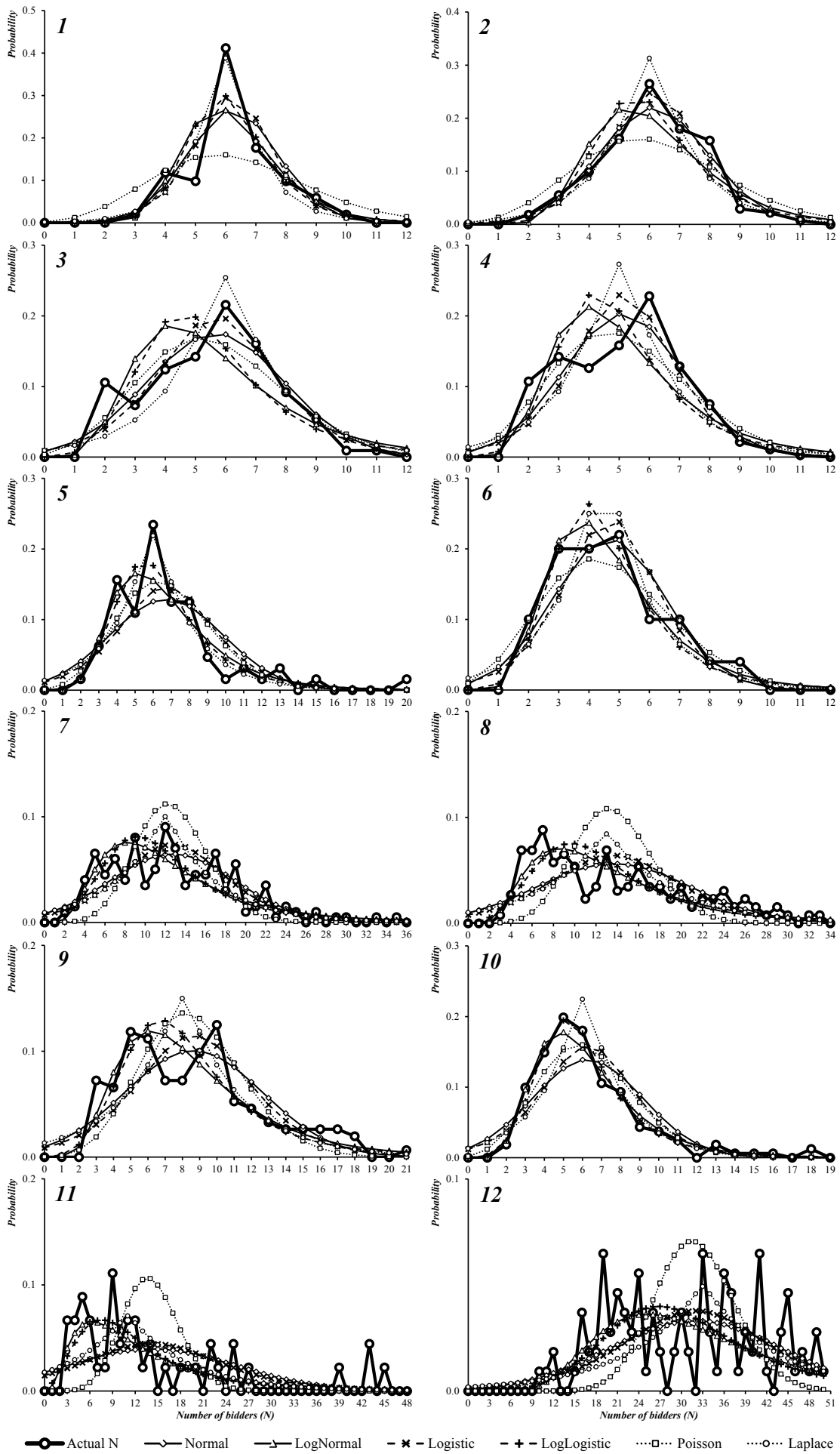


Figure 1. Poisson, Normal, LogNormal, Logistic, LogLogistic and Laplace distribution fitting to the Number of bidders distribution for the twelve datasets

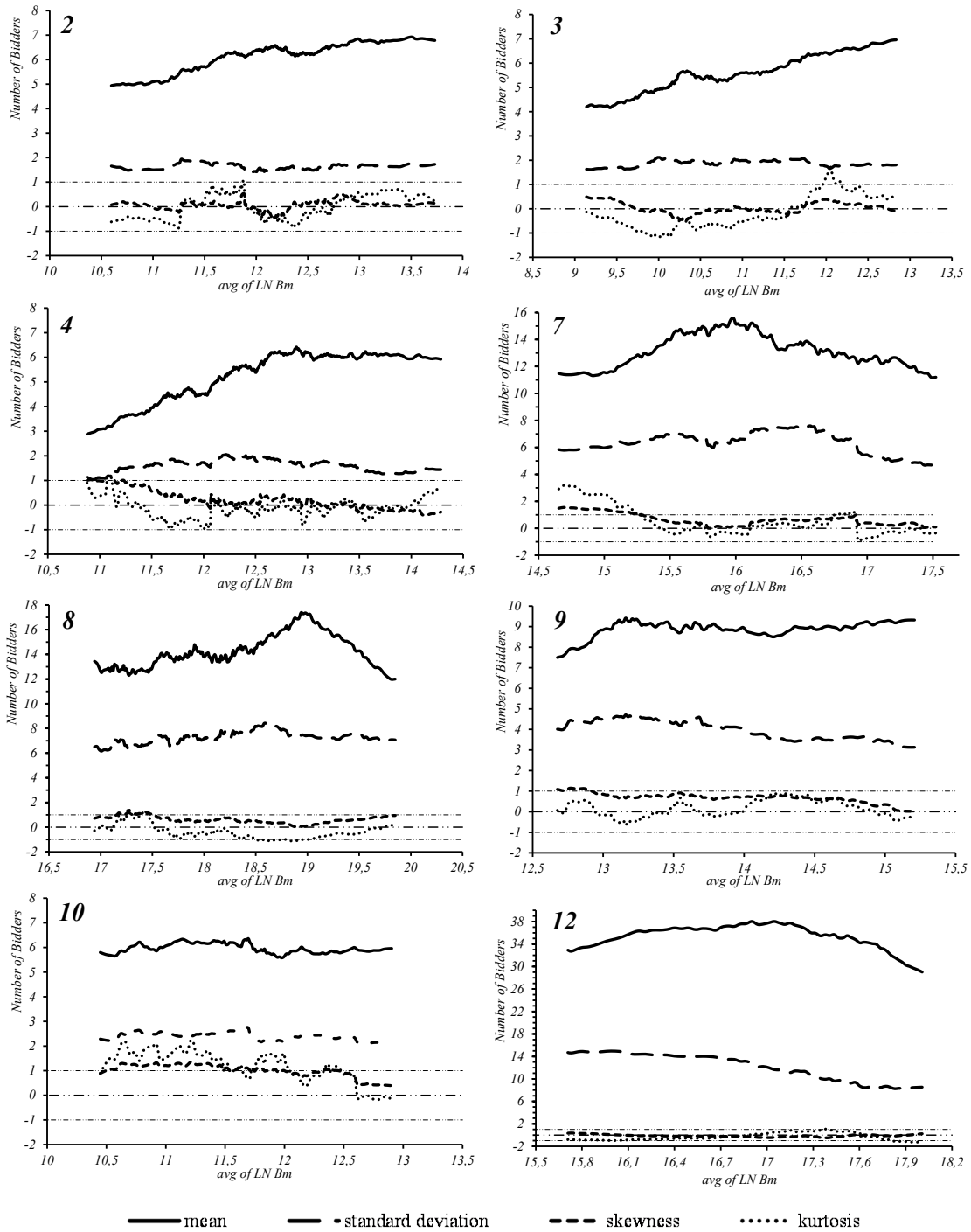


Figure 2. Variation of the mean, standard deviation, skewness and kurtosis of the Number of bidders distribution in sliding windows of 50 tenders for datasets 2-4, 7-10 and 12

