Size Distributions for All Cities: Which One is Best?

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Abstract

This paper analyses in detail the features offered by three distributions used in urban economics to describe city size distributions: lognormal, q-exponential and double Pareto lognormal, and another one of use in other areas of economics: the log-logistic. We use a large database which covers all cities with no size restriction in the US, Spain and Italy from 1900 until 2010, and, in addition, the last available year for the rest of the countries of the OECD. We estimate the previous four density functions by maximum likelihood. To check the goodness of the fit in all periods and for the thirty-four countries we use the Kolmogorov-Smirnov and Cramér-von Mises tests, and compute the Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC). The results show that the distribution which best fits the data in most of the cases (86.76%) is the double Pareto lognormal.

Keywords: city size distribution, double Pareto lognormal, log-logistic, q-exponential, lognormal

JEL: C13, C16, R00.

1. Introduction

The study of city size distribution has a long tradition in urban economics. To cite just a few examples, see Rosen and Resnick (1980), Black and Henderson (2003), Ioannides and Overman (2003), Soo (2005), Anderson and Ge (2005), and Bosker et al. (2008). These distributions have an interest beyond the purely statistical, essentially for two reasons, which feed back to and influence each other. First, because city size distribution defines the resulting economic landscape. It may be more concentrated or dispersed, or biased towards an excessive number of large or small centres, with cities which are similar or very different in size, and all of this has a direct impact on the spatial distribution of income, on public investment in infrastructure of various kinds in certain areas, and on imbalances between territories in general. And second, because this size distribution is susceptible to change over time, according to certain, essentially economic, incentives.

Over the years, the Pareto distribution (Pareto, 1896) has generated a huge amount of research and greater acceptance. Considering the rank r (1 for the most populous city, 2 for the second, and so on) of the N cities, we can obtain the expression for the Pareto distribution usually estimated,

$$\ln r = const. - b \ln x, \qquad (1)$$

which relates the logarithm of rank with the logarithm of the size of the cities if they follow a Pareto distribution. In the case of $b = 1$, we obtain the well-known Zipf's law (Zipf, 1949) or rank-size rule (see the surveys on this subject by Cheshire, 1999, and Gabaix and Ioannides, 2004).[1]

[1] Zipf's law also holds at the level of cities belonging to regions (Giesen and Suedekum, 2011) or when cities are defined as actual economic areas using different methods (Rozenfeld et al., 2011; Berry and Okulicz-Kozaryn, 2012).

In an important paper regarding city size distributions, Eeckhout (2004) essentially proposes three ideas: (1) that when all cities are taken, without any size restriction, Pareto's distribution breaks down and the best representation of the data is a lognormal function; (2) as a theoretical result, if the underlying distribution is lognormal, which generates a concave rank-size plot, the Pareto exponent decreases with sample size, meaning that a sample size can be found which verifies Zipf's law exactly (these first two contributions clearly show the importance of taking all cities, as to do otherwise can lead to biased or spurious results); and (3) the data for all US cities in 1990 and 2000 support the hypothesis of lognormality and the fulfilment of Gibrat's law, or the law of proportionate growth, something which was already anticipated from a theoretical viewpoint by Gibrat (1931) and Kalecki (1945). As a consequence, there has been a revival of interest in the lognormal distribution, proposed a long time ago as a good description of city size distribution (Parr and Suzuki, 1973).

Moreover, other statistical distributions have been proposed in studying city size: the q-exponential distribution (Malacarne et al., 2001; Soo, 2007) and double Pareto lognormal distribution (Reed, 2002, Giesen et al., 2010). Ioannides and Skouras (2013) have even proposed a new distribution function which switches between a lognormal and a power distribution. There is also an older literature that explores alternative functional forms; see, for example, Cameron (1990), Hsing (1990) or Kamecke (1990). This paper is in line with all this literature.

With respect to the q-exponential distribution, Malacarne et al. (2001) show that, when all cities are taken, it has a very close fit to the data. They use data from American and Brazilian cities. As far as we know, the only other work to test this statement is that of Soo (2007) who, taking the largest cities of Malaysia (over 10,000 inhabitants) obtains negative results regarding the features of the q-exponential, leading us to think, as with the lognormal, that this distribution is suitable when no truncation point is defined.

The double Pareto lognormal distribution proposed by Reed (2001) has strong theoretical foundations. Reed (2002) fits the distribution to the smallest settlements of two US states (West Virginia and California) in 1998 and two Spanish provinces (Cantabria and Barcelona) in 1996, obtaining good results. The recent paper by Giesen et al. (2010) shows that the double Pareto lognormal almost always offers a better description than the lognormal of the city size data for eight countries (Brazil, the Czech Republic, France, Germany, Hungary, Italy, Switzerland, and the US) in the first decade of the 21st century, offering the strongest evidence in favour of the double Pareto lognormal to date.

Apart from these three distributions (the lognormal, the q-exponential and the double Pareto lognormal), we have observed that the log-logistic distribution also offers a close description of the data. Thus we add it to the study. The log-logistic has been used as a simple model of the distribution of wealth or income by Fisk (1961); hence the name of Fisk distribution in economics. In other fields, it is widely used in survival analysis when the failure rate function presents a unimodal shape; it has also been used in hydrology to model stream flow and precipitation. However, to the best of our knowledge, this is its first appearance in urban economics.

Recently much more complete databases have been constructed, which enable us to bring more statistical information to bear on the problem dealt with in this work. Specifically, González-Val (2010) considers all the cities in the US during the entire 20th century; González-Val et al. (2012) do the same for Spain and Italy, as well as for the US. If these data are used to represent the logarithm of the rank against the logarithm of city size, a clear deviation from linearity can be observed in all cases, opening the way for the consideration of non-Pareto distributions. What we want to emphasise is that, except for Eeckhout (2004) and Giesen et al. (2010), no previous studies have considered the entire distribution of cities[2], as all of them impose a truncation point, either explicitly by taking cities above a minimum population threshold, or implicitly by working with MSAs[3]. This is usually due to a practical reason of data availability. Furthermore, these few studies focus only on static city size distributions in one or two periods, as data over time is rarely available.

Against this background, the first aim of this article is to estimate the density functions of the double Pareto lognormal, the lognormal, the q-exponential and the log-logistic for describing city size distributions. Second, we perform standard statistical tests to assess when the proposed distributions have a close fit to the empirical ones. Third, standard AIC and BIC information criteria are computed to discriminate in an accurate way between the four distributions. In any case, as far as we know, this is the first time that these matters have been subjected to empirical testing with such comprehensive databases. On the one hand, we use un-truncated city population data; on the other hand, we take into account in an explicit way the temporal dimension (considering data from more than a hundred years for three countries: the US, Spain and Italy, a time span which can be considered as a long-term study) as well as the geographic or spatial dimension (we analyze data from the last census of the 34 countries of the OECD, a cross-sectional sample of countries comprising many different urban systems).

