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I am submitting herewith a thesis written by Jennifer Susan Chastain entitled "A Statistical Reliability Analysis of the Variability and Upper Percentiles of the Wood Strand Thickness of Oriented Strand Board." I have examined the final electronic copy of this thesis for form and content and recommend that it be accepted in partial fulfillment of the requirements for the degree of Master of Science, with a major in Statistics.

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A Statistical Reliability Analysis of the Variability and Upper Percentiles of the Wood Strand Thickness of Oriented Strand Board

A Thesis
Presented for the
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Jennifer Susan Chastain

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Dedication

This thesis is dedicated to my parents, my brother Brad, and my grandmother Alma, all of whom have helped and stood by me over the years. Thank you for all your loving support and encouragement in my pursuit of this degree. Mom, I appreciate all you do and for being there for me no matter what the circumstances. Dad, thank you for always lending a listening ear and for being the rock that keeps me grounded. Brad, you have always been able to help me keep things in perspective, especially when trying to see the forest instead of the trees. Knoxville definitely would not have been the same experience without you. Alma, you are my role model. I can only hope to be half the woman you are. I am truly blessed to have all of you in my life.

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Abstract

Oriented strand board (OSB) is an important structural engineered wood product used predominately in housing construction, with OSB revenue of around $14 billion in 2005. OSB is a product with a low environmental impact or "carbon footprint." In this thesis, reliability and statistical tools are applied to gain insights of the strand thickness for OSB panels manufactured in the Eastern United States. The thesis, also, develops new techniques to more realistically estimate upper percentiles via induced left censoring.

An OSB panel consists of thousands of resinated wood strands that are formed in mats of oriented strands and pressed with heat causing thermal-activated bonding. The variability of OSB strand thickness for six manufacturers is examined. Strand thickness variability has been documented in the literature as having a strong influence on mat formation quality and subsequently the strength properties of OSB wood panels. However, there is an absence in the literature of assessing strand thickness variability from OSB mills. The goals of the thesis are to quantify and characterize strand thickness, plus apply reliability techniques, such as Kaplan-Meier curves and left censoring, to better characterize the probability and percentiles of strand thickness. The thesis further explores graphically and statistically the thickness of the strands through histograms, probability plots, box plots, and so on. Using induced percentile left censoring for improved model fitting, bootstrapping methods are employed for better estimating the upper percentiles, which are of particular interest due to their importance in the manufacturing process. If the OSB strands are too thick, machines and presses can be damaged at great expense. A comparison of the upper percentiles for six OSB mills identifies mills at greater risk for equipment damage and financial loss. Left percentile censoring is explored and

used in conjunction with bootstrapping to calculate confidence intervals for the upper percentiles. Appropriate parametric models are used for the bootstrapping and nonparametric bootstrapping methods are presented as a means of comparison. Better estimation of upper percentiles promotes continuous improvement of preventive maintenance and product quality. Continuous improvement has never been more important for manufacturers than it is now given the severely constrained housing markets and the economic recession of 2009.

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Chapter 1

Introduction

Oriented Strand Board (OSB) is an important engineered wood product created using wood strands cut from small round logs which are resinated with phenolic or isocyanates resins and pressed together under heat and pressure. The panels of OSB are layered with strands in non-random directions to form mats that are then cut to specific dimensions. The direction of the strands gives the mats strength and durability. Generally, the strands are up to six inches (152.4 mm) long and approximately one inch (25.4 mm) wide with a uniform thickness across the surface of the strand. The thickness of the strands can be custom-made depending on the use and thickness of the final OSB panel (e.g., OSB panel thicknesses vary in inches from $\frac{1}{4}, \frac{3}{8}, \frac{7}{16}, \frac{15}{32}, \frac{1}{2}, \frac{19}{32}, \frac{5}{8}, \frac{23}{32}, \frac{3}{4}$; the most common thicknesses are 7/16” used for roof sheathing and 22/32” used for flooring underlayment); see, Anonymous (2007).

OSB is a direct substitute for plywood, which is a traditional engineered veneered-layered wood panel used primarily for housing construction (Wang 2007). It is used to a lesser extent in furniture, as well as shelving, and has some applications in industrial construction. OSB is commonly used in housing construction as roof sheathing, wall sheathing, and flooring. Many architects and contractors prefer OSB to plywood because it can be tailored for certain specialized uses (e.g., varying thickness and density) and has a price advantage to plywood (Anonymous 2007).

As Wang, Young, Guess, and León (2007) noted, OSB is aggressively replacing plywood as the primary sheathing used in new construction in North America. Approximately

65 percent of the 43 billion square feet of construction sheathing used in 2005 consisted of OSB, while the remaining 35 percent consisted of plywood sheathing (Adair 2005). Plywood sheathing continues to decline in use. Note that 73 percent of all OSB sheathing produced is used in residential housing construction. Residential housing construction in the U.S.A. is predicted to decline from a record of almost 2.0 million annual new housing starts in 2005 (Adair 2005) to approximately 0.5 million housing starts in 2009 (Anonymous 2009e). The decline in housing starts, in conjunction with recent OSB newer technology mill expansion, has put OSB producers under tremendous pressure with record low prices for OSB panels. These economic pressures will require existing OSB manufacturers to maintain a strong focus on reliability, quality, and costs, including an emphasis on strand yield per tree log processed.

OSB is made from a renewable resource with a low “carbon footprint” on the environment (e.g., small and poor quality trees), unlike other non-renewable products such as steel and cement that have very large environmental “carbon footprints.” OSB is accommodating in terms of thickness density and can be tailored to specific uses.

The purpose of this thesis is to explore the thickness variability of OSB strands from six manufacturers in the Eastern United States. Samples of strands were collected from six mills and measured in terms of length, width, and thickness. Various reliability techniques are used to characterize the variability and estimate the upper percentiles of the strand thickness measurements. The six data sets are examined individually and compared.

Chapter 2 of this thesis is a literature review that briefly discusses OSB but focuses mainly on the statistical methods used by the researchers. The statistical methods used in this thesis are primarily reliability analyses since estimating the upper percentiles is of interest. A discussion of why the upper percentiles are so important is also covered in Section 2.1. Reliability analyses, including Kaplan-Meier curves and forced percentile censoring, are discussed in Section 2.2. Section 2.3 explains the bootstrapping methods used to estimate the upper percentiles. Many books and website references are included so that the reader has numerous options for further study on the statistical methods if so desired.

Chapter 3 focuses on getting to know the data sets and finding the best distribution for each. Section 3.1 compares the descriptive statistics and best reliability models of thickness across the six mills. In Section 3.2, each mill's descriptive statistics are reported, along with figures of individual box plots and histograms, probability plots, and reliability curves. The probability plots are used in visualizing the best-fitting distribution for the data set. Kaplan-Meier curves are used to analyze the probability of thickness of the data (Kaplan and Meier 1958). The statistical software used to perform this analysis includes JMP, S-PLUS, and SPLIDA, the add-on to S-PLUS. Information about these software packages can be found at Anonymous (2008a), Anonymous (2008b), and Meeker (2008), respectively. Section 3.3 provides a summary of the findings in the chapter. It also focuses on the mill having the least variability and how its results can be used by other manufacturers to improve their own processes.

In Chapter 4, bootstrapping is used to find confidence intervals for the 0.90, 0.95, and 0.99 quantiles. Forced censoring at certain percentiles is used to find more precise confidence limits for these quantiles. For instance, each data set is censored at the following quantiles: 0.10, 0.15, 0.20, and 0.25. For each of these censoring percentiles, nine distributions are fit to the data set to determine the best distribution according to scoring the AIC. Next, the prevailing distribution (i.e., the one which minimizes the AIC) is used as the underlying distribution for bootstrapping. Finally, the confidence intervals for the 0.90, 0.95, and 0.99 quantiles at each censoring value, as well as nonparametric bootstrap estimates, are compared to determine the most precise intervals. SPLIDA is used to carry out the computations in bootstrapping when a distribution is assumed. MATLAB is used to calculate the nonparametric estimates.

Chapter 5 is a summary of the thesis. An outcome of this thesis is to promote the use of statistics and reliability methods among scientists and practitioners that are interested in understanding sources of variation in OSB. This chapter also provides a brief explanation of how the statistical methods in this thesis may be used to analyze the internal bond strength, thickness swell, or other important characteristics of OSB strands and panels.

Future research is discussed in Chapter 6. Specifically, Bayesian analysis might be an important area to explore with this data. Co-variables are also discussed as they can be important in quantile regression analysis and predictive modeling.

Chapter 2

Literature Review

This chapter focuses on the importance of OSB flake thickness, as well as the statistical methods used in the thesis. More emphasis on statistical methods is given in this chapter.

2.1. OSB Background

Thickness of the individual strands making up the OSB panel is of high importance to the manufacturers. If the strands are too thin, costs rise because the process requires more strands to form the panel and very small strands or “fines” absorb more resin which is costly. On the other hand, if the strands are too thick, they can damage the expensive pressing machines that compress the resinated flakes into final panels. The latter issue is of interest in this thesis. Particularly, the upper percentiles (i.e., 90^{th}, 95^{th}, and 99^{th}) are very important. Extreme variability in the strand thickness makes it difficult to have a good process for manufacturing the OSB. Characterizing that variability may be useful to manufacturers so that they can improve their processes to increase efficiency. Also, estimating values and confidence intervals for the upper percentiles can help predict how thick the strands may be based on the current process and promote preventive maintenance.

Strand thickness variability may directly influence mat formation, which impacts final board reliability and strength and may influence thickness swell of the final OSB panel (Tackie, Wang, Bennett, and Shi 2008; Hermawan, Ohuchi, Tashima, and Murase 2006; Paul, Ohlmeyer, Leithoff, Boonstra, and Pizzi 2005). Tackie, Wang, Bennett, and Shi (2008) mention the variability in the thickness of the strands as they are placed on top of each other to form a mat.

Specifically, there may be more strands overlapped in one area of the mat than another, which can potentially cause internal problems for the final OSB panel (Tackie, Wang, Bennett, and Shi 2008). Since the panels contain three layers and the middle layer is oriented perpendicular to the outer layers, strand thickness clearly impacts the strength of the final board (Tackie, Wang, Bennett, and Shi 2008). Thus, not only does the thickness of the individual flakes have an effect on the pressing machines, but the strand thickness may determine how long the final panel will last when used in housing construction. Additionally, Hermawan, Ohuchi, Tashima, and Murase (2006) note that "[OSB's] mechanical properties could be improved by using longer and thinner strands." If manufacturers have a clearer specification for thinner strands as related to panel strength properties, they may be able to improve the final properties of OSB.

Sharma and Sharon (1993) discuss the importance of the orientation of flakes used in making the final OSB panels. Particularly, if the flakes are optimally placed on top of each other, the final panel yields desirable properties, such as increased strength and better performance for the given application (i.e., roofing, flooring, or walling); see Sharma and Sharon (1993). The variability of the thickness of the individual flakes has a direct impact on the orientation of the flakes during forming, thus impacting mat formation. If manufacturers want to optimize forming and panel strength, a focus on control of manufactured flake thickness is required. See Canadido et al. (1990) for strand thickness effects on final OSB board properties.