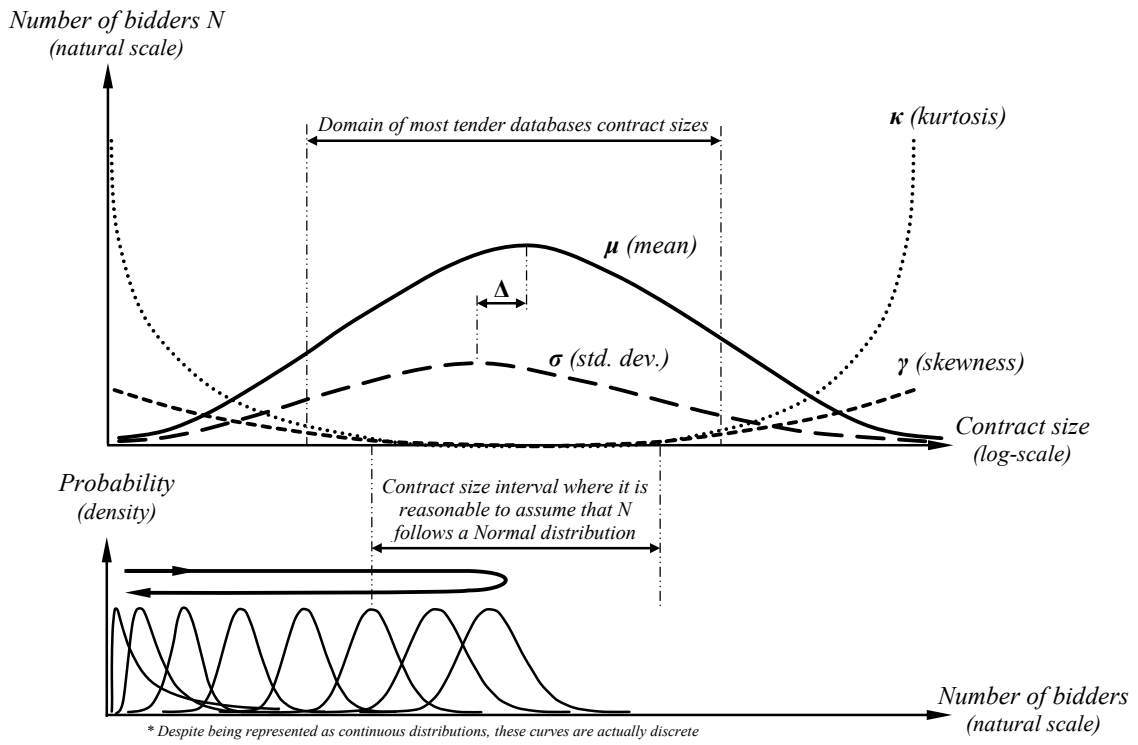


Figure 3. Variation in the mean, standard deviation, skewness and kurtosis of N in terms of contract size

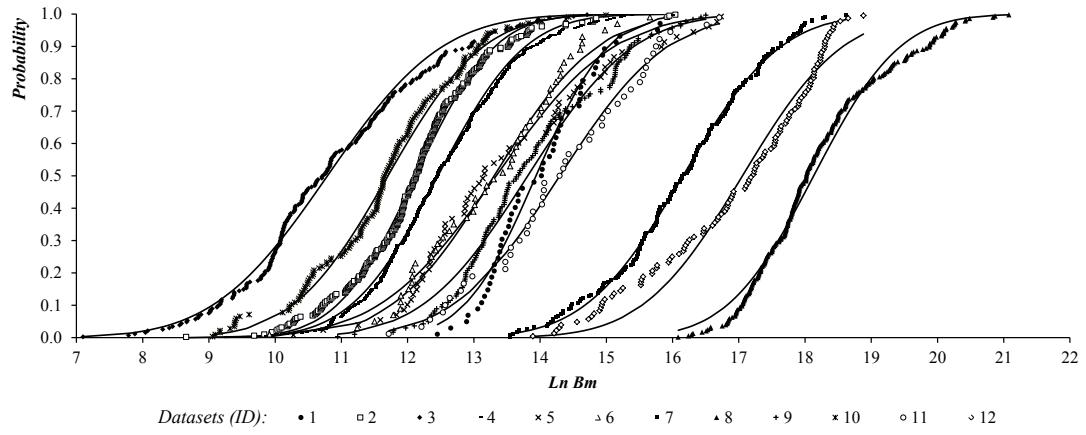


Figure 4. Lognormal distribution fitting to the Contract size opportunities for the twelve datasets

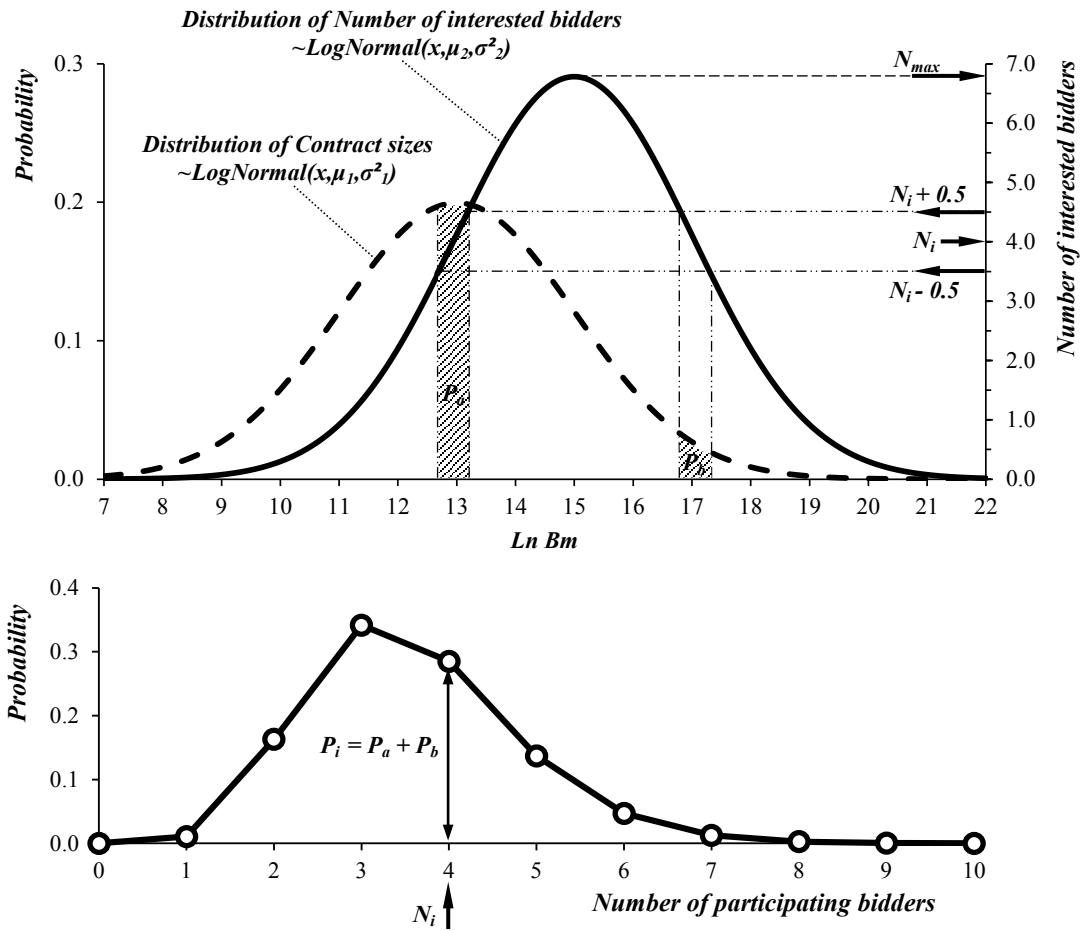


Figure 5. Calculation of the Number of participating bidders distribution as a function of the Contract size opportunities and Number of interested bidders distributions