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[2] Michaels et al. (2012) use data from minor civil divisions (MCDs) to track the evolution of population across both rural and urban areas in the United States from 1880 to 2000.

[3] In the US, classification as an MSA requires a city of at least 50,000 inhabitants or the presence of an urban area of at least 50,000 inhabitants and a total metropolitan population of a minimum of 100,000 inhabitants (75,000 in New England), according to the official definition. Other countries follow similar criteria, although the minimum population threshold needed to be considered a metropolitan area may vary.

The article is organised as follows. The second section recalls the definition and main properties of the four distributions studied. The third summarises and explains the databases used. Section four shows the results. In section five we discuss the main results. Finally, section six concludes.

2. Description of the distributions

2.1. The lognormal distribution (ln)

The probability density function (pdf) of the lognormal is given by:

$$f(x) = \frac{1}{x\sigma\sqrt{2\pi}} e^{-\frac{(\ln x - \mu)^2}{2\sigma^2}} \quad , \quad x > 0, \qquad (2)$$

where μ and σ^2 are the mean and variance of $\ln x$, which in this case denotes the natural logarithm of the population of the cities. The expression of the corresponding cumulative distribution function (cdf) is:

$$cdf(x) = \frac{1}{2} + \frac{1}{2} erf\left(\frac{\ln x - \mu}{\sigma\sqrt{2}}\right), \qquad (3)$$

where erf denotes the error function associated with the normal distribution.

The lognormal distribution has been considered for many years to study city size (see Richardson, 1973, and references therein). More recently, Eeckhout (2004) estimates the lognormal distribution, with no truncation point, to study city size in the US. He defines an equilibrium theory of local externalities as a process generating data of such a distribution, and justifies the coexistence of proportionate growth and the resulting lognormal distribution.

2.2. The q-exponential distribution (qe)

The probability density function of the q-exponential is given by:

$$f(x)=\frac{a}{q}\left(1+\frac{q-1}{q}ax\right)^{\frac{q}{1-q}}, \qquad x>0, \tag{4}$$

where $a>0$ and $q>1$ are parameters and x denotes the population of the cities. The expression of the corresponding cumulative distribution function is:

$$cdf(x)=1-\left(1+\frac{q-1}{q}ax\right)^{\frac{1}{1-q}}. \tag{5}$$

In the case that $q \to 1$, $f(x) \to ae^{-ax}$, a property which justifies the name of q-exponential.

This distribution has been used extensively by Tsallis (1988) and his group of collaborators, arguing for its theoretical applicability to systems with long-range interactions (Malacarne et al., 2001, can be included in this line of argument). Soo (2007) uses this distribution to study city size in the case of Malaysia, obtaining low descriptive performance probably due to the fact that he uses a cut-off of 10,000 inhabitants to define the cities. However, the q-exponential is a particular case of the distribution known as generalised type II Pareto, which has been considered in various earlier works (for example, Hosking and Wallis, 1987; Grimshaw, 1993; Choulakian and Stephens, 2001).

2.3. The double Pareto lognormal distribution (dPln)

The probability density function of the double Pareto lognormal distribution (see Reed, 2002) is:

$$
\begin{aligned}
f(x) = {} & \frac{\alpha\beta}{2x(\alpha+\beta)} \exp\left(\alpha\mu + \frac{\alpha^2\sigma^2}{2}\right) x^{-\alpha} \left(1 + erf\left(\frac{\ln(x) - \mu - \alpha\sigma^2}{\sqrt{2}\sigma}\right)\right) \\
& - \frac{\alpha\beta}{2x(\alpha+\beta)} \exp\left(-\beta\mu + \frac{\beta^2\sigma^2}{2}\right) x^{\beta} \left(erf\left(\frac{\ln(x) - \mu + \beta\sigma^2}{\sqrt{2}\sigma}\right) - 1\right)
\end{aligned}
\tag{6}
$$

where $x > 0$ and $\alpha, \beta, \mu, \sigma > 0$ are the distribution parameters. The dPln distribution has the property that it follows different power laws in its two tails, namely $f(x) \approx x^{-\alpha-1}$ when $x \to \infty$ and $f(x) \approx x^{\beta-1}$ when $x \to 0$, hence the name of double Pareto. The central part of the distribution is approximately lognormal, although it is not possible to exactly delineate the lognormal body part and the Pareto tails (Giesen et al., 2010).

The expression of the corresponding cumulative distribution function is:

$$
\begin{aligned}
cdf(x) = {} & \frac{1}{2}\left(1 + erf\left(\frac{\ln(x) - \mu}{\sqrt{2}\sigma}\right)\right) \\
& - \frac{\beta}{2(\alpha+\beta)} \exp\left(\alpha\mu + \frac{\alpha^2\sigma^2}{2}\right) x^{-\alpha} \left(1 + erf\left(\frac{\ln(x) - \mu - \alpha\sigma^2}{\sqrt{2}\sigma}\right)\right) \\
& - \frac{\alpha}{2(\alpha+\beta)} \exp\left(-\beta\mu + \frac{\beta^2\sigma^2}{2}\right) x^{\beta} \left(erf\left(\frac{\ln(x) - \mu + \beta\sigma^2}{\sqrt{2}\sigma}\right) - 1\right)
\end{aligned}
\tag{7}
$$

The dPln distribution arises as the steady-state distribution of an evolutionary process of a simple stochastic model of settlement formation and growth based on Gibrat's law and a Yule process; see Reed (2002) for details. For more recent work on an economic model which incorporates the stochastic derivation of Reed (2002), see Giesen and Suedekum (2012a). The key in this latest model is the endogenous city creation and the resulting age heterogeneity in cities within the distribution. Giesen and Suedekum (2012a) argue that Eeckhout's (2004) theoretical framework and the lognormal distribution represent a particular scenario of their model, the case when there is no city creation and all cities are the same age.

2.4. The log-logistic distribution (ll)

The probability density function of the log-logistic distribution is:

$$f(x) = \frac{\exp\left(-\frac{\ln(x)-\mu}{\sigma}\right)}{x\sigma\left(1+\exp\left(-\frac{\ln(x)-\mu}{\sigma}\right)\right)^2}, \qquad x>0 \tag{8}$$

where $\mu, \sigma > 0$ are the distribution parameters. This pdf can be written in other mathematically equivalent ways, but we have chosen this form to compare it with that of the ln and dPln (see Singh and Maddala, 2008, for references and for derivations of the log-logistic distribution). The cumulative distribution function can be written as:

$$cdf(x) = \frac{1}{1+\exp\left(-\frac{\ln(x)-\mu}{\sigma}\right)}. \tag{9}$$

Although there is no specific theoretical foundation for the log-logistic, Hsu (2012) develops a model of central place theory using an equilibrium entry model to generate a Pareto upper tail in the city size distribution if the distribution of scale economies is a regularly varying function. This class of distributions includes the log-logistic.[4] As shown in the fourth section, the log-logistic provide a better fit to empirical city size data than the other studied distributions in some cases.