The statistical and reliability methods outlined in this thesis can be used to improve the yield of OSB wood strands sheathing by proactively preventing potential wood fiber waste. See Guess, Hollander, and Proschan (1986), Guess and Proschan (1988), Guess, Walker, and Gallant (1992), Young and Guess (1994), Young and Guess (2002), Guess, León, Chen, and Young

(2004), and Guess, Zhang, Young, and León (2005) for discussions on various measures and approaches to understanding reliability. The following section is a brief overview of reliability analyses.

2.2. Reliability

Meeker and Escobar (1998) provide the following definition of reliability: "Reliability is…the probability that a system, vehicle, machine, device, and so on will perform its intended function under operating conditions, for a specified period of time." This definition generally refers to something that can fail after a certain amount of time. As it applies to this thesis, this definition can be interpreted slightly differently. The manufacturers are interested in the upper percentiles of the data, especially the extreme upper percentiles, i.e., when flakes are too thick, they can damage the OSB presses. Thus, "failing" for wood strands occurs when they are thicker than a specified value.

Since the upper percentiles of the OSB flakes are of particular interest, reliability analysis helps focus on estimating quantiles rather than the traditional mean, median, and standard deviation. Probability plots are very useful in determining which distribution best fits the data set. These plots can also be used to visually approximate probabilities and percentiles (Meeker and Escobar 1998). Akaike's Information Criterion (AIC) is a more objective way to determine the best-fitting distribution. AIC is calculated as

$$\text{AIC} = -2(\text{Loglikelihood}) + 2k$$

where

k is the number of parameters in the model (Akaike 1973).

The minimum AIC score is considered best, and the distribution corresponding to the lowest score is the best fit for the data set. Please see Anonymous (2009a) for more information on this useful statistic.

In addition to probability plotting, nonparametric Kaplan-Meier curves are useful in determining the percentage of data values that survive after a given time (Kaplan and Meier 1958). Since the thickness measurements are raw data and have not been tested in any way, the definition of a survival curve must be redefined. As they apply to this thesis, Kaplan-Meier curves show the probability that a wood strand will be a given thickness or higher. This is important since the manufacturers most likely have a specification range over which strands are considered acceptable. The survival curves also help in estimating the upper quantiles by examining the graph and finding the value above which only one percent of the data falls.

In reliability the issue of censoring is an important topic. Generally, censoring occurs because of incomplete data: the units may have failed at an unknown time before a given time period, or the units could have failed after the test ended (Meeker and Escobar 1998). The devices may also fail at some time within an interval so that the exact failure time is not known (Tobias and Trindade 1995). Since no testing was done on the thickness measurements, there are no actual failures. Thus, forced censoring is used to improve the estimates further. Censoring at lower quantiles, such as the 0.10 or 0.15 quantile, up to the 0.25 quantile, helps alleviate the problem of infant mortality. When many units fail at an early time, these failures can have an adverse impact on the distribution chosen. Please see Tobias and Trindade (1995) for an explanation of the "bathtub curve." This curve plots the failure rates for the units against time (Tobias and Trindade 1995). The curve is shaped like a bathtub because the failure rates decrease at early times, then become stable, then increase at later times (Tobias and Trindade 1995). The early failures can be explained by manufacturing defects or parts that were weak before being used by the researcher or consumer (Tobias and Trindade 1995). Censoring at low values gets rid of these infant mortalities and allows for better estimates of the upper percentiles (Meeker and Escobar 1998). If the early failures are censored, they will not have an effect on the choice of distribution for the rest of the data. Thus, removing (or censoring) these infant mortalities will provide better estimates for the upper portion of the data. As it applies to this thesis, left censoring involves removing thin strands so that the thicker strands can be estimated without the effect of the thinner strands. In other words, removing the effect of infant mortality involves removing the effect of the thinnest strands. For more information on general reliability theory, please see Gertsbakh (1989), Anonymous (2008c), and Anonymous (2009c). For more on reliability as it relates to engineering, please see O'Connor (1985), Modarres (1993), and Anonymous (2009b).

2.3. Bootstrapping

Manufacturers are interested in obtaining highly accurate estimates of the upper (or lower) percentiles so that they can better understand or alter processes for continuous improvement. Bootstrapping of the data sets can help accomplish this objective. According to Meeker and Escobar (1998), "Bootstrap intervals, when used properly, can be expected to be more accurate than the normal-approximation methods and are competitive with the likelihood-based methods." Bootstrapping is a computer-intensive strategy to determine better estimates for parameters and quantiles of a data set. According to Efron and Tibshirani (1993), "The bootstrap is a data-based simulation method for statistical inference." The general idea is to resample from the original sample, treating the original sample as if it were the population (Efron and Tibshirani 1993). For each sample that is drawn from the original sample, a parameter or quantile is estimated (Efron and Tibshirani 1993). The standard error should then be estimated so that confidence intervals can be calculated for the parameter (Efron and Tibshirani 1993).

There are numerous bootstrap methods to use. Efron and Tibshirani (1993) provide very helpful information on this topic. Please see Chernick (1999) as well for practical uses of the bootstrap. Due to the number of data sets used in this thesis, the bootstrap percentile method was used. From the original sample, B bootstrap samples are generated with replacement and the parameter or quantile of interest is estimated for each sample (Efron and Tibshirani 1993). The B parameter estimates are then ordered and the confidence limits are chosen according to the specified level of α (Efron and Tibshirani 1993). For example, with 1000 bootstrap samples and a confidence level of 95 percent, the lower limit will be the parameter estimated in ordered position 25, and the upper limit will be the parameter estimated in ordered position 975 (Efron and Tibshirani 1993). The percentile method is easy to use and easy to understand. It can be used nonparametrically as well as parametrically, where an underlying distribution is assumed for the data (Efron and Tibshirani 1993). This method is also useful when it is difficult to estimate the standard error (Meeker and Escobar 1998). Efron and Tibshirani (1993) also note that the percentile method is better to use than the bootstrap-t as the latter can be greatly influenced by outliers.

There are also assumptions that can be made when bootstrapping. Specifically, a distribution can be assumed for the data set and bootstrapping can commence. Or, the researcher can assume no underlying distribution of the data and make nonparametric inferences. SPLIDA is used in this thesis for the bootstrap confidence interval estimates when a parametric distribution is assumed. MATLAB is used in this thesis for the nonparametric bootstrap confidence intervals. The method used in SPLIDA is actually a mixture of parametric and nonparametric inference. Specifically, samples are drawn with replacement from the original sample (Meeker and Escobar 1998). For each sample, the maximum likelihood estimates of the parameters are estimated based on the underlying distribution (Meeker and Escobar 1998). The parameter estimates can then be used to find confidence intervals based on the percentile method described above. This mixture of parametric and nonparametric inference is especially helpful for censored data because it keeps the censoring mechanism in tact, and the censoring mechanism does not have to be explicitly stated (Meeker and Escobar 1998). Both the completely nonparametric bootstrap and the mixture of parametric and nonparametric bootstrap methods are used in Chapter 4 of this thesis. A detailed explanation of the results will show the advantages and disadvantages of each method. Please see Anonymous (2009d) for more information on general bootstrapping.

Chapter 3

Using Reliability Tools to Characterize Wood Strand Thickness of Oriented Strand Board Panels

3.1. Exploring Statistically the Thickness of OSB for All Mills

Data on thickness of strands were collected from six OSB mills in the Eastern United States in 2007. These mills are examined as a group and individually. Descriptive statistics are generated to determine center, variability, and shape of the data sets. The center is measured by the mean and median, while variability is determined by standard deviation, coefficient of variation (CV), and interquartile range. The skewness and kurtosis coefficients, as well as the box plots and histograms, can explain the shape of the distributions. Table 3.1 summarizes key statistics for each complete data set.

Table 3.1. OSB strand thickness descriptive statistics for each mill's complete data.

Statistic	**Mill A**	**Mill B**	**Mill C**	**Mill D**	**Mill E**	**Mill F**
Mean	0.0357	0.0311	0.0288	0.0318	0.0364	0.0291
Median	0.0335	0.0310	0.0275	0.0308	0.0365	0.0268
Standard Deviation	0.0124	0.0058	0.0127	0.0137	0.0151	0.0134
CV	34.73%	18.65%	44.10%	43.08%	41.48%	46.05%
IQR	0.0135	0.0040	0.0140	0.0159	0.0222	0.0162
Minimum	0.0130	0.0210	0.0045	0.0070	0.0085	0.0067
Maximum	0.0955	0.1030	0.0715	0.1155	0.0890	0.0876
Skewness	1.0293	9.3936	0.9477	1.7258	0.2927	1.3612
Kurtosis	2.2333	116.4694	1.6523	8.3946	0.0281	2.9531
Sample Size	300	200	140	150	150	304

The mean and median for each data set fall close to 0.03 inches (0.762 mm). Most of the standard deviations fall around 0.01 inches (0.254 mm) with the coefficient of variation ranging from 18.7 percent to 46.1 percent, while Mill B distinctly has the least variability. Mill B has a sample standard deviation less than 50 percent of that of the other five mills. Also, Mill B has a much lower interquartile range of 0.004 inches (0.1016 mm) when compared to the other five mills, while Mill E's interquartile range of 0.0222 inches (0.5368 mm) is larger than the other mills' data sets. Mill B is skewed the most as assessed by the skewness coefficient, and this can be explained partially by an extreme outlier in the complete data. Mill B also has the highest kurtosis, meaning it is the most peaked distribution.

Nine distributions are examined to determine the best-fitting distribution for each mill. These distributions are Exponential, Frechet, Largest Extreme Value, Logistic, Loglogistic, Lognormal, Normal, Smallest Extreme Value, and Weibull. Akaike's Information Criterion (AIC) is used to score each of these distributions, and the lowest score is judged the best (Akaike 1973). See, also, the insightful, helpful work of Bozdogan (2000). This AIC criterion depends on the log likelihood function. Table 3.2 shows the log likelihood of each distribution for each mill, and Table 3.3 contains the corresponding AIC scores.

The bolded cells in Table 3.3 are the lowest AIC scores for each mill. These minimized AIC values correspond to the best-fitting distribution for a particular mill. The Largest Extreme Value and Loglogistic distributions are the most popular for the mill wood strands. Mill E, which produces the thickest wood strand among the six mills, has the only Weibull distribution.

Each data set contains at least one outlier, just like numerous other data sets. For comparison, the researchers removed the highest outlier from each data set and found the

Table 3.2. Log likelihood of nine distributions for each mill's complete data.