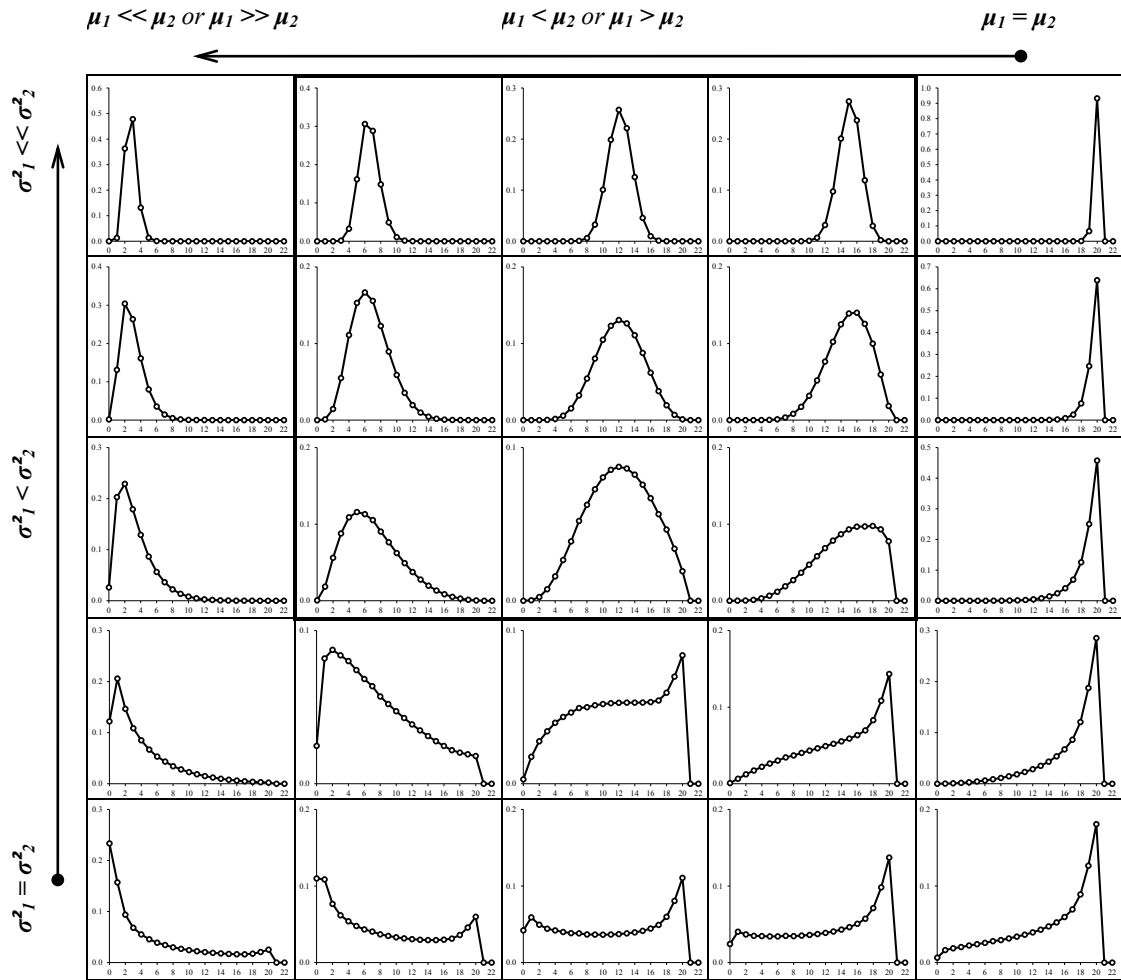


Figure 6. Possible Number of bidders distributions as a function of the relative magnitudes of the Contract size opportunities distribution (1) and the Number of interested bidders distribution (2) assuming both lognormal

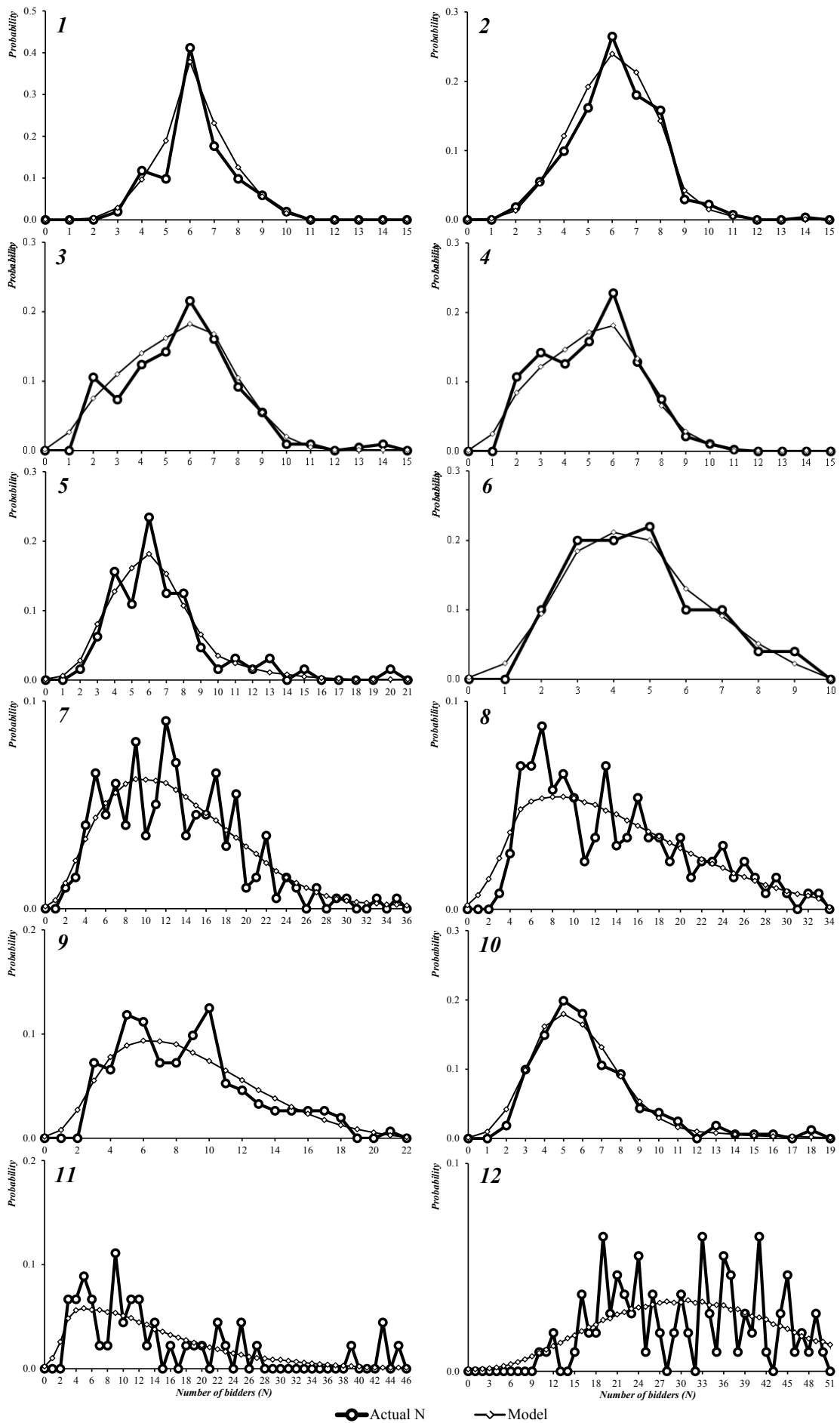


Figure 7. Model distribution fitting to the Number of bidders considering the complete dataset for the twelve datasets