3. The databases

We use un-truncated city population data from all OECD member countries. We have taken the data corresponding to the last available census for each country, though for the US, Spain and Italy the data corresponding to the census of each decade of the 20th century is also included. Table 1 shows the number of cities for each decade for

[4] See Table C1 in Hsu (2012).

these last three countries, and the descriptive statistics, and Table 2 reports the number of cities and the descriptive statistics for the remaining OECD countries.

The data on the geographical unit of reference of all countries comes from the official statistical information services. The urban unit considered is the lowest spatial subdivision, so they represent the whole territory of the country, with the exception of Israel, Ireland and the United States; the first because data is only available for municipalities with more than 5,000 inhabitants; the second because only incorporated places are taken into account until 2000[5] (they represent 46.99% of the total population of the US in 1900 and 61.49% in 2000); and the third because legal towns have expanded beyond their legally defined boundaries and, as a result, a high number of persons in the communities is excluded. So, while there are problems of international comparability, because the administrative definition of a city varies from one country to another, they do have the major advantage that the size distribution of these 'legal' cities comprises, in general, 100% of the population of each country.

This dataset considered is motivated, first, by the availability of a large number of countries in order to confirm the robustness of our results across countries but, second, also by the possibility of comparing the time evolution of the urban structure in three countries; Spain and Italy, as two examples of consolidated and old urban structures, in contrast to the US, a "young" country whose inhabitants are characterised by high mobility (Cheshire and Magrini, 2006). Moreover, unlike Italy and Spain, where urban growth is produced by the increase in population living in existing cities, in the US urban growth has a double dimension: as well as increases in city size, the

[5] See González-Val (2010) for more information. For the US we consider two different samples for the year 2000: one sample including only the incorporated places and another sample including all places (incorporated and unincorporated), as in Eeckhout (2004). The US census in 2000 is the first to include all unincorporated places with no size restriction. Results are robust for both samples. The US sample for 2010 also considers all the places (incorporated and unincorporated).

number of cities almost doubles in the period considered, with potentially different effects on city size distributions. Therefore, our databases seem to offer an excellent opportunity to test empirically the Giesen and Suedekum (2012a) and Eeckhout (2004) models and the influence of city creation on the shape of the city size distribution.

4. Results

4.1. Estimation of the distributions

Maximum likelihood (ML) is a standard technique which allows the estimation of the parameters of distributions given a sample of data. Out of the four distributions used in this article, only one has a closed form for the corresponding estimators, namely for the lognormal. The estimators for μ and σ are, respectively, the mean and standard deviation of the logarithm of the data. For the q-exponential, double Pareto lognormal and log-logistic we must use numerical methods in order to maximise the log-likelihood value for each sample. However, the log-likelihood functions to be maximised are easy to find: see Reed and Jorgensen (2004) for the dPln and Shalizi (2007) for the qe. The case of ll can be treated in a similar fashion. The results of the estimations are shown for a selection of years in Table 3[6].

Figure 1 offers a first visual approximation of the goodness of the fit provided by the four proposed distributions (ln, qe, dPln and ll) to describe empirical city size distributions. We have taken the last available year of the US, Spain and Italy. We obtain similar graphs for the rest of the years and different countries.[7] Thus, the figure shows the density kernel estimate of the empirical distribution using an adaptive kernel compared with the four distributions with the parameters estimated by ML. As in Levy (2009) and (Giesen et al., 2010), a zoom for the upper tail distribution is also shown.

[6] The complete estimation results are available from the authors upon request.
[7] Again, all the results are available from the authors on request.

It is hard to find in Figure 1 any strong differences between the four competing distributions because all of them capture reasonably well the shape of the empirical one. Therefore, to be able to discriminate between the four functions, numerical methods and tests are required rather than graphical tools. Only in this way can we conclude which one is dominant (although the differences between them are very small) and, thus, which of the urban theories that are behind the distributions studied (see Sections 1 and 2), are confirmed by the empirical data. This analysis is performed in Subsections 4.2 and 4.3.

4.2. Standard statistical tests

In this subsection we aim to provide independent tests in order to verify the goodness of the fit in all cases. We have chosen the Kolmogorov-Smirnov (KS) test, which is mentioned in a study of similar characteristics to ours (Giesen et al., 2010) and is standard in the literature, and also the Cramér-von Mises (CM) test. The reason for including this second test is that its statistic measures the sum of the squared deviations of the cdf tested with respect to the empirical one. Thus, this statistic has an interpretation similar to Figures 2a, 2b and 2c in Giesen et al. (2010) and, in this way, they give similar information. Consequently, here we only show the p-values of the CM test.[8] Moreover, the KS and CM tests have similar power: it is quite low for small sample sizes but very high for large ones (Razali et al., 2011). Both tests are extremely precise for large and very large sample sizes, not rejecting the null hypothesis just because of very small deviations. We recall that the null hypothesis of both KS and CM tests is that the empirical and the estimated statistical cdfs of the two samples are equal.

[8] The accumulated squared deviations of the cdfs are available from the authors upon request. We have also plotted the accumulated absolute values of the deviations of the estimated and empirical cdfs. The results, not shown due to size restrictions, show that the distribution with the lower accumulated deviations in most of the cases is the double Pareto lognormal.

From a long-term perspective, the results for the US, Spain and Italy during the twentieth century are summarized as follows. The significance level is always 5%. For the US and Spain, the four distributions are rejected by both KS and CM in almost all years; the only exception is the dPln in 1900 and 1920 for the US using the CM test. In Italy the qe is always rejected, the ln almost always, the ll can never be rejected except in 1901, 2001 and 2010, and the dPln cannot be rejected in any case except in 1901.

Table 4 reports cross-sectional evidence. It shows the p-values of both tests for our sample of the OECD countries, including the first decade of the 21st century for the US, Spain and Italy. The cases in which the statistical distribution cannot be rejected at the 5% significance level are highlighted in bold. Looking at the columns of the table corresponding to each distribution, the qe shows the highest number of rejections (59 out of 66 contrasts performed, 89.39%). The second worst distribution is the ln (60.29% of rejections), followed by the ll (39.71%); the best distribution is the dPln, which can only be rejected in 18.51% of the tests performed.

Reading the table by rows, we can observe that there are countries in which the four distributions can be rejected by both the KS and CM tests (Australia 2001, Germany 2010, Poland 2010, Spain 2010, Turkey 2011 and the US 2010), while in others none of the distributions can be rejected by any of the tests (Iceland 2012 and New Zealand 2006). The former group of six countries have a high number of cities, while the latter pair are the two countries with the lowest sample size. In general, although there are some counter-examples, the number of rejections tends to increase with sample size, something that could be anticipated because the power of the KS and CM tests increases with sample size. This result can explain the high number of rejections detected for the US, Spain and Italy during the twentieth century: since the beginning of the century these countries have comprised a high number of cities, compared to other countries.