Distribution	Mill A	Mill B	Mill C	Mill D	Mill E	Mill F
Exponential	699.9	493.9	356.4	367.2	346.9	771.4
Frechet	876.3	833.2	386.0	414.3	383.0	889.8
LEV	911.9	838.7	420.9	444.3	413.8	917.8
Logistic	901.1	854.9	418.0	441.1	414.3	892.6
Loglogistic	912.4	864.7	419.4	443.9	408.9	916.8
Lognormal	911.5	851.9	415.4	441.0	408.8	918.8
Normal	892.9	859.0	413.6	430.9	416.5	879.7
SEV	812.1	858.5	382.0	399.1	396.8	791.8
Weibull	893.6	860.8	418.5	436.4	419.5	898.5

Table 3.3. AIC score of nine distributions for each mill's complete data.

Distribution	Mill A	Mill B	Mill C	Mill D	Mill E	Mill F
Exponential	-1395.8	-983.8	-708.8	-730.4	-689.8	-1538.8
Frechet	-1748.6	-1662.4	-768.0	-824.6	-762.0	-1775.6
LEV	-1819.8	-1673.4	**-837.8**	**-884.6**	-823.6	-1831.6
Logistic	-1798.2	-1705.8	-832.0	-878.2	-824.6	-1781.2
Loglogistic	**-1820.8**	**-1725.4**	-834.8	-883.8	-813.8	-1829.6
Lognormal	-1819.0	-1699.8	-826.8	-878.0	-813.6	**-1833.6**
Normal	-1781.8	-1714.0	-823.2	-857.8	-829.0	-1755.4
SEV	-1620.2	-1713.0	-760.0	-794.2	-789.6	-1579.6
Weibull	-1783.2	-1717.6	-833.0	-868.8	**-835.0**	-1793.0

resulting log likelihood values. The AIC values were calculated again when the highest outlier is removed. Any change in the choice of best distribution for a data set shows how the outlier influences the results. After removing the highest outlier from each mill, the resulting log likelihoods and AIC scores indicate that the most common distribution among the six mills is the Weibull, followed by the Largest Extreme Value. Please see Tables 3.4 and 3.5 for the log likelihoods and AIC scores for each mill with the highest outlier removed.

3.2. Exploring Graphically and Statistically the Thickness of OSB for Each Individual Mill

Each mill is examined below on an individual basis. This section shows the graphs and plots that determine the summaries in Section 3.1.

3.2.1. Mill A

Mill A has several high outliers that skew the distribution to the right, as seen in the box plot for this data set (see Figure 3.1). The mean and median values are very close to each other, but the skewness coefficient of 1.0293 indicates a positive (right) skewness. There is one high outlier very far from the rest of the data, and the AIC is scored with and then without this outlier to determine the best fit for the distribution. Table 3.6 shows the log likelihood values and AIC scores for Mill A, both with and without the outlier.

On the complete data set, the Loglogistic distribution is the best fit for the data. With the large outlier excluded, the best-fitting distribution is the Largest Extreme Value, followed by the Loglogistic and Lognormal distributions. Figure 3.2 shows the probability plots for the three best distributions for Mill A when the outlier is excluded. It is difficult to determine the best-fitting distribution by looking at these three plots, so it is very useful to have AIC as a

Table 3.4. Log likelihood (excluding highest outlier) of nine distributions for each mill.

Distribution	Mill A	Mill B	Mill C	Mill D	Mill E	Mill F
Exponential	699.3	493.7	355.4	367.5	346.1	770.9
Frechet	876.3	839.8	385.2	414.7	382.4	889.7
LEV	913.9	856.1	421.1	448.2	414.0	919.7
Logistic	905.2	885.1	419.5	448.4	415.7	896.2
Loglogistic	913.8	881.5	419.3	446.0	408.8	917.7
Lognormal	913.7	880.2	415.2	444.1	408.8	920.1
Normal	901.7	886.1	416.1	449.1	419.6	886.2
SEV	840.8	885.5	386.4	427.8	409.2	803.4
Weibull	902.0	889.0	420.0	451.1	422.0	902.7

Table 3.5. AIC score (excluding highest outlier) of nine distributions for each mill.

Distribution	Mill A	Mill B	Mill C	Mill D	Mill E	Mill F
Exponential	-1394.6	-983.4	-706.8	-731.0	-688.2	-1537.8
Frechet	-1748.6	-1675.6	-766.4	-825.4	-760.8	-1775.4
LEV	**-1823.8**	-1708.2	**-838.2**	-892.4	-824.0	-1835.4
Logistic	-1806.4	-1766.2	-835.0	-892.8	-827.4	-1788.4
Loglogistic	-1823.6	-1759.0	-834.6	-888.0	-813.6	-1831.4
Lognormal	-1823.4	-1756.4	-826.4	-884.2	-813.6	**-1836.2**
Normal	-1799.4	-1768.2	-828.2	-894.2	-835.2	-1768.4
SEV	-1677.6	-1767.0	-768.8	-851.6	-814.4	-1602.8
Weibull	-1800.0	**-1774.0**	-836.0	**-898.2**	**-840.0**	-1801.4

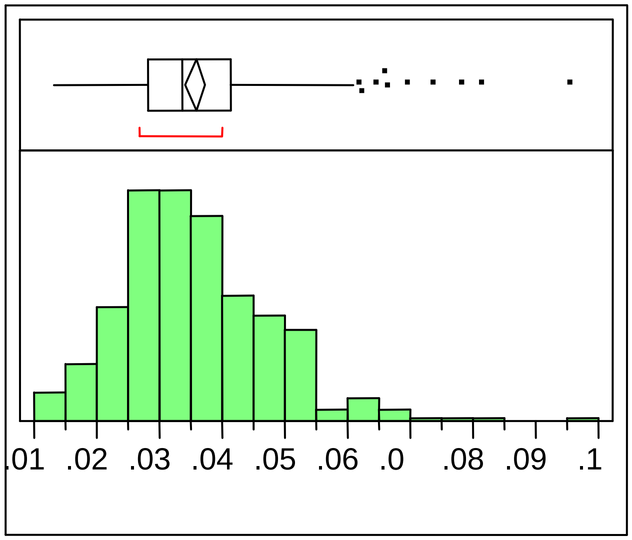
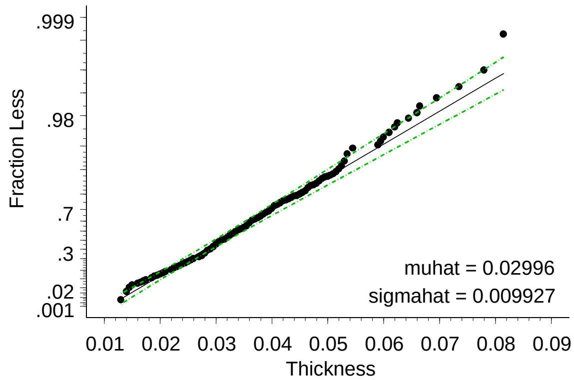


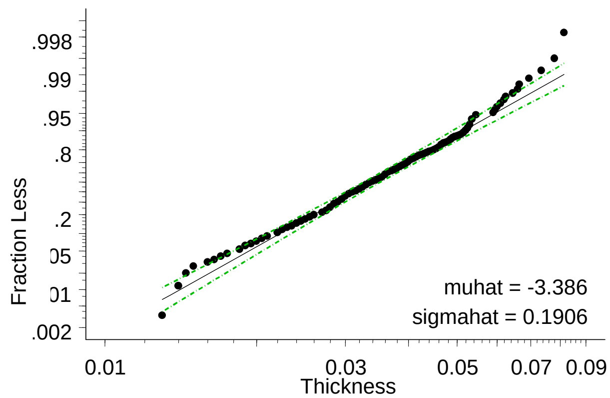
Figure 3.1. Mill A's strand thickness histogram and boxplot from JMP.

Table 3.6. Mill A's model scores for strand thickness data, complete and excluding an outlier.

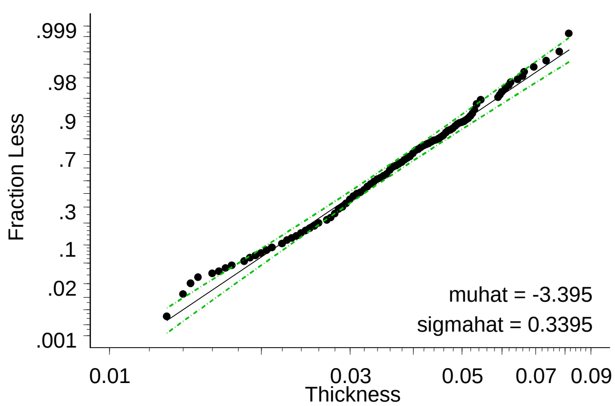
Distribution	Complete data		Data with one outlier excluded	
	Log Likelihood	AIC	Log Likelihood	AIC
Loglogistic	**912.4**	**-1820.8**	913.8	-1823.6
LEV	911.9	-1819.8	**913.9**	**-1823.8**
Lognormal	911.5	-1819.0	913.7	-1823.4
Logistic	901.1	-1798.2	905.2	-1806.4
Weibull	893.6	-1783.2	902.0	-1800.0
Normal	892.9	-1781.8	901.7	-1799.4
Frechet	876.3	-1748.6	876.3	-1748.6
SEV	812.1	-1620.2	840.8	-1677.6
Exponential	699.9	-1395.8	699.3	-1394.6



(a) Largest extreme value plot



(b) Loglogistic plot



(c) Lognormal plot

Figure 3.2. Mill A's strand thickness versus fraction less probability plots from S-PLUS and SPLIDA.

quantitative measure of the best distribution. Please see Akaike (1973) for more information on this valuable statistic.

Kaplan-Meier curves can be used to analyze the time to failure or pressure to failure of a product; compare Meeker and Escobar (1998), Guess, Steele, Young, and León (2006), and Wang, Young, Guess, and León (2007). In this study, Kaplan-Meier curves are used to plot the probability of strand thickness of oriented strand board. Kaplan-Meier plots are used as they are very popular and easy to interpret. They are also nonparametric, so no distributional assumptions need to be made. The Kaplan-Meier curve for Mill A is shown in Figure 3.3.

Figure 3.3 shows from the Kaplan-Meier, for instance, the probability that strand thickness will be greater than 0.03 inches (0.762 mm) is approximately 0.60, while the probability that thickness will be greater than 0.04 inches (1.016 mm) is approximately 0.30. Statistically, five percent of strands have a thickness less than 0.0185 inches (0.4699 mm) and 95 percent of strands have a thickness less than 0.0590 inches (1.4986 mm) for Mill A. The plot also indicates that the probability that strand thickness is larger than a given value decreases at an increasing rate between 0.03 and 0.04 inches (0.762 and 1.016 mm).

3.2.2. Mill B

Mill B has one low outlier as seen in the box plot in Figure 3.4, but this plot excludes an extremely high outlier from the original data. The mean and median are very close, plus the middle 50 percent of the data falls within a fairly tight range as compared to the tails of the distribution. The extreme outlier has an influence on the choice of the best-fitting distribution; thus, log likelihood and AIC are shown with and without the outlier in Table 3.7.