Order	ID	B_m	N	Order	ID	B_m	N	Order	ID	B_m	N	Order	ID	B_m	N
Dataset 1															
1	49	255,475	5	16	153	30,060	5	83	192	119,960	6	150	188	200,765	8
2	17	312,916	10	17	42	30,846	6	84	191	122,423	5	151	103	202,149	6
3	50	397,252	5	18	105	32,330	7	85	94	123,751	7	152	112	202,168	4
4	5	406,027	6	19	39	38,903	5	86	172	123,752	8	153	202	204,300	6
5	18	470,578	6	20	7	40,225	5	87	110	129,204	8	154	168	204,482	8
6	26	499,016	7	21	162	40,962	6	88	260	129,318	3	155	123	206,321	6
7	2	520,943	4	22	149	41,843	5	89	115	129,918	6	156	180	206,432	9
8	38	547,634	5	23	256	42,201	3	90	14	130,043	7	157	170	207,578	8
9	32	565,353	6	24	129	43,721	4	91	34	134,108	7	158	205	211,129	6
10	29	580,262	6	25	160	44,195	5	92	56	134,131	6	159	210	214,249	6
11	22	602,953	6	26	220	44,690	6	93	185	135,792	5	160	29	217,260	6
12	51	604,565	6	27	163	44,973	5	94	252	136,210	6	161	66	217,446	7
13	14	638,915	6	28	239	45,573	3	95	121	139,907	5	162	189	218,332	8
14	13	655,085	4	29	76	46,808	5	96	145	140,355	8	163	208	219,037	4
15	31	666,511	6	30	156	46,828	3	97	186	141,088	7	164	263	222,316	7
16	4	679,706	6	31	146	48,194	8	98	19	141,172	6	165	158	224,650	7
17	43	714,806	6	32	8	50,173	4	99	77	143,545	5	166	78	225,170	6
18	39	749,287	7	33	9	50,871	5	100	197	145,920	10	167	151	230,210	5
19	48	764,006	7	34	58	51,998	7	101	182	146,810	4	168	266	230,476	7
20	36	784,334	6	35	224	52,655	7	102	241	147,346	8	169	233	230,554	7
21	33	829,005	6	36	232	54,562	4	103	96	147,706	6	170	215	232,022	5
22	16	865,610	3	37	225	55,555	5	104	17	148,493	7	171	30	236,352	4
23	35	865,760	6	38	63	63,381	6	105	161	149,968	3	172	184	237,491	4
24	9	922,574	6	39	130	64,193	8	106	254	150,922	7	173	108	238,521	6
25	10	1,099,822	4	40	157	64,430	2	107	10	150,978	6	174	31	240,525	5
26	12	1,230,384	6	41	80	65,612	5	108	97	151,169	5	175	54	243,298	3
27	24	1,244,998	8	42	61	66,534	7	109	259	151,653	8	176	22	243,855	6
28	45	1,264,500	4	43	131	67,182	4	110	245	153,161	8	177	199	244,124	8
29	3	1,388,291	7	44	88	68,601	8	111	230	154,097	5	178	169	245,394	6
30	1	1,469,900	6	45	62	69,502	3	112	173	154,405	7	179	92	246,461	5
31	47	1,485,788	8	46	203	71,184	7	113	212	154,486	5	180	165	247,102	8
32	15	1,533,303	6	47	90	72,605	2	114	81	154,944	5	181	207	251,498	6
33	41	1,587,053	6	48	50	72,648	4	115	74	155,037	6	182	57	253,158	8
34	23	1,648,883	5	49	195	76,842	4	116	138	156,122	6	183	24	254,885	8
35	27	1,658,920	4	50	204	77,745	6	117	179	156,794	6	184	13	257,123	9
36	11	1,840,047	6	51	255	77,748	4	118	111	157,101	6	185	217	259,894	6
37	6	2,175,920	9	52	201	78,599	6	119	33	157,391	5	186	117	260,829	4
38	34	2,193,878	7	53	89	82,153	4	120	59	163,843	4	187	3	262,157	5
39	40	2,224,161	8	54	86	83,042	6	121	159	164,295	5	188	164	266,082	5
40	28	2,228,506	7	55	137	83,206	4	122	234	165,137	7	189	190	276,485	6
41	44	2,299,880	5	56	116	84,398	3	123	253	165,936	6	190	107	276,824	9
42	25	2,709,641	6	57	67	84,717	6	124	262	166,609	7	191	128	278,246	5
43	30	2,787,458	6	58	60	85,427	6	125	200	168,631	4	192	150	278,880	4
44	46	2,858,348	7	59	104	86,547	5	126	23	170,477	6	193	93	279,423	6
45	19	3,098,473	9	60	181	86,857	6	127	126	174,111	7	194	4	280,954	8
46	7	3,190,937	7	61	258	87,192	3	128	242	175,115	8	195	177	282,886	5
47	42	3,811,024	8	62	119	88,932	6	129	152	175,328	8	196	99	286,431	5
48	21	4,026,060	7	63	98	89,109	6	130	226	176,334	6	197	124	288,278	7
49	37	7,092,871	9	64	109	91,469	6	131	114	176,778	8	198	166	293,985	7
50	8	7,387,959	4	65	106	93,184	5	132	70	178,821	4	199	257	298,370	7
51	20	8,070,280	8	66	95	93,683	6	133	85	180,630	8	200	46	314,221	5
Dataset 2															
1	65	5,752	2	67	41	95,009	6	134	135	183,550	6	201	246	316,789	7
2	132	16,055	6	68	268	99,293	3	135	11	183,924	7	202	84	332,029	6
3	36	18,745	2	69	68	99,585	6	136	187	184,729	8	203	87	334,262	7
4	175	20,872	8	70	40	100,055	7	137	27	185,639	8	204	194	335,961	7
5	1	21,043	3	71	133	101,205	7	138	171	186,284	8	205	265	336,091	10
6	271	22,602	4	72	147	101,678	5	139	28	187,459	6	206	249	336,868	8
7	221	22,847	6	73	269	101,960	8	140	167	189,190	8	207	102	352,430	6
8	154	23,606	4	74	193	103,719	8	141	12	192,949	7	208	15	356,801	14
9	148	24,296	4	75	71	109,643	2	142	183	193,093	7	209	219	357,349	8
10	6	26,599	6	76	72	112,067	8	143	113	194,181	6	210	83	366,464	6
11	176	26,985	6	77	100	112,958	8	144	238	194,557	7	211	140	371,239	7
12	38	27,498	5	78	174	114,272	8	145	178	195,704	3	212	26	376,399	6
13	227	29,002	5	79	16	114,342	11	146	122	197,390	9	213	53	377,927	6
14	222	29,309	3	80	218	115,621	5	147	206	198,031	9	214	101	378,556	6
15	155	29,800	4	81	244	119,564	6	148	250	199,406	5	215	5	401,972	6
				82	118	119,621	4	149	43	199,638	5	216	261	405,297	8