In summary, considering the overall results of the tests for each distribution (the sum of cases of non-rejections), it follows that the distributions which best fit the data (out of the four studied here) are, in descending order, the double Pareto lognormal, the log-logistic, followed closely by the lognormal, and finally the q-exponential. Therefore, a distribution which has been proposed in the literature, the q-exponential, is clearly outperformed by others more recently proposed, such as the double Pareto lognormal and the log-logistic.

4.3. Information criteria

In order to discriminate between the studied distributions, here we take another approach. We compute two information criteria that are very well suited to the maximum likelihood method which we have used previously to estimate the parameters of the four distributions studied: the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC; see, e.g., Giesen et al., 2010, and references therein). The results are shown in Tables 5, 6 and 7 for the US, Spain and Italy, respectively, and in Table 8 for the rest of the OECD countries. The interpretation is easy: the distribution with the lower numerical value out of the AIC or BIC is favoured. In general, the outcomes confirm most of the results obtained from the statistical tests carried out in Subsection 4.2.

There are 68 cases: 13 periods for the US, 12 for Spain and Italy, and one for each of the rest of the 31 OECD countries. In 62 of them there is a coincidence between the AIC and BIC in the selection of the best fit. The discrepancies appear in Finland (2011), Greece (2011), Mexico (2010), Portugal (2011), Switzerland (2010) and the UK

(2001). In all of these, the AIC chooses the dPln, while the BIC selects the ln three times, the ll two times and the qe one time. In these six situations when the criteria do not agree, we follow Burnham and Anderson (2002, 2004), who argue with theoretical arguments and simulations that the AIC is preferable to the BIC. Therefore, out of the 68 cases, the dPln is the selected model in 59 cases (86.76%), the ll in 7 cases (Belgium 2010, Chile 2002, Denmark 2012, Estonia 2012, Israel 2008, New Zealand 2006 and Slovenia 2012), the ln in one case (Iceland 2012) and the qe also in one case (Korea 2012).

We wonder if there is any kind of geographic regularity in these results, but, apparently, there is not. However, we have observed a certain relationship between sample size and the best distribution for each country. When the sample size is below 106 cities (three cases) the dPln never provides the best fit. If the sample size is above 589 cities the dPln is always the selected distribution (51 cases). Finally, for between 106 and 589 cities the result is mixed: the dPln is the best distribution in 8 out of 14 cases. In short, there is a threshold in sample size (in our results around 600 cities) above which the dPln clearly dominates; the only way that any of the other studied distributions can be selected is if the sample size is low enough.[9]

5. Discussion

In this paper we compare four statistical distributions (the double Pareto lognormal, the lognormal, the q-exponential and the log-logistic) used to fit the overall city size distribution with un-truncated city size data. We combine a long-term perspective for three countries (the US, Spain and Italy) with a long cross-sectional sample of countries (the rest of the OECD countries).

[9] For example, the lowest sample size out of the eight countries analyzed in Giesen et al. (2010) is 2,075 cities.

A first important result is that the dPln is clearly in most of the cases and using several criteria the best distribution out of the four studied. This result confirms the conclusions obtained by Giesen et al. (2010) with a small sample of countries. It is a reassuring result because it allows us to reconcile all the old literature about the validity of the Pareto distribution (in the upper tail) and the particular case of Zipf´s law, with more recent studies which raise doubts about its performance for the overall city size distribution, and propose the lognormal as the most suitable distribution for un-truncated city size data. There is indeed a new mainstream in the literature, to which we contribute with this work, that argues that the best fit to un-truncated city size data is provided by a mixture of Pareto and lognormal distributions, such as the dPln, which is lognormal in the body and Pareto in the tails. In this line we can also include the contribution by Ioannides and Skouras (2013), who have proposed a new statistical distribution, but also combining lognormal and Pareto. It seems that the discussion raised by Levy (2009) has been solved: "*most cities* obey a lognormal; but the upper tail and therefore *most of the population* obeys a Pareto law" (Ioannides and Skouras, 2013).

Regarding the other distributions, out of the 68 cases studied, and according to the AIC and BIC information criteria, the dPln is the best distribution in 59 of them (86.76%), the ll in 7 (Belgium, Chile, Denmark, Estonia, Israel, New Zealand and Slovenia), the ln in one case (Iceland) and the qe in another one (Korea). Considering all the statistical information, we can rank in descending order the performance of the distributions as follows: the dPln, the ll, the ln and finally the qe. It is surprising that a newcomer distribution to urban economics, the log-logistic, appears in second place, with the additional advantage of having a simpler functional form than the double Pareto lognormal and two parameters instead of four.

With so many results and so much information, we wonder if there is any kind of regularity that helps to explain the cases in which the dPln is the best or not. And we find that the key issue is the sample size. We have detected that below a very small sample size, in our data a lower bound around of 100 cities, the dPln is outperformed by other distributions; however, above a certain threshold of the sample size, in our data around 600 cities, the dPln clearly dominates the other studied distributions. For intermediate sample sizes between 100 and 600 cities, the dPln is the best in roughly half of the cases.

Finally, we would like to discuss a difficult and technical, but interesting, issue, which is introduced in the theoretical model by Giesen and Suedekum (2012a): the effect of age heterogeneity across cities on city size distribution. Giesen and Suedekum (2012b) add empirical evidence relating to the cases of France and the US. Giesen and Suedekum's (2012a) theoretical model generates a dPln city size distribution based on two basic features. Firstly, in each period new cities do enter at a constant rate. Secondly, the age distribution of cities is heterogeneous. Both assumptions are different from those of the theoretical model proposed by Eeckhout (2004), which yields to a lognormal city size distribution. Focusing on the US, Spain and Italy (the three countries we analyse from a temporal perspective), we find that the dPln is always better than the ln although, according to the theoretical predictions, the relative edge that the dPln has over the ln would be greater if the age heterogeneity arises from constant growth in the number of cities. In our results the dPln performs relatively better than the ln in the US. In Spain and Italy the lognormal performs not so badly (the mean AIC of the ln over the mean AIC of the dPln is 1.00401 for the US, 1.00298 for Spain and 1.00172 for Italy). Is this result consistent with the theoretical model of Giesen and Suedekum (2012a)? The answer to this question would require a detailed historical study of the entry rate of cities and their age distribution in the three countries, a study beyond the scope of this paper. We can only say that in our samples, considering the whole twentieth century, there is city entry in the US, while in Spain and Italy the number of cities remains almost constant. However, the age heterogeneity of the European cities is much higher (the foundation of many European cities dates back to the Middle Ages) than that of the United States (from 1600 to 2000 approximately). In short, this is an open question deserving further research.

6. Conclusions

City size distribution has been the subject of numerous empirical investigations by urban economists, statistical physicists, and urban geographers. From the point of view of urban economics, the study of city size distribution has deep economic implications related to labour markets, income distribution, public expenditure, etc.