The Loglogistic distribution minimizes the AIC for the complete data set. When

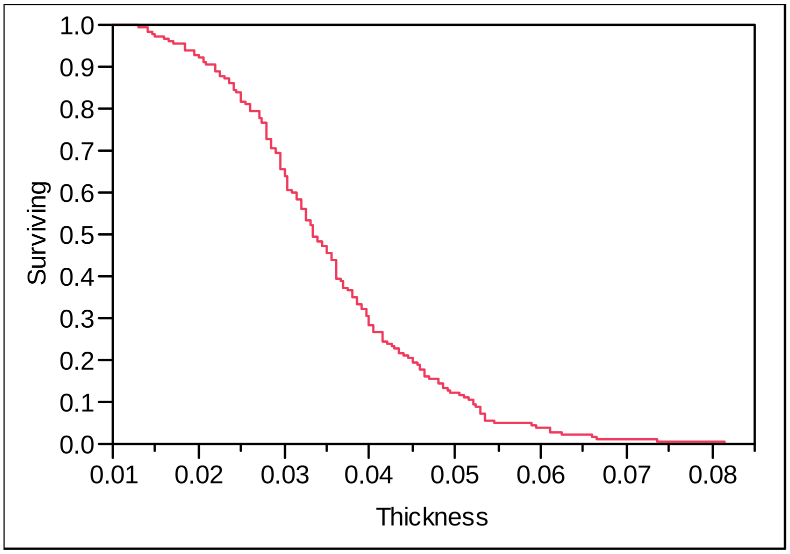


Figure 3.3. Mill A's reliability Kaplan-Meier plot of strand thickness.

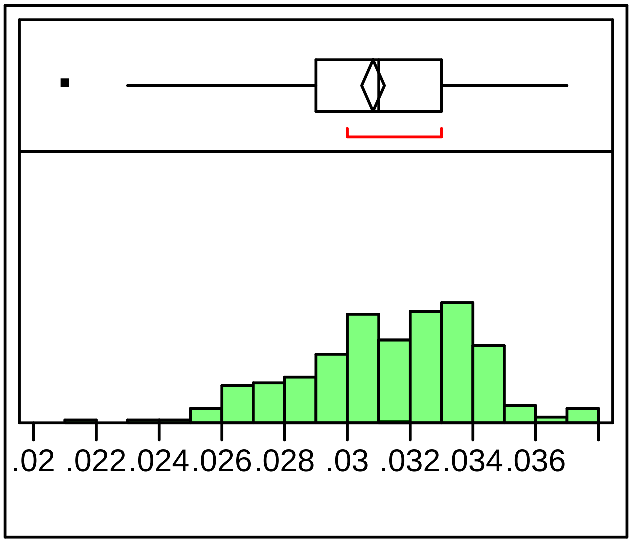


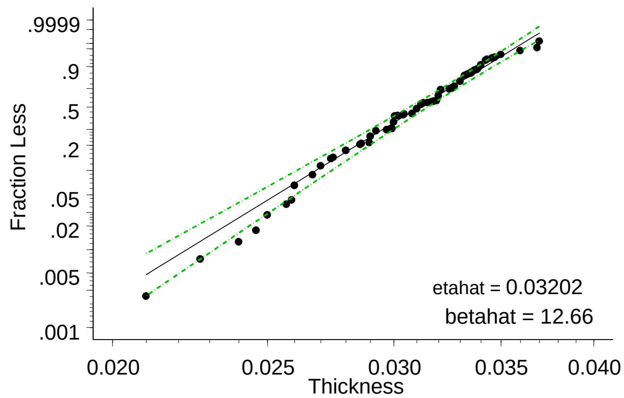
Figure 3.4. Mill B's strand thickness histogram and boxplot from JMP (excluding one extreme outlier).

Table 3.7. Mill B's model scores for strand thickness data, complete and excluding an outlier.

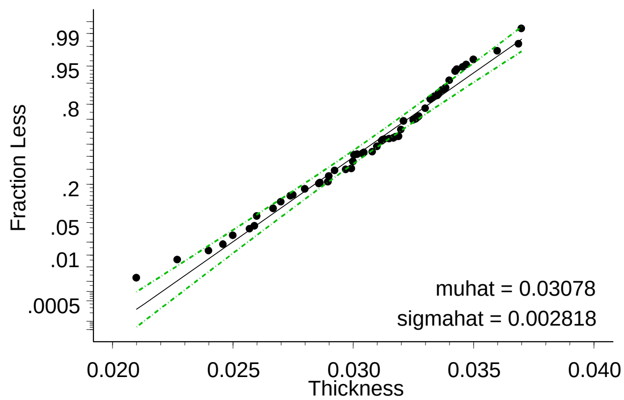
Distribution	Complete data		Data with one outlier excluded	
	Log Likelihood	AIC	Log Likelihood	AIC
Loglogistic	**864.7**	**-1725.4**	881.5	-1759.0
Weibull	860.8	-1717.6	**889.0**	**-1774.0**
Normal	859.0	-1714.0	886.1	-1768.2
SEV	858.5	-1713.0	885.5	-1767.0
Logistic	854.9	-1705.8	885.1	-1766.2
Lognormal	851.9	-1699.8	880.2	-1756.4
LEV	838.7	-1673.4	856.1	-1708.2
Frechet	833.2	-1662.4	839.8	-1675.6
Exponential	493.9	-983.8	493.7	-983.4

excluding the high outlier, the best-fitting distribution is the Weibull, followed by the Normal and Smallest Extreme Value distributions. The difference in AIC scores with and without the extreme value suggest that this extreme maximum data point is indeed an outlier. Figure 3.5 shows the probability plots for the three best distributions for Mill B when the outlier is excluded.

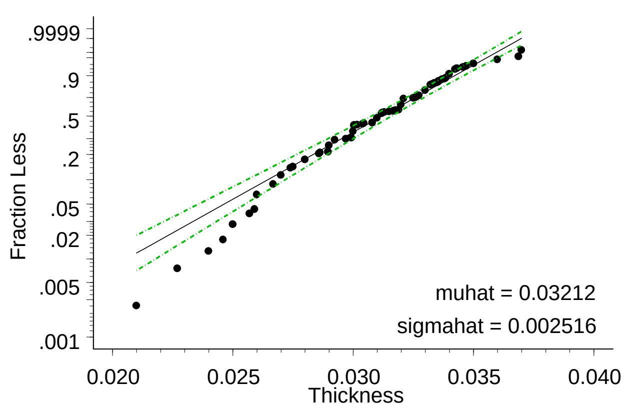
A Kaplan-Meier plot is shown in Figure 3.6 to model the probability of thickness for OSB strands for Mill B. Figure 3.6 shows from the Kaplan-Meier, for instance, the probability that strand thickness will be greater than 0.028 inches (0.711 mm) is approximately 0.80, while the probability that thickness will be greater than 0.032 inches (0.813 mm) is approximately 0.30. Statistically, five percent of strands have a thickness less than 0.026 inches (0.6604 mm) and 95 percent of strands have a thickness less than 0.035 inches (0.889 mm) for Mill B. The



(a) Weibull plot



(b) Normal plot



(c) Smallest extreme value plot

Figure 3.5. Mill B's strand thickness versus fraction less probability plots from S-PLUS and SPLIDA.

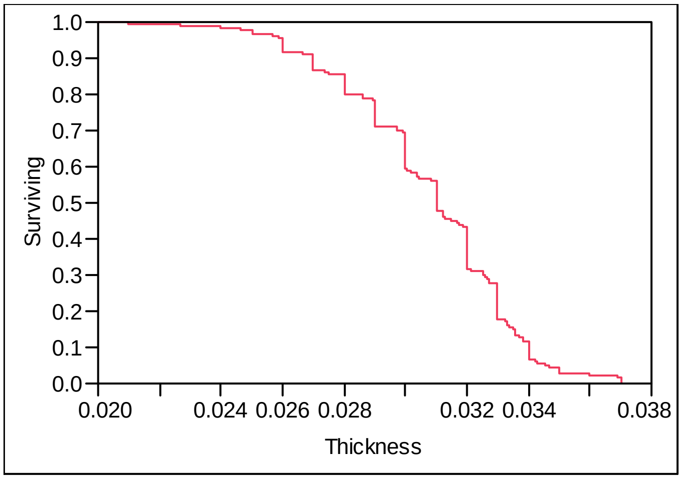


Figure 3.6. Mill B's reliability Kaplan-Meier plot of strand thickness.

plot also indicates that the probability of strand thickness greater than a given value decreases at an increasing rate between 0.028 and 0.032 inches (0.711 and 0.813 mm).

Mill B with the extreme outlier removed has much less variability than any of the other mills. If the extreme value is indeed an outlier and not a recording error committed when the data was collected, the very thick strand would very likely be removed from the process before reaching the pressing machine. Because the strand is so much thicker than any others in the data set, the quality control process at that mill would likely find the thick flake and remove it. Thus, much of the analysis for Mill B focuses on excluding the outlier.

3.2.3. Mill C

Mill C has numerous high outliers which skew the distribution to the right, as seen in the box plot in Figure 3.7. The mean and median are almost identical, and the skewness coefficient of 0.9477 indicates a positive skewness. The highest outlier is used for the AIC and then removed in order to score the AIC and find the best distribution for the data. Table 3.8 contains the scores for Mill C.

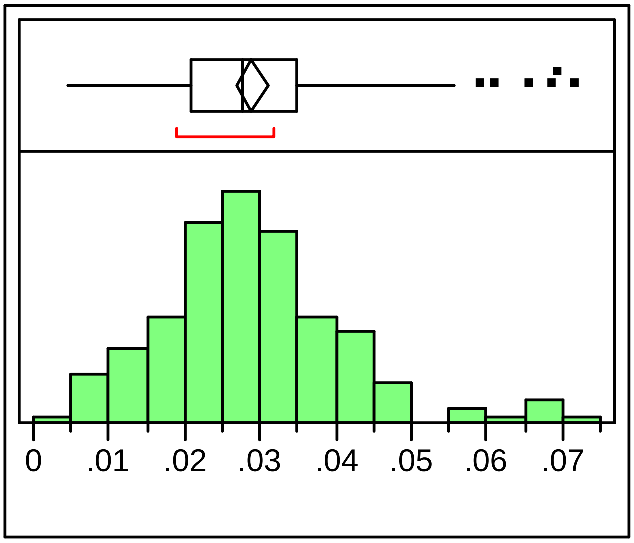


Figure 3.7. Mill C's strand thickness histogram and boxplot from JMP.

Table 3.8. Mill C's model scores for strand thickness data, complete and excluding an outlier.