Order	ID	B_m	N	Order	ID	B_m	N	Order	ID	B_m	N	Order	ID	B_m	N
217	247	406,191	7	11	61	5,796	5	78	122	25,623	6	145	6	92,596	10
218	267	406,191	7	12	92	5,861	3	79	198	26,406	8	146	143	93,938	6
219	51	408,980	10	13	8	6,629	8	80	58	26,541	3	147	203	94,027	7
220	198	409,354	4	14	64	6,919	2	81	87	26,960	5	148	183	97,760	5
221	64	415,820	7	15	182	6,927	6	82	193	27,311	9	149	140	99,405	7
222	55	425,958	6	16	195	7,202	6	83	20	27,732	2	150	88	100,567	6
223	120	431,343	8	17	145	8,110	4	84	185	27,757	8	151	93	102,126	6
224	91	439,911	5	18	83	8,282	5	85	82	29,038	4	152	150	104,115	6
225	127	444,029	5	19	7	8,298	3	86	49	29,575	5	153	33	107,038	7
226	141	455,627	8	20	114	8,517	4	87	111	29,713	5	154	48	111,189	6
227	270	465,382	3	21	63	9,159	2	88	156	29,808	5	155	196	112,007	9
228	44	478,889	7	22	90	9,326	4	89	206	29,852	7	156	57	113,796	7
229	248	486,656	9	23	154	9,635	5	90	78	31,271	5	157	137	115,081	6
230	18	487,318	11	24	91	9,670	4	91	24	32,420	2	158	141	115,471	6
231	251	491,287	5	25	167	9,787	4	92	117	32,952	4	159	97	119,885	7
232	209	494,573	7	26	190	9,807	4	93	208	32,962	6	160	50	121,158	3
233	240	503,235	6	27	73	11,545	3	94	215	33,354	7	161	139	122,544	8
234	25	506,462	10	28	69	11,676	6	95	59	33,385	3	162	164	122,895	8
235	243	511,560	6	29	153	11,803	6	96	191	33,509	7	163	94	129,329	6
236	223	515,963	6	30	218	11,889	5	97	113	33,641	3	164	180	130,153	6
237	134	529,380	6	31	177	11,890	5	98	62	34,764	6	165	41	130,359	5
238	82	538,110	4	32	159	12,807	4	99	13	35,358	6	166	17	134,443	14
239	211	541,719	7	33	213	13,666	3	100	71	35,818	6	167	9	146,246	7
240	2	542,347	8	34	168	14,264	6	101	178	36,433	5	168	101	148,013	2
241	45	560,949	8	35	104	14,287	4	102	205	38,145	9	169	187	152,111	9
242	144	564,537	8	36	70	14,314	5	103	135	40,184	6	170	81	155,835	5
243	69	662,731	7	37	116	14,425	2	104	217	40,452	8	171	125	157,494	4
244	196	664,835	9	38	1	15,046	8	105	2	40,862	8	172	169	170,593	7
245	20	740,024	7	39	129	16,996	4	106	34	41,282	6	173	15	174,266	7
246	21	749,178	7	40	60	17,763	5	107	112	42,041	4	174	39	175,981	7
247	228	760,179	7	41	4	17,767	3	108	211	44,620	7	175	155	186,359	7
248	143	768,544	3	42	173	18,010	3	109	36	44,724	8	176	157	195,637	7
249	216	775,630	6	43	14	18,551	6	110	28	45,707	4	177	194	198,405	11
250	52	776,894	6	44	199	18,817	5	111	214	47,248	6	178	165	199,653	7
251	139	789,119	7	45	67	18,973	4	112	44	47,534	7	179	119	204,132	5
252	214	845,629	7	46	55	19,801	2	113	130	48,582	4	180	52	213,544	7
253	125	871,134	7	47	68	20,069	4	114	11	48,682	7	181	40	226,280	4
254	229	907,487	6	48	21	20,116	2	115	115	49,769	5	182	152	227,459	5
255	48	987,521	9	49	118	20,423	3	116	54	50,375	2	183	10	242,757	11
256	235	987,774	5	50	216	20,469	8	117	134	50,520	6	184	100	255,876	5
257	272	1,004,402	6	51	142	20,545	6	118	179	50,695	4	185	51	257,050	5
258	32	1,006,498	8	52	37	20,802	2	119	128	50,856	2	186	47	259,844	7
259	136	1,030,093	6	53	85	20,925	6	120	74	51,410	4	187	43	261,374	6
260	236	1,057,545	8	54	25	21,219	2	121	133	51,549	6	188	103	264,877	6
261	49	1,059,427	7	55	19	21,305	2	122	184	52,254	8	189	212	268,807	4
262	47	1,238,914	6	56	84	21,416	4	123	131	53,644	6	190	106	272,708	7
263	35	1,767,575	7	57	107	21,787	2	124	148	54,101	4	191	42	284,132	5
264	213	1,780,238	6	58	175	21,993	6	125	99	55,239	4	192	110	287,760	7
265	79	2,279,604	7	59	160	22,073	7	126	32	58,195	5	193	35	289,899	6
266	237	2,683,822	10	60	132	22,210	6	127	163	60,332	5	194	109	336,040	6
267	264	2,683,828	10	61	186	22,551	6	128	66	65,616	7	195	105	370,847	8
268	231	2,776,352	8	62	126	22,889	4	129	147	67,072	4	196	144	410,514	7
269	142	2,815,698	6	63	123	23,524	6	130	197	67,652	7	197	151	426,977	9
270	73	8,234,520	5	64	86	23,829	7	131	53	69,894	2	198	172	428,115	10
271	75	8,489,562	5	65	124	23,832	6	132	98	74,280	5	199	138	431,616	7
272	37	9,296,868	4	66	174	23,858	6	133	45	74,587	2	200	108	445,232	6
Dataset 3				67	121	23,986	6	134	76	76,183	3	201	3	509,741	9
1	189	1,211	2	68	176	24,023	6	135	188	77,321	9	202	102	530,878	8
2	5	2,413	5	69	171	24,310	7	136	79	78,715	5	203	166	537,637	6
3	72	2,654	5	70	22	24,438	2	137	89	79,745	3	204	56	547,061	6
4	31	3,112	2	71	120	24,447	6	138	95	81,210	7	205	181	562,081	8
5	18	3,222	3	72	200	24,624	8	139	149	81,450	6	206	46	580,737	7
6	127	4,036	3	73	170	24,912	8	140	77	84,110	3	207	38	607,239	6
7	136	4,464	6	74	209	24,946	7	141	146	86,481	7	208	29	720,865	8
8	27	4,685	2	75	80	25,279	5	142	12	89,978	13	209	158	779,079	9
9	192	5,217	5	76	23	25,288	2	143	75	91,422	4	210	210	851,480	9
10	201	5,366	2	77	26	25,523	2	144	202	92,063	9	211	204	885,689	9