Elsewhere, since the work of Eeckhout (2004), the risks of considering only the largest cities have been demonstrated; that is, only the upper tail. In turn, if the availability of data allows it, the analysis of city size distribution should be done as a long-term analysis. With both considerations as premises, this article combines un-truncated census data for the entire 20th century in decades, of three countries: the US, Spain and Italy, with cross-sectional data from the most recent census of the rest of the OECD countries. Using such comprehensives databases, with no size restriction, and such a vast temporal and spatial horizon undoubtedly adds robustness to the results.

This work has minutely examined three density functions with relatively recent use in urban economics, namely the lognormal, the q-exponential, the double Pareto lognormal and an almost new distribution, the log-logistic. After estimating the parameters of the four distributions by maximum likelihood, we have tested the fit provided by each distribution using the Kolmogorov-Smirnov and Cramér-von Mises tests. Afterwards, we have computed the AIC and BIC information criteria. Our results show that, in general, the best function to describe city size distribution, out of the four studied here, is the double Pareto lognormal.

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Table 1. Number of cities and descriptive statistics: the US, Spain and Italy

US					
Year	Cities	Mean	Standard deviation	Minimum	Maximum
1900	10,596	3,376.04	42,323.90	7	3,437,202
1910	14,135	3,560.92	49,351.24	4	4,766,883
1920	15,481	4,014.81	56,781.65	3	5,620,048
1930	16,475	4,642.02	67,853.65	1	6,930,446
1940	16,729	4,975.67	71,299.37	1	7,454,995
1950	17,113	5,613.42	76,064.40	1	7,891,957
1960	18,051	6,408.75	74,737.62	1	7,781,984
1970	18,488	7,094.29	75,319.59	3	7,894,862
1980	18,923	7,395.64	69,167.91	2	7,071,639
1990	19,120	7,977.63	71,873.91	2	7,322,564
2000	19,296	8,968.44	78,014.75	1	8,008,278
2000 (all places)	25,358	8,231.53	68,390.23	1	8,008,278
2010 (all places)	28,664	7,871.53	61,631.70	1	8,175,133
Spain					
Year	Cities	Mean	Standard deviation	Minimum	Maximum
1900	7,800	2,282.40	10,177.75	78	539,835
1910	7,806	2,452.01	11,217.02	92	599,807
1920	7,812	2,621.92	13,501.02	82	750,896
1930	7,875	2,892.18	17,513.90	79	1,005,565
1940	7,896	3,180.65	20,099.96	11	1,088,647
1950	7,901	3,479.86	26,033.29	64	1,618,435
1960	7,910	3,801.71	33,652.11	51	2,259,931
1970	7,956	4,240.98	43,971.93	10	3,146,071
1981	8,034	4,701.40	45,995.35	5	3,188,297
1991	8,077	4,882.27	45,219.85	2	3,084,673
2001	8,077	5,039.37	43,079.46	7	2,938,723
2010	8,114	7,795.05	47,529.80	5	3,273,049
Italy					
Year	Cities	Mean	Standard deviation	Minimum	Maximum
1901	7,711	4,274.84	14,424.61	56	621,213
1911	7,711	4,648.11	17,392.98	58	751,211
1921	8,100	4,863.80	20,031.61	58	859,629
1931	8,100	5,067.10	22,559.85	93	960,660
1936	8,100	5,234.38	25,274.48	116	1,150,338
1951	8,100	5,866.12	31,137.52	74	1,651,393
1961	8,100	6,249.82	39,130.55	90	2,187,682
1971	8,100	6,683.52	45,581.66	51	2,781,385
1981	8,100	6,982.33	45,329.33	32	2,839,638
1991	8,100	7,009.63	42,450.26	31	2,775,250
2001	8,100	7,021.20	39,325.47	33	2,546,804
2010	8,094	7,490.29	41,505.4	34	2,761,477

Note: No census exists in Italy for 1941 due to its participation in the Second World War, so we have taken the data for 1936.

Table 2. Number of cities and descriptive statistics: Rest of the OECD countries

Country	Year	Cities	Mean	Standard deviation	Minimum	Maximum
Australia	2001	1,559	10,756.6	132,419	200	3,502,301
Austria	2001	2,359	3,405.23	32,855.2	60	1,550,123
Belgium	2010	589	18,403.9	29,353.6	80	483,505
Canada	2011	4,931	6,789.03	57,345.8	5	2,615,060
Chile	2002	342	44,200.1	68,452	130	492,915
Czech Republic	2011	6,251	1,684.97	17,825	3	1,257,158
Denmark	2012	99	56,435.2	65,246.2	104	551,900
Estonia	2012	232	23,108.3	129,319	67	1,339,662
Finland	2011	335	16,062.5	42,665.6	103	595,384
France	2009	36,716	1,790.92	8,253.09	1	447,396
Germany	2010	11,292	7,239.78	46,688.7	8	3,460,725
Greece	2011	325	33,187.3	49,804.8	150	655,780
Hungary	2001	3,121	3,245.99	33,161.7	12	1,777,921
Iceland	2012	75	4,261	14,446.2	52	118,814
Ireland	2011	824	3,850.91	39,696.9	90	1,110,627
Israel	2008	169	39,203.6	76,876.4	5000	759,700
Japan	2010	2,102	25,863	74,416.4	140	1,468,382
Korea	2012	251	191,198	149,616	7,737	640,732
Luxemburg	2012	106	4,951.44	10,370.9	677	99,852
Mexico	2010	2,456	45,092.8	130,512	93	1,794,969
Netherlands	2001	504	31,717.3	54,134.7	1,017	734,533
New Zealand	2006	74	54,431.8	75,920.8	417	404,658
Norway	2012	429	11,622.1	35,497.4	218	613,285
Poland	2010	2,479	15,409.5	50,664	1,361	1,720,398
Portugal	2011	308	34,291	56,055.8	430	547,631
Slovakia	2001	2,926	1,844.51	5,857.66	8	105,842
Slovenia	2012	211	9,741.69	21,846.4	379	280,607
Sweden	2010	290	32,442.5	64,826.9	2,446	845,777
Switzerland	2010	2,495	3,154.36	10,879.7	12	372,857
Turkey	2011	2,934	21,362.9	75,364.6	328	831,229
United Kingdom	2001	354	138,810	93,289.1	2,153	977,087