Distribution	Complete data		Data with one outlier excluded	
	Log Likelihood	AIC	Log Likelihood	AIC
LEV	**420.9**	**-837.8**	**421.1**	**-838.2**
Loglogistic	419.4	-834.8	419.3	-834.6
Weibull	418.5	-833.0	420.0	-836.0
Logistic	418.0	-832.0	419.5	-835.0
Lognormal	415.4	-826.8	415.2	-826.4
Normal	413.6	-823.2	416.1	-828.2
Frechet	386.0	-768.0	385.2	-766.4
SEV	382.0	-760.0	386.4	-768.8
Exponential	356.4	-708.8	355.4	-706.8

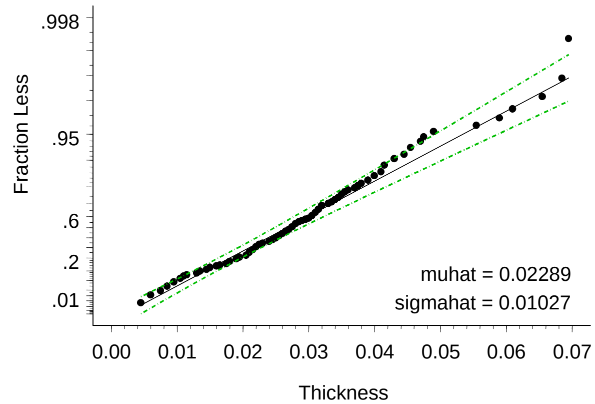
The best-fitting distribution for the entire data set is the Largest Extreme Value. With the highest data point excluded, the best distribution is still the Largest Extreme Value, followed by the Weibull and the Logistic distributions. The probability plots of these three distributions when the outlier is excluded can be found in Figure 3.8.

Figure 3.9 shows a Kaplan-Meier curve for the probability of thickness for Mill C. Figure 3.9 shows from the Kaplan-Meier, for instance, the probability that strand thickness will be greater than 0.02 inches (0.508 mm) is approximately 0.80, while the probability that thickness will be greater than 0.03 inches (0.762 mm) is approximately 0.30. Statistically, five percent of strands have a thickness less than 0.0095 inches (0.2413 mm) and 95 percent of strands have a thickness less than 0.049 inches (1.2446 mm) for Mill C. The plot also indicates that the probability that strand thickness is larger than a given value decreases at an increasing rate between 0.02 and 0.03 inches (0.508 and 0.762 mm).

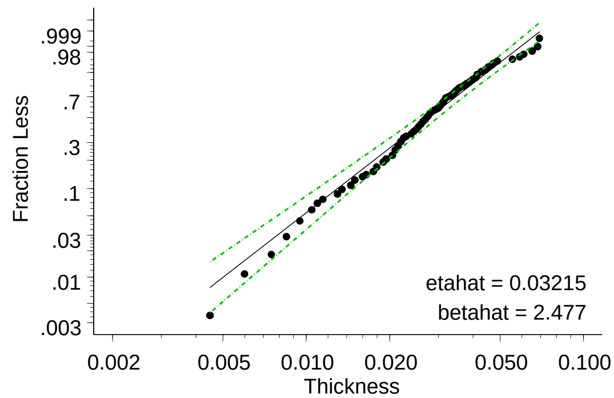
3.2.4. Mill D

Mill D has two mild outliers (see Figure 3.10) and one extreme outlier, which has been removed from the box plot. The distribution looks very slightly skewed right according to both the box plot and the histogram. The box plot shows that the mean and median values are very close to one another. The extreme outlier is removed to score the AIC.

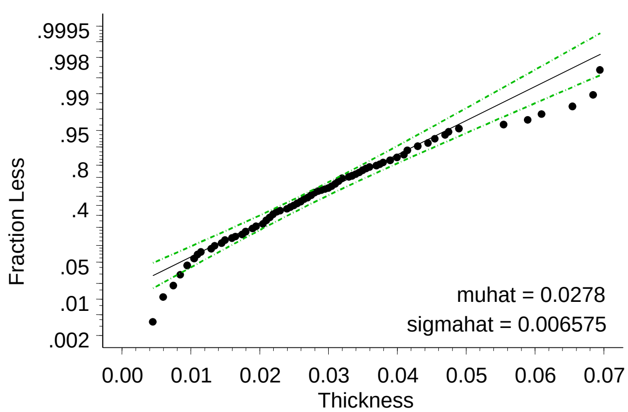
The log likelihood values and AIC scores are shown for Mill D in Table 3.9. On the complete data set, the Largest Extreme Value distribution fits the data best. With the high outlier removed, the best-fitting distribution is the Weibull, followed by the Normal and Logistic distributions. The change in AIC values indicates that the maximum data point is an outlier influencing the choice of distribution. This result is similar to Mill B, although the outlier for



(a) Largest extreme value plot



(b) Weibull plot



(c) Logistic plot

Figure 3.8. Mill C's strand thickness versus fraction less probability plots from S-PLUS and SPLIDA.

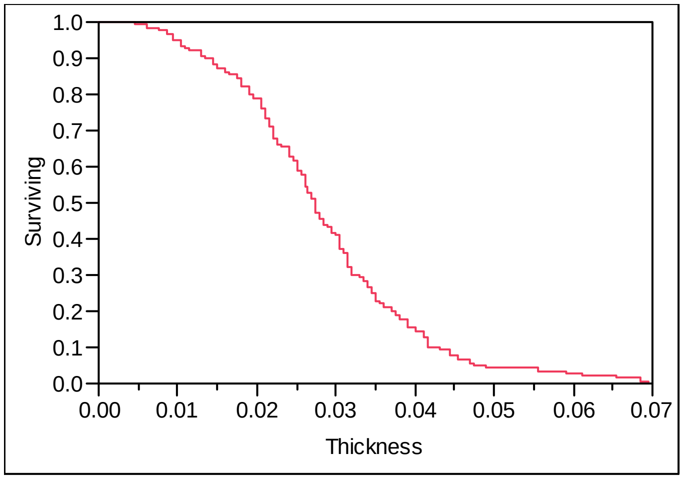


Figure 3.9. Mill C's reliability Kaplan-Meier plot of strand thickness.

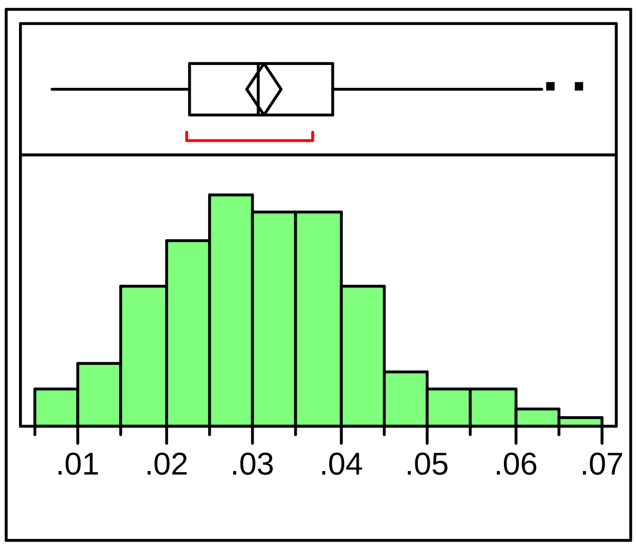


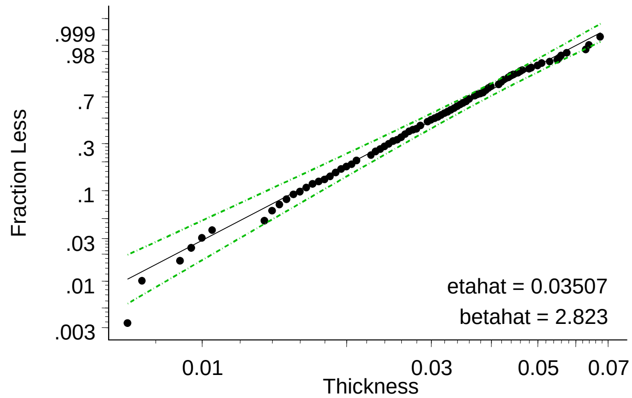
Figure 3.10. Mill D's strand thickness histogram and boxplot from JMP (excluding one extreme outlier).

Table 3.9. Mill D's model scores for strand thickness data, complete and excluding an outlier.

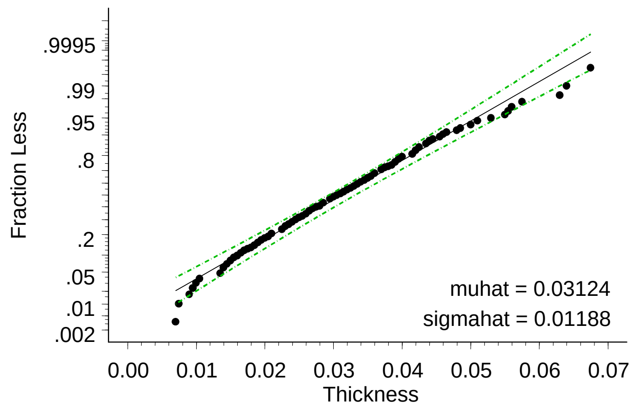
Distribution	Complete data		Data with one outlier excluded	
	Log Likelihood	AIC	Log Likelihood	AIC
LEV	**444.3**	**-884.6**	448.2	-892.4
Loglogistic	443.9	-883.8	446.0	-888.0
Logistic	441.1	-878.2	448.4	-892.8
Lognormal	441.0	-878.0	444.1	-884.2
Weibull	436.4	-868.8	**451.1**	**-898.2**
Normal	430.9	-857.8	449.1	-894.2
Frechet	414.3	-824.6	414.7	-825.4
SEV	399.1	-794.2	427.8	-851.6
Exponential	367.2	-730.4	367.5	-731.0

Mill D is not quite as extreme. Figure 3.11 contains probability plots for the three best-fitting distributions when the outlier is excluded.

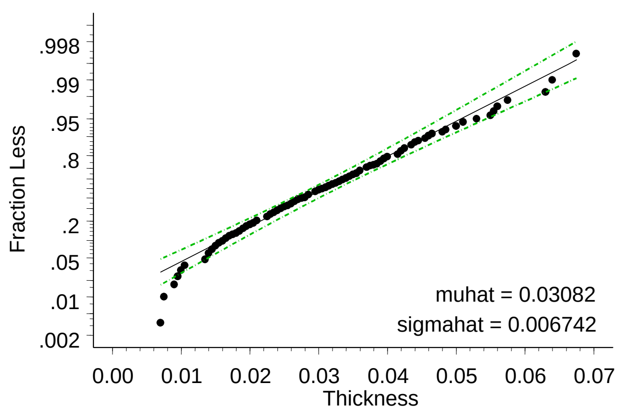
A Kaplan-Meier curve is shown in Figure 3.12 to model the probability of thickness for Mill D. Figure 3.12 shows from the Kaplan-Meier, for instance, the probability that strand thickness will be greater than 0.03 inches (0.762 mm) is approximately 0.50, while the probability that thickness will be greater than 0.04 inches (1.016 mm) is approximately 0.20. Statistically, five percent of strands have a thickness less than 0.0135 inches (0.3429 mm) and 95 percent of strands have a thickness less than 0.054 inches (1.3716 mm) for Mill D. The plot also indicates that the probability that strand thickness is greater than a given value decreases at an increasing rate between 0.02 and 0.04 inches (0.508 and 1.016 mm). It is clear from these results that although Mill D contains an extreme outlier like Mill B, Mill D is still much more variable in terms of strand thickness.