Order	ID	B_m	N	Order	ID	B_m	N	Order	ID	B_m	N	Order	ID	B_m	N
212	65	1,025,652	8	60	115	99,086	6	127	344	165,774	5	194	134	257,506	3
213	161	1,154,586	7	61	230	99,339	6	128	207	166,162	6	195	149	259,653	5
214	96	1,156,500	7	62	297	99,470	6	129	300	168,570	4	196	347	260,232	6
215	30	1,169,669	14	63	187	100,309	4	130	286	168,656	3	197	138	261,590	7
216	207	1,383,514	9	64	262	101,130	8	131	92	168,704	4	198	39	263,795	4
217	162	1,996,684	8	65	37	104,858	4	132	244	171,307	2	199	364	268,421	4
218	16	2,443,593	8	66	97	105,919	3	133	356	172,202	6	200	120	273,857	6
Dataset 4				67	313	106,138	2	134	21	174,101	2	201	281	275,082	10
1	270	10,266	2	68	48	106,193	5	135	232	175,982	5	202	200	275,553	3
2	201	18,756	2	69	371	106,300	3	136	99	177,015	2	203	339	277,997	7
3	162	20,607	2	70	81	107,887	6	137	51	177,396	3	204	305	292,008	7
4	192	22,609	2	71	206	110,050	2	138	373	177,447	6	205	194	292,696	7
5	10	25,800	2	72	197	110,194	4	139	258	178,802	3	206	121	293,169	5
6	189	32,296	4	73	291	110,884	4	140	332	182,529	2	207	363	293,720	6
7	71	35,050	2	74	246	111,308	3	141	148	183,077	5	208	75	295,163	6
8	131	39,459	4	75	62	112,400	2	142	158	183,573	3	209	311	295,839	9
9	3	42,309	3	76	199	112,882	3	143	215	183,956	3	210	105	296,576	5
10	76	42,335	2	77	271	113,112	6	144	145	185,581	6	211	327	301,196	6
11	59	46,230	2	78	278	114,144	3	145	216	185,766	6	212	85	306,749	6
12	218	46,965	3	79	301	114,593	4	146	315	185,777	3	213	102	307,320	8
13	93	47,257	2	80	163	114,748	2	147	152	186,199	7	214	11	308,365	6
14	127	48,179	3	81	345	116,618	2	148	239	188,155	6	215	309	308,864	5
15	173	48,643	2	82	33	116,931	5	149	273	189,592	5	216	104	315,881	3
16	57	49,786	3	83	91	117,739	7	150	68	190,001	8	217	329	316,722	4
17	166	49,788	2	84	14	118,503	2	151	151	192,221	3	218	367	320,945	7
18	4	50,011	3	85	171	119,032	4	152	220	193,145	5	219	211	325,739	3
19	31	50,709	3	86	272	119,270	6	153	252	195,882	6	220	234	326,936	5
20	135	51,024	3	87	26	119,631	6	154	12	198,895	4	221	132	329,463	5
21	98	51,737	3	88	83	123,004	4	155	119	199,253	7	222	90	330,003	7
22	302	51,762	3	89	219	123,418	6	156	223	199,539	6	223	354	331,138	6
23	46	52,509	4	90	348	124,383	8	157	322	201,565	6	224	243	336,799	8
24	369	52,517	5	91	47	124,537	3	158	240	203,383	6	225	265	339,929	8
25	227	57,866	2	92	182	125,622	3	159	164	203,517	6	226	320	341,272	5
26	88	59,237	2	93	298	125,771	4	160	43	204,325	10	227	144	346,369	11
27	114	59,666	4	94	326	126,402	5	161	285	205,432	7	228	266	346,650	8
28	42	60,154	3	95	212	126,660	5	162	140	207,530	7	229	95	350,441	8
29	170	61,560	2	96	107	126,800	4	163	150	209,994	6	230	53	351,739	3
30	86	62,747	2	97	79	129,460	5	164	108	213,588	5	231	190	354,912	4
31	183	64,407	5	98	84	130,632	5	165	146	217,099	7	232	340	357,137	9
32	168	64,768	3	99	287	131,416	5	166	204	219,550	6	233	109	357,794	8
33	8	64,870	2	100	74	131,565	8	167	295	220,081	6	234	167	358,237	6
34	154	65,584	2	101	312	133,233	3	168	20	221,482	6	235	156	362,705	5
35	259	67,107	5	102	128	133,540	7	169	153	221,736	2	236	56	364,978	7
36	306	69,055	3	103	24	133,971	3	170	241	222,186	6	237	228	367,800	9
37	289	70,535	2	104	38	134,815	7	171	208	222,858	10	238	231	368,037	7
38	25	72,051	3	105	317	135,358	8	172	352	225,887	8	239	349	385,951	6
39	269	73,042	6	106	125	135,369	2	173	40	226,345	3	240	233	390,881	8
40	191	75,073	3	107	307	135,660	2	174	222	228,306	3	241	129	391,214	5
41	23	75,675	2	108	87	144,477	5	175	324	228,548	6	242	372	393,297	7
42	303	77,774	4	109	157	146,759	2	176	28	228,611	2	243	293	393,967	5
43	172	78,675	4	110	343	148,003	7	177	89	228,686	7	244	253	398,477	6
44	279	81,868	3	111	341	148,421	3	178	54	229,444	4	245	257	398,555	4
45	6	83,477	3	112	69	150,081	5	179	370	231,175	6	246	139	398,680	5
46	96	83,722	2	113	70	151,904	5	180	34	234,544	8	247	112	400,523	7
47	185	84,382	2	114	193	152,157	5	181	251	235,048	7	248	136	401,065	5
48	169	84,652	2	115	52	152,238	5	182	226	240,781	3	249	296	401,373	6
49	274	86,141	3	116	237	153,443	4	183	292	240,785	3	250	217	407,210	6
50	116	86,209	4	117	174	153,789	7	184	314	242,726	7	251	82	411,514	6
51	101	88,478	5	118	165	158,196	3	185	264	245,385	3	252	275	412,354	4
52	196	89,054	4	119	7	158,521	3	186	342	247,403	4	253	290	415,477	7
53	359	89,544	6	120	328	158,794	4	187	117	249,180	6	254	358	416,033	5
54	213	90,931	3	121	368	159,037	4	188	355	249,957	4	255	133	416,141	4
55	142	92,008	3	122	19	159,861	6	189	235	250,595	6	256	277	419,637	8
56	159	92,742	4	123	362	160,155	5	190	45	250,649	3	257	66	421,229	7
57	1	93,246	7	124	276	160,607	5	191	147	251,652	6	258	203	423,123	4
58	181	97,951	4	125	325	161,488	6	192	335	252,577	6	259	122	425,352	8
59	15	98,687	2	126	113	163,868	5	193	319	253,958	7	260	180	428,382	6