Table 3. Estimated parameters of the distributions

		Lognormal distribution		q-exponential distribution		Log-logistic distribution		Double Pareto lognormal distribution			
Country	Year	μ	σ	q	a	μ	σ	α	β	μ	σ
Australia	2001	7.04	1.33	1.75	0.0016	6.88	0.70	0.66	24.89	5.57	0.21
Austria	2001	7.39	0.89	1.22	0.0006	7.37	0.48	1.59	1.98	7.27	0.37
Belgium	2010	9.39	0.87	1.14	0.0001	9.38	0.47	1.85	2.26	9.30	0.50
Canada	2011	6.66	1.86	2.05	0.0027	6.65	1.01	0.78	0.82	6.60	0.69
Chile	2002	9.82	1.38	1.53	0.0001	9.82	0.77	2.89	1.42	10.18	1.14
Czech Republic	2011	6.15	1.22	1.56	0.0030	6.07	0.67	1.07	4.72	5.43	0.77
Denmark	2012	10.58	0.99	1.05	1.9e-5	10.66	0.43	--	--	--	--
Estonia	2012	7.84	1.33	1.73	0.0007	7.69	0.63	--	--	--	--
Finland	2011	8.78	1.21	1.49	0.0002	8.72	0.67	1.10	1.82	8.41	0.62
France	2009	6.21	1.35	1.67	0.0031	6.14	0.75	1.00	3.32	5.52	0.88
Germany	2010	7.52	1.51	1.77	0.0009	7.49	0.87	1.34	3.73	7.04	1.29
Greece	2011	9.73	1.34	1.19	4.5e-5	9.84	0.72	2.46	0.88	10.46	0.60
Hungary	2001	6.82	1.30	1.56	0.0015	6.78	0.72	1.18	2.05	6.47	0.86
Iceland	2012	6.85	1.59	1.89	0.0020	6.79	0.90	1.00	3.93	6.10	1.21
Ireland	2011	6.64	1.29	1.72	0.0023	6.49	0.69	0.76	13.91	5.39	0.37
Israel	2008	9.89	1.03	1.38	0.0001	9.80	0.58	--	--	--	--
Italy	2010	7.85	1.34	1.55	0.0005	7.83	0.76	1.58	3.65	7.49	1.15
Japan	2010	9.14	1.24	1.56	1.4e-4	9.07	0.68	0.99	1.69	8.72	0.48
Korea	2012	11.76	0.98	0.62	2.3e-6	11.82	0.59	7.06	1.43	12.32	0.73
Luxemburg	2012	7.96	0.88	1.25	0.0004	7.89	0.48	1.22	12.45	7.22	0.41
Mexico	2010	9.41	1.55	1.77	0.0001	9.40	0.88	1.41	3.26	9.01	1.35
Netherlands	2001	9.91	0.85	1.18	4.6e-5	9.86	0.47	1.52	2.78	9.61	0.42
New Zealand	2006	10.25	1.22	1.27	3.2e-5	10.29	0.66	1.55	1.17	10.46	0.58
Norway	2012	8.50	1.17	1.44	0.0002	8.45	0.66	1.29	5.66	7.90	0.86
Poland	2010	9.07	0.82	1.25	0.0001	8.99	0.43	1.36	9.10	8.44	0.35
Portugal	2011	9.73	1.14	1.40	0.0001	9.67	0.66	1.25	5.47	9.11	0.82
Slovakia	2001	6.54	1.20	1.48	0.0018	6.50	0.65	1.21	1.77	6.27	0.64
Slovenia	2012	8.58	0.99	1.26	0.0002	8.55	0.55	1.50	2.37	8.34	0.60
Spain	2010	6.58	1.85	2.29	0.0041	6.49	1.07	0.75	3.84	5.52	1.31
Sweden	2010	9.82	0.94	1.25	0.0001	9.76	0.53	1.33	8.58	9.19	0.59
Switzerland	2010	7.11	1.32	1.48	0.0010	7.10	0.75	1.93	2.44	7.00	1.14
Turkey	2011	8.27	1.44	1.92	0.0006	8.06	0.74	0.75	3.59	7.21	0.34
United Kingdom	2001	11.68	0.59	--	--	11.67	0.31	2.24	2.94	11.57	0.16
US	2010	7.13	1.83	2.17	0.0020	7.09	1.05	1.17	2.97	6.61	1.59

Note: It has not been possible to estimate the dPln for Denmark (2012), Estonia (2012), Israel (2008) and the qe for the UK (2001). In these few cases, the proposed density function seems to give rise to a poorly defined likelihood function and therefore cannot be estimated. The reason seems to be an extremely flat lower tail.

Table 4. p -values of the Kolmogorov-Smirnov (KS) and Cramér-von Mises (CM) tests

	Lognormal distribution		q -exponential distribution		Double Pareto lognormal distribution		Log-logistic distribution	
	KS	CM	KS	CM	KS	CM	KS	CM
Australia 2001	0	0	0	0	-	-	0	0
Austria 2001	0	0	0	0	**0.854**	**0.809**	**0.181**	**0.164**
Belgium 2010	**0.382**	**0.224**	0	0	**0.993**	**0.985**	**0.998**	**0.993**
Canada 2011	0	0	0.006	0.017	**0.112**	**0.187**	0.002	0.011
Chile 2002	**0.172**	**0.131**	0	0	**0.094**	**0.118**	**0.249**	**0.247**
Czech Republic 2011	0	0	0	0	**0.173**	**0.362**	0	0.007
Denmark 2012	0	0	0	0	-	-	**0.434**	**0.266**
Estonia 2012	0.002	0	0	0	-	-	0.045	**0.619**
Finland 2011	**0.134**	**0.177**	0.002	0.015	**0.963**	**0.970**	**0.736**	**0.619**
France 2009	0	0	0	0	0.046	**0.070**	0	0
Germany 2010	0	0	0	0	0.002	0.008	0	0
Greece 2011	0.001	0.009	**0.172**	**0.376**	**0.706**	**0.766**	**0.300**	**0.259**
Hungary 2001	0.002	0.005	0	0	**0.682**	**0.653**	**0.134**	**0.193**
Iceland 2012	**0.855**	**0.932**	**0.959**	**0.980**	**0.987**	**0.992**	**0.979**	**0.991**
Ireland 2011	0	0	0	0	**0.397**	**0.456**	0	0
Israel 2008	**0.093**	**0.128**	0	0	-	-	**0.060**	**0.276**
Italy 2010	**0.096**	**0.062**	0	0	**0.978**	**0.942**	0.016	0.017
Japan 2010	0	0	0	0	**0.435**	**0.483**	0.027	0.009
Korea 2012	0	0.003	0.043	**0.096**	0.002	0.008	0	0.002
Luxemburg 2012	**0.289**	**0.322**	0	0.007	-	-	**0.662**	**0.617**
Mexico 2010	**0.243**	**0.246**	0	0	**0.168**	**0.210**	**0.151**	**0.141**
Netherlands 2001	0.043	0.044	0	0	**0.896**	**0.913**	**0.532**	**0.518**
New Zealand 2006	**0.778**	**0.591**	**0.372**	**0.458**	**0.668**	**0.870**	**0.670**	**0.850**
Norway 2012	**0.310**	**0.236**	0	0	**0.842**	**0.851**	**0.465**	**0.388**
Poland 2010	0	0	0	0	-	-	0	0
Portugal 2011	**0.244**	**0.111**	0	0	**0.373**	**0.384**	**0.364**	**0.179**
Slovakia 2001	0	0	0	0	**0.670**	**0.584**	**0.495**	**0.534**
Slovenia 2012	**0.502**	**0.385**	0	0.006	**0.860**	**0.847**	**0.692**	**0.541**
Spain 2010	0	0	0	0	0	0	0	0
Sweden 2010	0.015	**0.066**	0	0	-	-	**0.094**	**0.160**
Switzerland 2010	**0.819**	**0.930**	0	0	**0.809**	**0.959**	**0.162**	**0.259**
Turkey 2011	0	0	0	0	0.001	0.005	0	0
United Kingdom 2001	0.016	0.049	-	-	**0.500**	**0.476**	**0.385**	**0.257**
US 2010	0	0	0	0	0	0	0	0