(a) Weibull plot



(b) Normal plot



(c) Logistic plot

Figure 3.11. Mill D’s strand thickness versus fraction less probability plots from S-PLUS and SPLIDA.

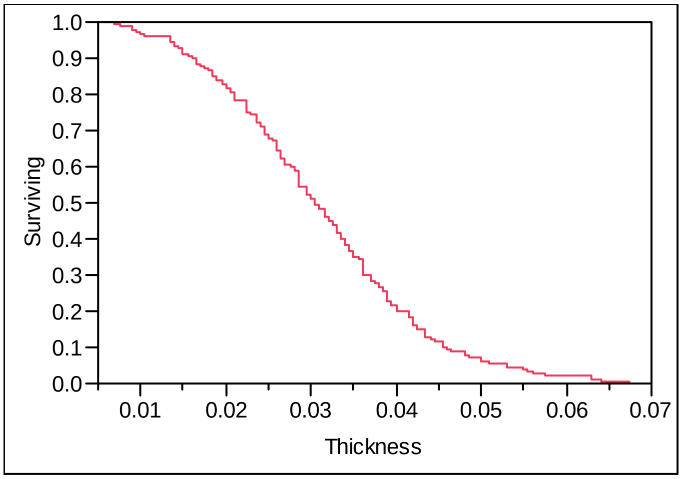


Figure 3.12. Mill D's reliability Kaplan-Meier plot of strand thickness.

3.2.5. Mill E

Mill E has one high outlier but otherwise has a fairly symmetric distribution, as seen from the box plot in Figure 3.13. The histogram shows very small tails that rise steeply to the middle of the data. The mean and median are almost identical. As mentioned previously, the histogram indicates the large variability of Mill E in relation to the other mills. The outlier is excluded to score the AIC. Table 3.10 shows the log likelihood and AIC values for Mill E both with and without the outlier. The best-fitting distribution is the Weibull regardless of the treatment of the outlier. The next-best distributions are the Normal and Logistic, again regardless of the treatment of the outlier. The probability plots of these three distributions when the outlier is removed are shown in Figure 3.14.

A Kaplan-Meier curve is shown for Mill E in Figure 3.15. Figure 3.15 shows from the Kaplan-Meier, for instance, the probability that strand thickness will be greater than 0.02 inches (0.508 mm) is approximately 0.80, while the probability that thickness will be greater than 0.04 inches (1.016 mm) is approximately 0.30. Statistically, five percent of strands have a thickness

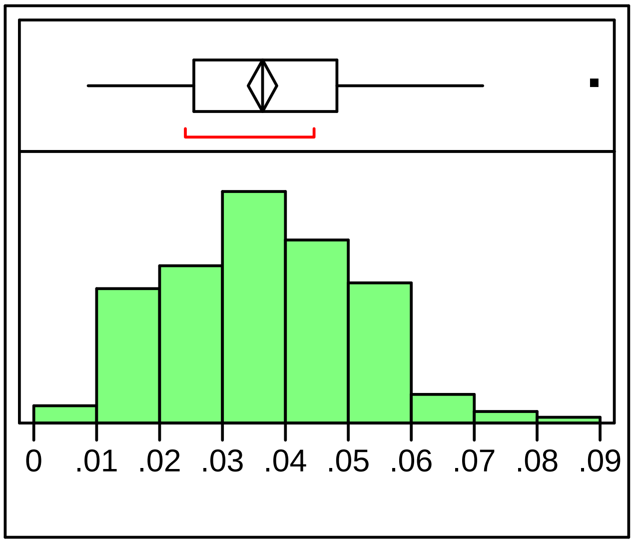
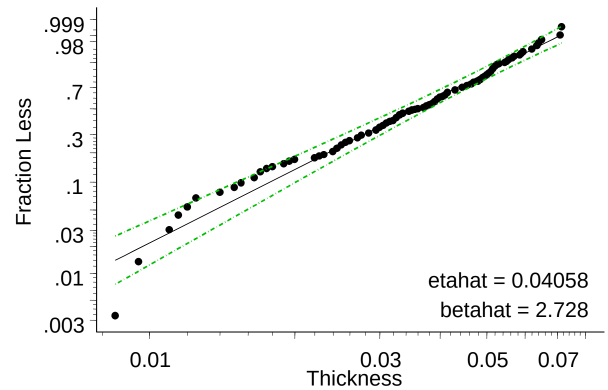


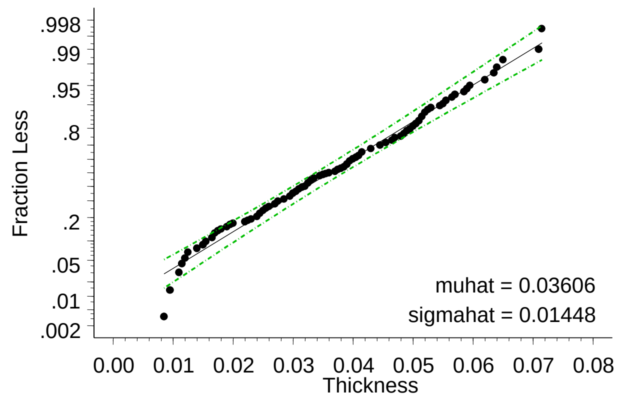
Figure 3.13. Mill E's strand thickness histogram and boxplot from JMP.

Table 3.10. Mill E's model scores for strand thickness data, complete and excluding an outlier.

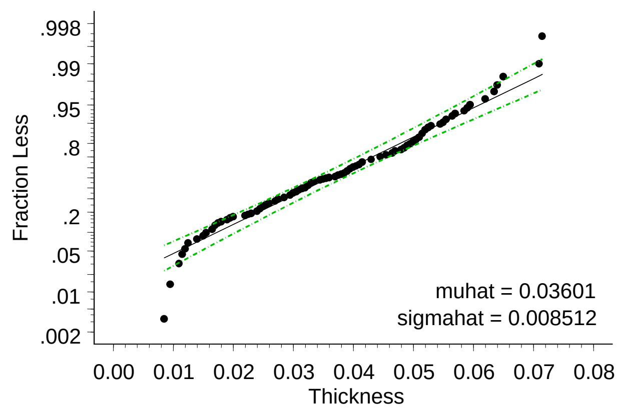
Distribution	Complete Data		Data with one outlier excluded	
	Log Likelihood	AIC	Log Likelihood	AIC
Weibull	**419.5**	**-835.0**	**422.0**	**-840.0**
Normal	416.5	-829.0	419.6	-835.2
Logistic	414.3	-824.6	415.7	-827.4
LEV	413.8	-823.6	414.0	-824.0
Loglogistic	408.9	-813.8	408.8	-813.6
Lognormal	408.8	-813.6	408.8	-813.6
SEV	396.8	-789.6	409.2	-814.4
Frechet	383.0	-762.0	382.4	-760.8
Exponential	346.9	-689.8	346.1	-688.2



(a) Weibull plot



(b) Normal plot



(c) Logistic plot

Figure 3.14. Mill E's strand thickness versus fraction less probability plots from S-PLUS and SPLIDA.

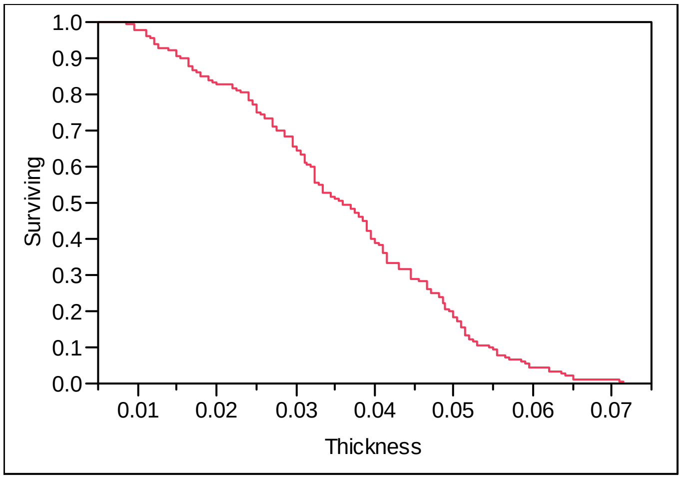


Figure 3.15. Mill E's reliability Kaplan-Meier plot of strand thickness.

less than 0.012 inches (0.3048 mm) and 95 percent of strands have a thickness less than 0.061 inches (1.5494 mm) for Mill E. The plot also indicates that the probability that strand thickness is larger than a given value decreases at an increasing rate between 0.02 and 0.05 inches (0.508 and 1.270 mm).

3.2.6. Mill F

Mill F is skewed right due to numerous high outliers that can be seen in Figure 3.16. Even without the highest outlier, the distribution appears to be skewed right as judged by both the box plot and the histogram. Table 3.11 contains the log likelihood and AIC values, both with and without the outlier, for Mill F. The best-fitting distribution is the Lognormal, regardless of the treatment of the highest data point. Also, regardless of the highest outlier, the next best-fitting distributions are the Largest Extreme Value and the Loglogistic. The probability plots for Mill F without the outlier are shown in Figure 3.17.

A Kaplan-Meier curve is plotted for Mill F in Figure 3.18. Figure 3.18 shows from the Kaplan-Meier, for instance, the probability that strand thickness will be greater than 0.02 inches

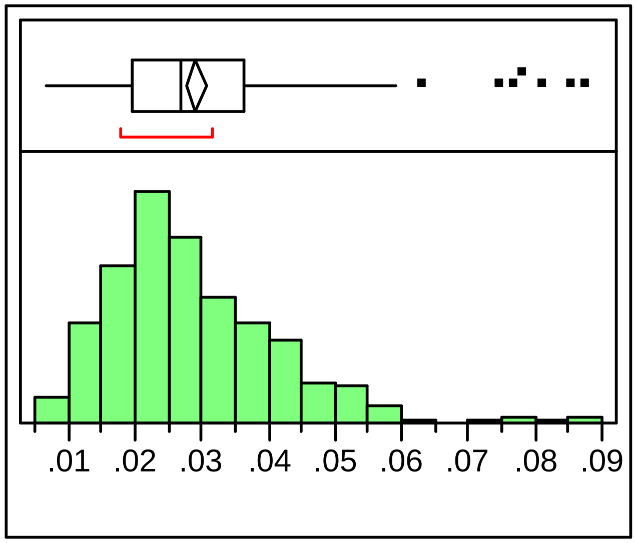
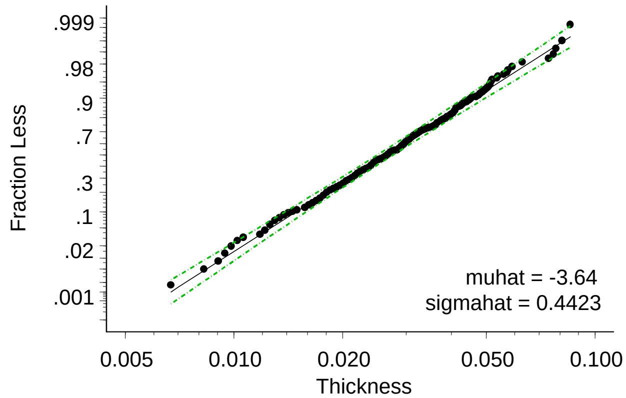


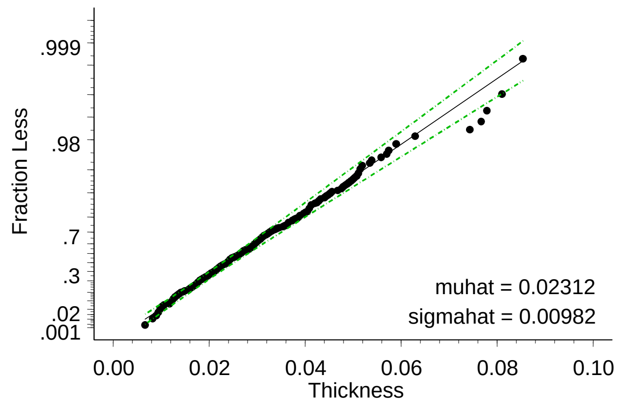
Figure 3.16. Mill F’s strand thickness histogram and boxplot from JMP.