Order	ID	B_m	N	Order	ID	B_m	N	Order	ID	B_m	N	Order	ID	B_m	N
261	263	430,774	6	328	256	904,120	6	21	64	285,590	13	7	20	522,621	7
262	9	443,592	8	329	18	926,226	6	22	43	286,220	6	24	15	537,500	2
263	13	453,216	8	330	299	927,109	4	23	49	287,666	5	25	6	598,250	4
264	316	457,125	5	331	17	927,566	5	24	62	319,228	15	26	7	686,000	3
265	238	457,601	6	332	334	929,771	4	25	29	382,367	10	27	38	767,358	3
266	73	462,459	4	333	161	959,114	8	26	42	387,837	3	28	46	787,940	4
267	100	471,945	6	334	103	964,725	6	27	52	393,076	5	29	29	804,355	3
268	304	474,179	9	335	229	1,004,630	6	28	46	402,341	5	30	25	838,808	2
269	111	477,075	7	336	5	1,026,480	7	29	51	424,831	6	31	4	861,231	7
270	63	495,134	6	337	41	1,054,996	9	30	27	446,274	6	32	8	904,356	6
271	337	495,743	8	338	188	1,120,178	6	31	63	478,377	6	33	11	965,780	6
272	357	502,889	3	339	130	1,124,186	6	32	21	506,707	4	34	27	1,035,251	3
273	35	505,227	7	340	30	1,166,292	7	33	61	520,026	4	35	19	1,197,103	5
274	32	509,133	5	341	255	1,187,921	3	34	6	524,399	6	36	13	1,220,968	5
275	186	516,209	6	342	338	1,191,547	7	35	50	598,986	11	37	24	1,315,074	7
276	260	516,448	4	343	184	1,219,109	6	36	47	670,525	9	38	21	1,375,299	9
277	143	533,213	6	344	94	1,231,401	5	37	10	747,552	2	39	41	1,409,432	4
278	310	533,285	5	345	137	1,253,170	7	38	24	757,616	5	40	43	1,527,585	6
279	214	534,462	7	346	202	1,320,747	6	39	11	868,992	4	41	17	1,635,392	5
280	72	542,917	9	347	336	1,344,893	7	40	40	949,038	12	42	34	1,635,426	9
281	308	546,775	7	348	261	1,360,551	4	41	34	1,316,515	6	43	10	1,725,065	6
282	209	547,133	6	349	205	1,381,556	7	42	33	1,376,083	9	44	32	1,906,357	4
283	58	555,493	10	350	2	1,472,162	6	43	25	1,481,536	7	45	22	2,205,996	4
284	282	558,570	5	351	177	1,562,410	7	44	44	1,484,631	6	46	48	2,269,116	4
285	346	562,844	4	352	22	1,568,224	7	45	48	1,515,446	8	47	39	2,277,616	2
286	360	567,769	7	353	179	1,581,625	6	46	56	1,584,305	8	48	1	3,203,337	8
287	124	567,999	5	354	321	1,583,369	6	47	38	1,601,454	4	49	42	3,869,281	3
288	247	578,837	2	355	36	1,633,361	4	48	60	1,883,560	5	50	33	6,321,544	4
289	323	595,331	5	356	106	1,659,637	5	49	5	2,003,500	7	Dataset 7			
290	64	602,094	3	357	78	1,999,840	6	50	28	2,110,914	3	7	43	763,896	17
291	225	603,995	7	358	350	2,005,694	6	51	17	2,303,748	4	2	128	765,264	4
292	44	605,672	9	359	61	2,071,215	6	52	41	3,013,188	8	3	77	800,696	9
293	236	605,815	5	360	198	2,189,824	5	53	18	3,197,054	4	4	173	852,246	13
294	250	609,716	6	361	160	2,217,761	5	54	58	3,214,767	5	5	32	872,496	18
295	254	621,330	7	362	267	2,446,742	3	55	3	3,492,159	6	6	34	983,245	9
296	141	621,751	4	363	318	2,473,213	6	56	4	3,676,250	4	7	74	1,099,338	14
297	155	623,702	8	364	65	2,662,722	6	57	1	4,150,514	7	8	44	1,329,758	11
298	67	625,582	8	365	175	2,730,352	6	58	23	7,532,342	6	9	140	1,345,589	9
299	248	639,203	6	366	27	2,824,961	9	59	31	7,865,411	7	10	22	1,417,487	5
300	224	647,075	4	367	123	3,229,167	8	60	2	9,463,718	11	11	36	1,455,436	7
301	284	656,363	8	368	126	3,387,660	2	61	54	12,201,531	8	12	80	1,457,550	12
302	294	660,556	6	369	280	3,596,202	6	62	59	15,379,320	9	13	1	1,521,264	5
303	268	667,073	5	370	245	3,985,016	6	63	20	17,429,631	5	14	123	1,579,990	11
304	365	673,507	7	371	331	4,187,295	5	64	22	18,465,333	3	15	16	1,639,043	7
305	29	678,044	6	372	16	4,726,542	5	Dataset 6				16	126	1,692,042	5
306	210	684,172	5	373	361	8,771,818	5	1	16	20,247	3	17	176	1,695,106	5
307	249	687,499	5	Dataset 5				2	49	76,211	3	18	91	1,861,218	8
308	55	695,530	6	1	9	29,044	7	3	31	98,962	5	19	40	1,932,775	12
309	242	711,072	5	2	30	45,653	7	4	37	131,278	3	20	130	1,933,606	11
310	178	718,094	7	3	13	77,294	7	5	28	145,951	5	21	79	1,945,299	16
311	353	730,250	6	4	12	107,840	6	6	44	147,051	5	22	21	2,125,224	6
312	221	731,243	7	5	39	137,589	20	7	26	147,200	5	23	76	2,197,257	10
313	77	731,953	8	6	26	154,196	4	8	18	165,117	5	24	60	2,237,624	12
314	118	733,926	6	7	53	162,505	13	9	23	174,157	2	25	65	2,315,028	9
315	176	734,159	5	8	37	171,720	8	10	47	174,666	3	26	38	2,531,162	11
316	333	736,153	4	9	8	176,835	3	11	3	174,981	5	27	124	2,604,669	9
317	80	741,370	6	10	15	186,726	6	12	35	183,188	8	28	45	2,869,188	16
318	351	760,367	7	11	36	188,702	6	13	9	233,860	7	29	134	2,923,644	6
319	50	767,523	6	12	32	203,945	6	14	14	249,480	2	30	106	2,978,741	12
320	49	779,007	8	13	16	204,247	8	15	36	255,602	4	31	117	3,077,471	10
321	283	798,192	6	14	14	224,953	6	16	40	278,273	3	32	53	3,097,133	16
322	110	799,855	4	15	57	228,182	8	17	30	305,750	4	33	72	3,103,435	7
323	195	820,054	7	16	19	229,316	4	18	5	326,991	5	34	94	3,162,445	6
324	330	841,216	5	17	7	230,766	6	19	45	399,197	6	35	109	3,374,166	18
325	288	856,166	7	18	45	243,824	4	20	12	438,765	4	36	37	3,488,874	8
326	366	863,234	8	19	35	263,014	8	21	50	448,149	5	37	158	3,793,233	21
327	60	890,692	8	20	55	269,513	7	22	2	453,341	7	38	48	3,879,931	25