Notes: The null hypothesis is that the empirical distribution follows the lognormal, q-exponential, dPln or log-logistic distribution. The cases in which the statistical distribution cannot be rejected at the 5% significance level are highlighted in bold. It has not been possible to perform the tests for the dPln distribution for Australia (2001), Denmark (2012), Estonia (2012), Israel (2008), Luxembourg (2012), Poland (2010) and Sweden (2010), and for the qe distribution for the UK (2001). In these few cases, we could not generate the samples with which the test are performed in the same way as in the other cases. The reason seems to be the extremely flat lower tail in these cases.

Table 5. Results of the information criteria: the US

Year	lognormal			q -exp.			dPln			log-logistic		
	Log-like.	AIC	BIC	Log-like.	AIC	BIC	Log-like.	AIC	BIC	Log-like.	AIC	BIC
1900	-87943.3	175890.6	175905.1	-88340.2	176684.4	176698.9	-87253.9	174515.8	174544.9	-87662.8	175329.6	175344.1
1910	-117640	235284	235299.1	-118120	236244	236259.1	-116727	233462	233492.2	-117327	234658	234673.1
1920	-129580	259164	259179.3	-130014	260032	260047.3	-128521	257050	257080.6	-129191	258386	258401.3
1930	-139194	278392	278407.4	-139443	278890	278905.4	-138129	276266	276296.8	-138813	277630	277645.4
1940	-143097	286198	286213.4	-143334	286672	286687.4	-142179	284366	284396.9	-142815	285634	285649.4
1950	-148254	296512	296527.5	-148396	296796	296811.5	-147593	295194	295225.0	-148066	296136	296151.5
1960	-159142	318288	318303.6	-159224	318452	318467.6	-158679	317366	317397.2	-159091	318186	318201.6
1970	-165171	330346	330361.6	-165233	330470	330485.6	-164831	329670	329701.3	-165187	330378	330393.6
1980	-171088	342180	342195.7	-171194	342392	342407.7	-170777	341562	341593.4	-171146	342296	342311.7
1990	-173472	346948	346963.7	-173547	347098	347113.7	-173243	346494	346525.4	-173576	347156	347171.7
2000	-177127	354258	354273.7	-177211	354426	354441.7	-176931	353870	353901.5	-177270	354544	354559.7
2000 (all places)	-234773	469550	469566	-235021	470046	470062	-234710	469428	469461	-235033	470070	470086
2010 (all places)	-262440	524884	524901	-262686	525376	525393	-262375	524758	524791	-262733	525470	525487

Note: The Akaike Information Criterion for distribution i is computed as $AIC_i = 2 \cdot k_i - 2 \cdot \ln(L_i)$ and the Schwarz Criterion as $BIC_i = k_i \cdot \ln(N) - 2 \cdot \ln(L_i)$, where k_i is the number of free parameters of distribution i, N is the number cities by year, and $\ln(L_i)$ is the log-likelihood (Giesen et al., 2010).

Table 6. Results of the information criteria: Spain

Year	lognormal			q -exp.			dPln			log-logistic		
	Log-like.	AIC	BIC	Log-like.	AIC	BIC	Log-like.	AIC	BIC	Log-like.	AIC	BIC
1900	-65873.6	131751.2	131765.1	-66536.4	133076.8	133090.7	-65627.3	131262.6	131290.4	-65894.4	131792.8	131806.7
1910	-66413.5	132831	132844.9	-67047.7	134099.4	134113.3	-66169.4	132346.8	132374.7	-66439.2	132882.4	132896.3
1920	-66762.6	133529.2	133543.1	-67346.8	134697.6	134711.5	-66520.8	133049.6	133077.5	-66789.1	133582.2	133596.1
1930	-67782.4	135568.8	135582.7	-68311.6	136627.2	136641.1	-67552.4	135112.8	135140.7	-67816.5	135637	135650.9
1940	-68291.6	136587.2	136601.1	-68759.9	137523.8	137537.7	-68042.6	136093.2	136121.1	-68304.4	136612.8	136626.7
1950	-68656.2	137316.4	137330.3	-69094.7	138193.4	138207.3	-68403.8	136815.6	136843.5	-68672.7	137349.4	137363.3
1960	-68762	137528	137542.0	-69116.1	138236.2	138250.2	-68514.4	137036.8	137064.7	-68786.7	137577.4	137591.4
1970	-68529.4	137062.8	137076.8	-68707.8	137419.6	137433.6	-68341.7	136691.4	136719.3	-68553	137110	137124.0
1981	-68568.1	137140.2	137154.2	-68634.7	137273.4	137287.4	-68424.2	136856.4	136884.4	-68597.8	137199.6	137213.6
1991	-68592.2	137188.4	137202.4	-68640.9	137285.8	137299.8	-68453.7	136915.4	136943.4	-68646.8	137297.6	137311.6
2001	-68833.3	137670.6	137684.6	-68889.6	137783.2	137797.2	-68687.2	137382.4	137410.4	-68916.1	137836.2	137850.2
2010	-69911.2	139826	139840	-69969.4	139943	139957	-69795.8	139600	139628	-70023.8	140052	140066

Note: The Akaike Information Criterion for distribution i is computed as $AIC_i = 2 \cdot k_i - 2 \cdot \ln(L_i)$ and the Schwarz Criterion as $BIC_i = k_i \cdot \ln(N) - 2 \cdot \ln(L_i)$, where k_i is the number of free parameters of distribution i, N is the number cities by year, and $\ln(L_i)$ is the log-likelihood (Giesen et al., 2010).