Table 3.11. Mill F’s model scores for strand thickness data, complete and excluding an outlier.

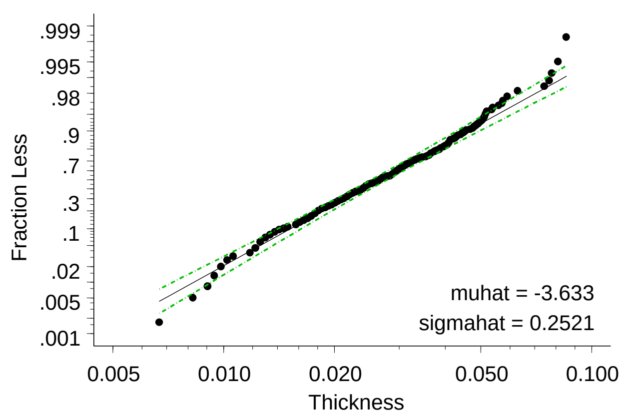
Distribution	Complete data		Data with one outlier excluded	
	Log Likelihood	AIC	Log Likelihood	AIC
Lognormal	**918.8**	**-1833.6**	**920.1**	**-1836.2**
LEV	917.8	-1831.6	919.7	-1835.4
Loglogistic	916.8	-1829.6	917.7	-1831.4
Weibull	898.5	-1793.0	902.7	-1801.4
Logistic	892.6	-1781.2	896.2	-1788.4
Frechet	889.8	-1775.6	889.7	-1775.4
Normal	879.7	-1755.4	886.2	-1768.4
SEV	791.8	-1579.6	803.4	-1602.8
Exponential	771.4	-1538.8	770.9	-1537.8



(a) Lognormal plot



(b) Largest extreme value plot



(c) Loglogistic plot

Figure 3.17. Mill F's strand thickness versus fraction less probability plots from S-PLUS and SPLIDA.

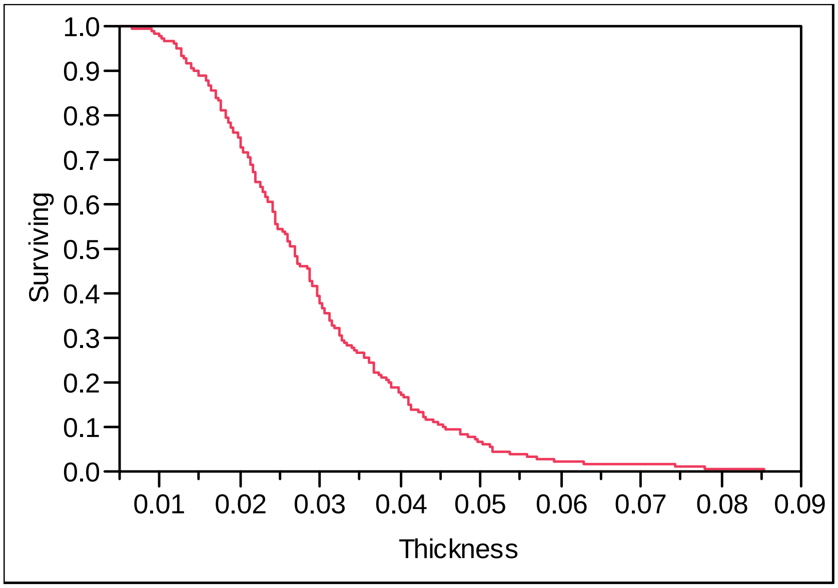


Figure 3.18. Mill F's reliability Kaplan-Meier plot of strand thickness.

(0.508 mm) is approximately 0.80, while the probability that thickness will be greater than 0.03 inches (0.762 mm) is approximately 0.30. Statistically, five percent of strands have a thickness less than 0.0123 inches (0.3124 mm) and 95 percent of strands have a thickness less than 0.0516 inches (1.3106 mm) for Mill F. The plot also indicates that the probability that strand thickness is greater than a given value decreases at an increasing rate between 0.02 and 0.03 inches (0.508 and 0.762 mm).

The survival curves for each individual mill tell a story about the variability in the data set, as well as the estimated probabilities of being greater than a given thickness value. An interesting comparison of the survival curves can be made when all mills are plotted on the same graph. The following section (3.2.7) makes a comparison of the mills' survival curves both graphically and verbally.

3.2.7. Summary

A summary table of the descriptive statistics on all six individual Kaplan-Meier curves follows in Table 3.12. This table shows fairly similar estimates of the mean and standard error for all six Kaplan-Meier plots. The mean tends to hover around 0.03 inches (0.762 mm), with the highest means for Mill A (0.03548 inches, 0.9012 mm) and Mill E (0.03606 inches, 0.9159 mm). The six standard errors are around 0.001 inches (0.0254 mm), with the smallest for Mill B at 0.0002 inches (0.00508 mm). All mills except Mill B tend to have the same amount of variability as measured by the range between the fifth and 95th percentiles. This range tends to fall between 0.03 and 0.05 inches (0.762 and 1.27 mm), but Mill B's range is much smaller at 0.009 inches (0.2286 mm). The same general conclusions are drawn from each individual Kaplan-Meier curve: the probability that a strand will be thicker than a given value decreases as thickness increases, and there is some range of thickness values over which the Kaplan-Meier

Table 3.12. Summary statistics of individual Kaplan-Meier plots.

Statistic	Mill A	Mill B	Mill C	Mill D	Mill E	Mill F
Mean	0.03548	0.03078	0.02853	0.03124	0.03606	0.02889
Standard Error	0.00069	0.0002	0.00103	0.00098	0.00119	0.00075
Lower 95%	0.0325	0.0305	0.0255	0.0285	0.0325	0.0244
Upper 95%	0.0355	0.0319	0.0295	0.033	0.0395	0.0287
5th Percentile	0.0185	0.026	0.0095	0.0135	0.012	0.0123
25th Percentile	0.028	0.029	0.021	0.023	0.0255	0.0197
50th Percentile	0.0335	0.031	0.0275	0.0305	0.036	0.0268
75th Percentile	0.0415	0.033	0.035	0.039	0.047	0.0362
95th Percentile	0.0590	0.035	0.0490	0.0540	0.061	0.0516

rate decreases rapidly. The practitioner may use Kaplan-Meier curves to determine the optimal range of thickness for OSB strands. Dinse, Piegorsch, and Boos (1993) discuss the use of survival plots for comparison among groups. Figure 3.19 shows all six Kaplan-Meier curves together for comparison. From this graph of all six Kaplan-Meier plots, Mill B's Kaplan-Meier curve decreases the quickest. Mill B also has the smallest range of data, indicating that the thickness measurements are more consistent for that mill which may imply better product quality of final OSB panels. The other five mills are fairly similar in strand thickness data.

3.3. Conclusions

Exploring the strand thickness of oriented strand board (OSB) from six Eastern U.S. mills has provided useful insight on the variability and possible distributions of the strand thickness data. Because OSB is commonly used in housing construction, understanding the variability of OSB strand thickness is important to manufacturers so they can reduce variation in the manufacture of OSB. This will improve engineering capability and customer value.

The Largest Extreme Value Distribution and the Weibull Distribution were common fits to the data sets both with and without an extreme outlier. Mill B clearly had the least variability in thickness measurements; thus, customers purchasing wood strands from this manufacturer can be more confident in the dimensions and quality of the product they are receiving. Other manufacturers may be able to learn from Mill B and seek to reduce variability in their strand thickness.

The various extreme values in the data sets may indicate a need for more uniform strand thickness during the flaking operation which will improve log yield. As mentioned above, Mill