<i>Order</i>	<i>ID</i>	<i>B_m</i>	<i>N</i>	<i>Order</i>	<i>ID</i>	<i>B_m</i>	<i>N</i>	<i>Order</i>	<i>ID</i>	<i>B_m</i>	<i>N</i>	<i>Order</i>	<i>ID</i>	<i>B_m</i>	<i>N</i>
113	27	2,363,846	8	27	33	35,838	8	94	44	137,428	5	161	9	3,260,798	8
114	38	2,508,048	9	28	153	36,136	9	95	145	138,328	9	<i>Dataset 11</i>			
115	2	2,561,172	9	29	1	36,406	5	96	18	140,514	5	1	4	122,657	3
116	107	3,001,627	7	30	75	37,130	7	97	73	144,143	5	2	39	201,402	5
117	59	3,006,421	13	31	119	38,501	5	98	148	144,165	6	3	11	229,253	11
118	16	3,445,830	9	32	155	39,087	6	99	116	151,571	4	4	35	277,774	5
119	140	3,457,929	5	33	112	39,092	5	100	22	155,400	4	5	3	287,515	14
120	99	3,589,080	9	34	129	39,623	9	101	15	162,267	4	6	44	308,259	4
121	134	3,606,215	11	35	25	42,790	5	102	13	162,467	6	7	17	364,765	18
122	85	3,634,841	6	36	91	44,749	7	103	40	164,516	13	8	38	380,479	12
123	138	3,710,882	6	37	26	48,035	4	104	21	166,160	8	9	26	433,576	9
124	136	3,731,703	12	38	28	48,104	7	105	151	167,233	5	10	40	713,573	12
125	50	3,746,593	10	39	37	51,107	5	106	64	169,798	7	11	6	713,584	5
126	130	3,754,805	11	40	23	51,411	7	107	72	170,011	6	12	34	771,586	9
127	123	3,758,103	12	41	3	59,141	4	108	106	173,237	6	13	2	775,167	4
128	28	3,806,591	5	42	49	60,871	6	109	10	175,457	3	14	7	883,144	6
129	115	3,847,477	9	43	80	62,909	10	110	16	180,415	7	15	31	987,694	3
130	86	3,947,517	13	44	70	63,753	5	111	149	184,394	4	16	37	1,002,202	3
131	119	4,069,052	14	45	35	67,006	5	112	20	187,599	6	17	10	1,077,819	25
132	36	4,327,794	3	46	97	67,851	5	113	101	195,421	6	18	5	1,082,862	11
133	131	4,407,398	10	47	77	69,098	5	114	138	198,183	6	19	42	1,243,280	20
134	98	4,499,075	8	48	125	69,972	7	115	117	202,766	3	20	23	1,260,234	4
135	117	4,548,821	10	49	50	74,176	6	116	133	206,866	8	21	22	1,275,801	19
136	128	4,612,678	9	50	78	76,067	8	117	95	208,540	3	22	21	1,286,376	7
137	105	4,637,181	8	51	41	79,709	4	118	104	211,821	4	23	32	1,616,923	6
138	35	4,778,909	3	52	62	80,054	7	119	5	220,093	5	24	41	1,708,144	8
139	147	5,008,153	14	53	43	80,104	2	120	114	229,196	4	25	43	1,764,662	11
140	42	5,281,779	4	54	76	80,332	5	121	8	236,497	6	26	18	1,856,797	14
141	139	5,313,098	8	55	139	81,413	6	122	83	244,161	3	27	25	2,179,868	25
142	94	6,372,181	13	56	29	82,727	4	123	113	245,606	2	28	33	2,536,349	9
143	47	6,478,101	13	57	82	84,454	14	124	86	272,561	7	29	45	2,612,412	5
144	108	7,248,956	10	58	51	87,037	10	125	140	274,551	6	30	36	3,071,591	9
145	93	8,573,757	10	59	27	87,929	13	126	120	285,500	5	31	9	3,080,428	10
146	90	8,846,539	15	60	131	89,418	6	127	65	296,019	11	32	19	3,363,910	6
147	145	10,041,043	6	61	30	94,961	10	128	74	313,076	6	33	8	3,885,370	22
148	143	10,041,371	11	62	94	96,562	4	129	56	314,483	9	34	24	4,289,341	22
149	142	10,902,881	12	63	134	98,450	6	130	118	343,941	11	35	29	4,749,403	9
150	144	12,104,566	10	64	150	102,114	3	131	92	346,422	5	36	1	5,450,186	13
151	116	13,685,053	8	65	132	102,160	6	132	11	355,518	7	37	27	5,719,436	16
152	11	14,674,315	10	66	152	102,360	4	133	146	359,106	10	38	12	5,959,673	43
<i>Dataset 10</i>				67	108	102,996	11	134	59	363,022	3	39	20	6,062,617	45
1	154	8,587	9	68	14	103,907	4	135	103	374,287	3	40	13	6,664,934	43
2	161	8,919	8	69	12	104,142	6	136	60	377,712	7	41	28	6,927,068	10
3	122	9,582	5	70	7	105,308	6	137	67	380,539	4	42	30	7,312,009	27
4	158	9,586	18	71	137	106,113	5	138	85	381,766	5	43	16	8,625,632	39
5	156	11,159	4	72	36	107,088	7	139	96	382,789	5	44	14	14,894,721	12
6	130	11,903	11	73	2	108,485	5	140	99	389,007	5	45	15	18,027,863	23
7	47	11,981	4	74	110	108,806	6	141	19	421,600	4	<i>Dataset 12</i>			
8	160	11,989	15	75	123	111,326	8	142	115	449,603	8	1	15	1,079,144	24
9	68	12,108	3	76	81	112,051	3	143	88	455,400	5	2	28	1,488,330	21
10	157	12,257	18	77	84	112,104	5	144	63	459,292	9	3	79	1,537,471	22
11	79	12,917	3	78	135	112,547	6	145	142	474,916	7	4	31	1,612,499	24
12	159	14,873	13	79	48	112,868	4	146	61	475,413	5	5	107	1,653,353	26
13	127	24,736	7	80	24	113,926	10	147	100	508,394	3	6	37	2,103,391	19
14	126	27,070	8	81	141	114,969	5	148	57	515,450	8	7	4	2,499,595	12
15	46	27,290	6	82	144	116,525	4	149	89	525,365	6	8	41	2,626,856	24
16	124	27,357	7	83	87	119,033	5	150	58	531,609	6	9	17	2,716,395	36
17	52	28,229	4	84	66	120,156	8	151	147	538,566	7	10	26	2,960,181	22
18	31	29,644	4	85	17	122,317	5	152	71	547,322	8	11	97	3,017,126	36
19	93	31,418	3	86	111	123,475	9	153	109	611,131	8	12	108	3,063,002	33
20	4	31,602	4	87	69	126,872	8	154	107	732,683	7	13	47	3,086,445	20
21	34	32,298	3	88	136	127,880	6	155	98	734,439	4	14	114	3,195,185	48
22	38	33,132	3	89	90	128,207	5	156	55	924,217	16	15	109	3,559,762	34
23	39	33,132	3	90	42	131,595	5	157	6	1,005,086	6	16	16	3,682,856	45
24	53	34,075	4	91	45	131,750	2	158	143	1,237,836	8	17	24	4,048,593	34
25	128	34,621	6	92	54	134,590	10	159	105	1,775,726	6	18	94	4,198,634	45
26	32	34,785	5	93	121	136,802	3	160	102	1,857,215	6	19	93	5,517,449	49

Order	ID	B_m	N
20	5	5,519,531	16
21	112	5,582,020	22
22	22	5,705,802	41
23	100	6,534,653	16
24	113	6,552,800	37
25	105	7,001,062	16
26	72	7,054,504	65
27	95	8,389,273	40
28	6	8,516,973	21
29	101	8,852,925	15
30	85	9,802,996	47
31	38	10,495,291	50
32	106	10,615,254	16
33	46	10,816,891	39
34	49	11,177,786	47
35	40	11,488,513	49
36	104	12,315,545	63
37	84	14,132,357	44
38	103	14,227,093	60
39	64	14,341,530	23
40	110	16,251,125	33
41	99	16,860,295	10
42	50	17,588,667	49
43	111	17,746,139	25
44	96	18,619,007	12
45	34	19,595,731	42
46	27	20,153,397	41
47	59	20,561,970	59
48	98	20,563,467	11
49	3	21,353,568	30
50	10	21,708,000	33
51	63	22,143,465	23
52	102	22,318,154	55
53	51	26,479,141	31
54	1	27,040,451	45
55	55	27,910,450	52
56	39	28,331,375	45
57	61	29,000,444	41
58	25	30,249,575	41
59	2	30,551,542	45
60	30	30,770,871	30
61	12	31,590,763	36
62	14	31,590,763	36
63	69	33,210,700	39
64	7	34,764,003	34
65	45	35,455,363	41
66	29	35,987,767	41
67	71	39,283,078	30
68	32	41,228,951	44
69	65	41,597,001	40
70	8	42,025,452	38
71	33	42,092,509	46
72	70	43,561,070	31
73	54	45,077,325	37
74	11	45,260,730	37
75	43	45,925,278	41
76	35	49,140,339	36
77	60	49,876,103	37
78	56	51,567,774	44
79	9	51,730,833	33
80	13	53,330,879	27
81	73	56,420,628	33
82	66	59,361,774	37
83	75	59,997,000	29
84	20	60,296,637	19
85	42	62,189,663	35
86	21	64,914,393	27

Order	ID	B_m	N
87	76	66,094,206	29
88	48	69,184,189	39
89	44	70,540,511	36
90	57	71,468,346	33
91	62	71,756,192	26
92	19	74,858,840	19
93	23	74,858,840	19
94	77	75,413,556	24
95	52	75,417,028	33
96	90	78,509,325	24
97	91	79,529,913	23
98	67	82,812,206	30
99	86	83,070,638	17
100	74	83,210,900	26
101	78	84,037,235	24
102	87	87,245,462	17
103	89	88,574,213	21
104	92	88,614,685	21
105	83	89,355,119	20
106	80	91,994,522	19
107	53	93,425,682	26
108	81	95,744,520	19
109	88	99,982,162	22
110	36	101,166,388	18
111	18	102,559,740	19
112	82	112,041,174	20
113	68	126,157,555	21
114	58	158,509,777	18