Table 7. Results of the information criteria: Italy

Year	lognormal			q -exp.			dPln			log-logistic		
	Log-like.	AIC	BIC	Log-like.	AIC	BIC	Log-like.	AIC	BIC	Log-like.	AIC	BIC
1901	-70325	140654	140667.9	-71222.5	142449	142462.9	-70148.4	140304.8	140332.6	-70204.2	140412.4	140426.3
1911	-70871.9	141747.8	141761.7	-71725.1	143454.2	143468.1	-70698.2	141404.4	141432.2	-70758	141520	141533.9
1921	-74657.4	149318.8	149332.8	-75471.4	150946.8	150960.8	-74474.5	148957	148985.0	-74548.2	149100.4	149114.4
1931	-74918.2	149840.4	149854.4	-75648.8	151301.6	151315.6	-74757.6	149523.2	149551.2	-74827.9	149659.8	149673.8
1936	-75091.6	150187.2	150201.2	-75767.9	151539.8	151553.8	-74942.3	149892.6	149920.6	-75003.9	150011.8	150025.8
1951	-75830.9	151665.8	151679.8	-76415.1	152834.2	152848.2	-75689.6	151387.2	151415.2	-75747.8	151499.6	151513.6
1961	-75836.7	151677.4	151691.4	-76335.2	152674.4	152688.4	-75675.3	151358.6	151386.6	-75743.8	151491.6	151505.6
1971	-75951.9	151907.8	151921.8	-76324	152652	152666.0	-75798	151604	151632.0	-75878.3	151760.6	151774.6
1981	-76390.6	152785.2	152799.2	-76679.9	153363.8	153377.8	-76284.1	152576.2	152604.2	-76358.4	152720.8	152734.8
1991	-76653.1	153310.2	153324.2	-76893.6	153791.2	153805.2	-76583.2	153174.4	153202.4	-76645	153294	153308.0
2001	-76865.2	153734.4	153748.4	-77074.6	154153.2	154167.2	-76818.1	153644.2	153672.2	-76872.1	153748.2	153762.2
2010	-77390.1	154784	154798	-77570.4	155145	155159	-77359.4	154727	154755	-77417.2	154838	154852

Note: The Akaike Information Criterion for distribution i is computed as $AIC_i = 2 \cdot k_i - 2 \cdot \ln(L_i)$ and the Schwarz Criterion as $BIC_i = k_i \cdot \ln(N) - 2 \cdot \ln(L_i)$, where k_i is the number of free parameters of distribution i, N is the number cities by year, and $\ln(L_i)$ is the log-likelihood (Giesen et al., 2010).

Table 8. Results of the information criteria: Rest of the OECD countries

	lognormal			q -exp.			dPln			log-logistic		
Country	Log-like.	AIC	BIC	Log-like.	AIC	BIC	Log-like.	AIC	BIC	Log-like.	AIC	BIC
Australia	-13635.8	27276	27286	-13667.3	27339	27349	-13374.3	26757	26778	-13568.7	27141	27152
Austria	-20516.7	41037	41049	-20807.5	41619	41631	-20415.5	40839	40862	-20429.7	40863	40875
Belgium	-6282.8	12570	12578	-6377.9	12760	12768	-6267	12542	12560	-6268	12540	12549
Canada	-42872.2	85748	85761	-42784	85572	85585	-42772.8	85554	85580	-42784.7	85573	85586
Chile	-3955.8	7916	7923	-3972.5	7949	7957	-3953.8	7916	7931	-3954.2	7912	7920
Czech Republic	-48577.4	97159	97172	-48852.3	97709	97172	-48284.2	96576	96603	-48451	96906	96916
Denmark	-1187.1	2378	2383	-1181.8	2368	2373	--	--	--	-11.68.4	2341	2346
Estonia	-2215.1	4434	4441	-2211.3	4427	4433	--	--	--	-2185.6	4375	4382
Finland	-3480.2	6964	6972	-3494.1	6992	7000	-3472.3	6953	6968	-3475.7	6955	6963
France	-291228	582460	582477	-292189	584382	584399	-290114	580236	580270	-290877	581758	581775
Germany	-105632	211268	211283	-105818	211640	211655	-105586	211180	211209	-105736	211476	211491
Greece	-3717.3	7439	7446	-3697.1	7398	7406	-3694.9	7398	7413	-3709.1	7422	7430
Hungary	-26540.9	53086	53098	-26619.5	53243	53255	-26482.7	52973	52998	-26504.3	53013	53025
Iceland	-654.6	1313	1318	-655.3	1315	1319	-653.7	1315	1325	-654.8	1314	1318
Ireland	-6851.8	13708	13717	-6885.4	13775	13784	-6726.6	13461	13480	-6829.2	13662	13672
Israel	-1915.9	3836	3842	-1948.5	3901	3907	--	--	--	-1915.9	3836	3842
Japan	-22651.3	45307	45318	-22735	45474	45485	-22567.4	45143	45165	-22607.8	45220	45231
Korea	-3304.08	6612	6619	-3290.3	6585	6592	-3303.7	6615	6630	-3314.3	6633	6640
Luxemburg	-980.4	1965	1970	-997.3	1999	2004	-972.4	1953	1963	-978.7	1961	1967
Mexico	-27675.1	55354	55366	-27730.3	55465	55476	-27669.6	55347	55370	-27684.9	55374	55385
Netherlands	-5629.3	11263	11271	-5703.1	11410	11419	-5609.8	11228	11245	-5617.9	11240	11248
New Zealand	-878.3	1761	1765	-877.4	1759	1763	-875.6	1759	1768	-876	1756	1761

Table 8. Results of the information criteria: Rest of the OECD countries – Continued

	lognormal			q -exp.			dPln			log-logistic		
Country	Log-like.	AIC	BIC	Log-like.	AIC	BIC	Log-like.	AIC	BIC	Log-like.	AIC	BIC
Norway	-4320.1	8644	8652	-4348.8	8702	8710	-4312.6	8633	8649	-4321.4	8647	8655
Poland	-25511.7	51027	51039	-26012.2	52028	52040	-25212.4	50433	50456	-25392	50788	50800
Portugal	-3473.8	6952	6959	-3509.1	7022	7030	-3470.6	6949	6964	-3477.8	6960	6967
Slovakia	-23804.8	47614	47626	-23921.8	47848	47860	-23712.7	47433	47457	-23732.9	47470	47482
Slovenia	-2107.6	4219	4226	-2126.8	4258	4264	-2104.1	4216	4230	-2105.4	4215	4222
Sweden	-3242.6	6489	6497	-3319.2	6642	6650	-3233	6474	6489	-3242	6488	6495
Switzerland	-21958.3	43921	43932	-22008.4	44021	44032	-21955.4	43919	43942	-21971.1	43946	43958
Turkey	-29486.3	58977	58989	-29492.4	58989	59001	-28876.7	57761	57785	-29330.6	58665	58677
United Kingdom	-4448.1	8900	8908	--	--	--	-4424.8	8858	8873	-4426.9	8858	8866

Note: The Akaike Information Criterion for distribution i is computed as $AIC_i = 2 \cdot k_i - 2 \cdot \ln(L_i)$ and the Schwarz Criterion as $BIC_i = k_i \cdot \ln(N) - 2 \cdot \ln(L_i)$, where k_i is the number of free parameters of distribution i, N is the number cities by year, and $\ln(L_i)$is the log-likelihood (Giesen et al., 2010).

Figure 1. Empirical and estimated pdfs in the US, Spain and Italy (2010)