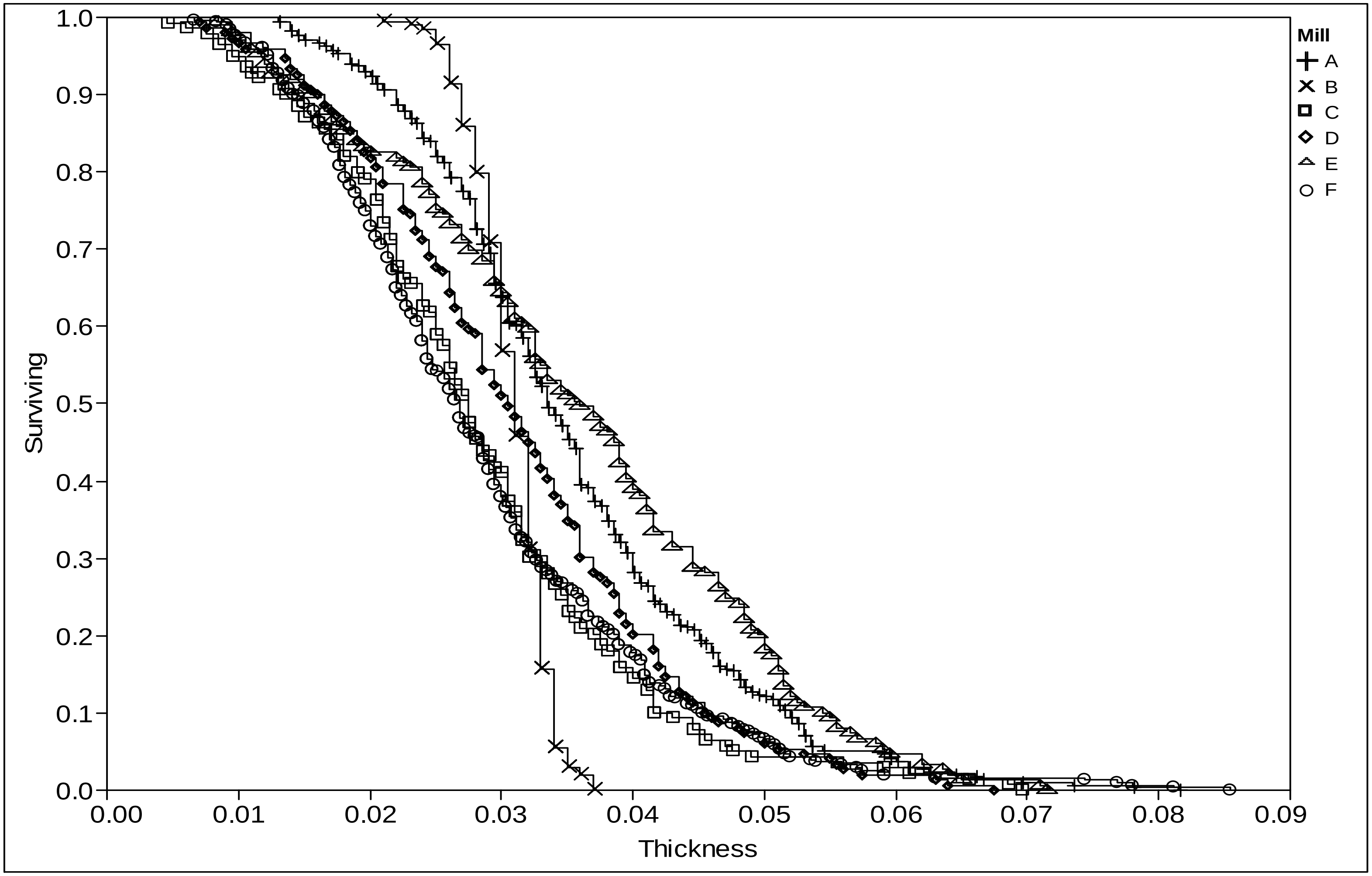


Figure 3.19. Reliability Kaplan-Meier plot of strand thickness for all mills.

B has the most consistent wood strand thickness. However, improvements can still be made in all mills to reduce variability. The mills generally had higher outliers, so some wood strands are unusually thick. Producing strands too thick may be problematic, even damaging, to the expensive machines producing the final OSB panels; hence, a more reliable thickness overall will be better for both the customer and the manufacturer. Now that the descriptive statistics on all data sets have been covered, the thesis moves to estimating the upper percentiles of the mills.

Chapter 4

Bootstrapping of Upper Percentiles

As mentioned in the Literature Review (Chapter 2), the upper percentiles are of particular interest to researchers as well as OSB manufacturers. The best estimates in terms of both accuracy and precision are desired. Thus, bootstrapping is invoked as a resampling method to provide better estimates of the upper percentiles. Additionally, left censoring is used to alleviate problems caused by infant mortality, or early failures. In this case, infant mortality refers to the thinnest OSB strands in the data set. Left censoring can also provide better estimates as it focuses on the upper portion of the data and removes the effect of thin strands on the choice of distribution. Censoring at lower quantiles was conducted to avoid the effect of infant mortality on the distribution of the data since interest lies in estimating the upper percentiles.

Each data set was censored at the following quantiles: 0.10, 0.15, 0.20, and 0.25. Nine distributions were fit to each data set after the censoring, and the best distribution, according to Akaike's Information Criterion (AIC), was used for bootstrapping. For instance, the best-fitting distribution for Mill A when censoring at the 0.10 quantile is the Logistic. This distribution was then assumed for the data set, and SPLIDA's bootstrapping function was used to find confidence intervals for the 0.99 quantile. This procedure was repeated for every mill using the best distribution for the particular data set. MATLAB was used to find nonparametric confidence intervals for the 0.99 quantile as a measure of comparison.

The researchers also found confidence intervals for the 0.90 and 0.95 quantiles as these high quantiles are important to manufacturers as well. Again, the best distribution based on the censoring was chosen and bootstrapping was performed in SPLIDA. MATLAB was again used to find the nonparametric bootstrap confidence intervals for the 0.90 and 0.95 quantiles. The following sections provide results of the aforementioned methods.

4.1. Mill A

Without any censoring, the best distribution for Mill A is the Loglogistic. With any amount of censoring up to the 0.25 quantile, the best-fitting distribution becomes the Logistic. Since these are the "winning" distributions, they are assumed as the underlying distributions for bootstrapping inference. Figure 4.1 shows the confidence intervals for estimating the 0.99 quantile for Mill A at the various censoring points. This graph has a horizontal axis scale that has been determined by all mills' 0.99 quantile results. In other words, every graph displaying the confidence intervals for the 0.99 quantile for each mill is on the same scale for comparison purposes. Please see Figure A.1 in the Appendix for the graph of Mill A's 0.99 quantile results on a scale that fits the data for Mill A. Additionally, the confidence intervals on the graphs are labeled according to both the distribution assumed and the percentile at which the censoring occurs. "None" on the right hand side of the confidence interval indicates that the data is complete (i.e., no censoring was performed for that particular interval).

Mill A's nonparametric confidence interval on the complete data set (i.e., no censoring) is the widest. This interval contains the ordered statistic 0.99 quantile, or the nonparametric point estimate for this quantile, which is 0.0735 for Mill A. In fact, this ordered statistic is contained in all confidence intervals except the complete data set based on the Loglogistic distribution with no censoring and the data set censored at the 0.10 quantile. As the censoring points increase from censoring at the 0.10 quantile to the 0.25 quantile, the confidence intervals tend to move to

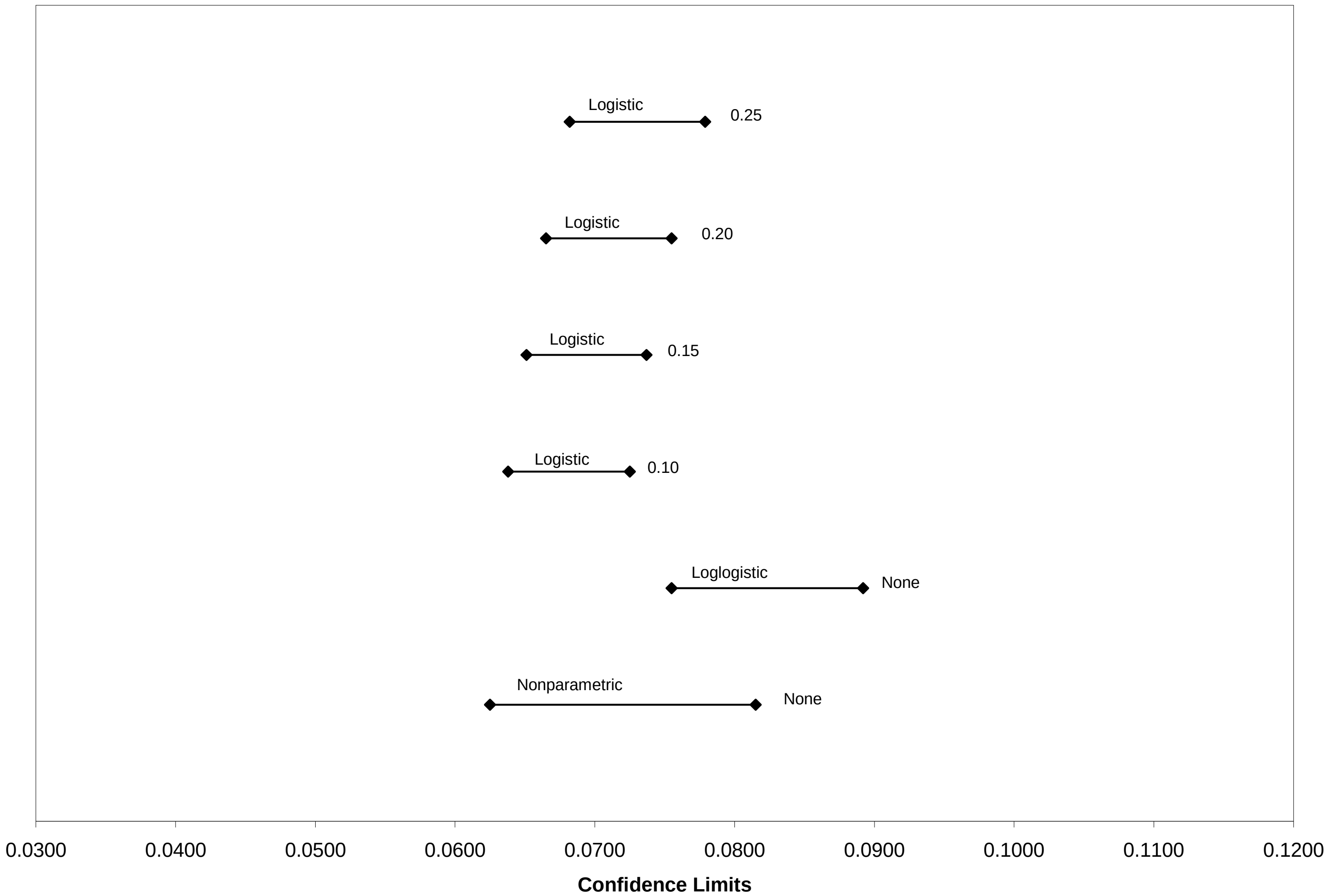


Figure 4.1. Mill A bootstrap confidence intervals based on the percentile method for the 0.99 quantile at various censoring points and based on the distributions assumed at those points.

the right, or become slightly higher at each successive censoring quantile.

When the data is not censored the Loglogistic is assumed as the underlying distribution and the confidence interval is poor. It misses the ordered statistic 0.99 quantile, and it is higher than the intervals for censoring at the lower percentiles. Censoring at the 0.10 quantile also seems to be inferior to the 0.15 and 0.20 quantiles as it misses the ordered statistic. Since infant mortality can affect the choice of distribution, censoring may be desired. For instance, Mill A is skewed to the right, and this can be seen in comparing the Loglogistic confidence interval with one of those for the censoring points. The no-censoring interval based on the Loglogistic distribution is much higher than the intervals produced when the data is censored at the 0.10 or 0.15 quantiles, for example.

To sum up the 0.99 quantile results, a modest amount of censoring may be best, such as censoring between the 0.15 and 0.25 quantiles. There is not much difference in the confidence intervals for these censoring values. Thus, the practitioner can choose how much data to keep as complete. Additionally, the nonparametric confidence interval is the most conservative for Mill A. Most conservative refers to the widest interval. However, censoring can be used to provide a more precise interval and may prevent the upper limit from being too high.

Manufacturers may also be interested in estimating other high quantiles, such as the 0.90 and 0.95 quantiles. Thus, the same analysis as above has been performed to obtain confidence interval estimates for these two quantiles. The graph showing confidence intervals for the 0.95 quantile can be found in Figure 4.2, and the 0.90 quantile confidence intervals are shown in Figure 4.3. These graphs have also been scaled based on the results from the other mills for the same quantiles. See Figures A.2 and A.3 in the Appendix for graphs of the 0.95 and 0.90

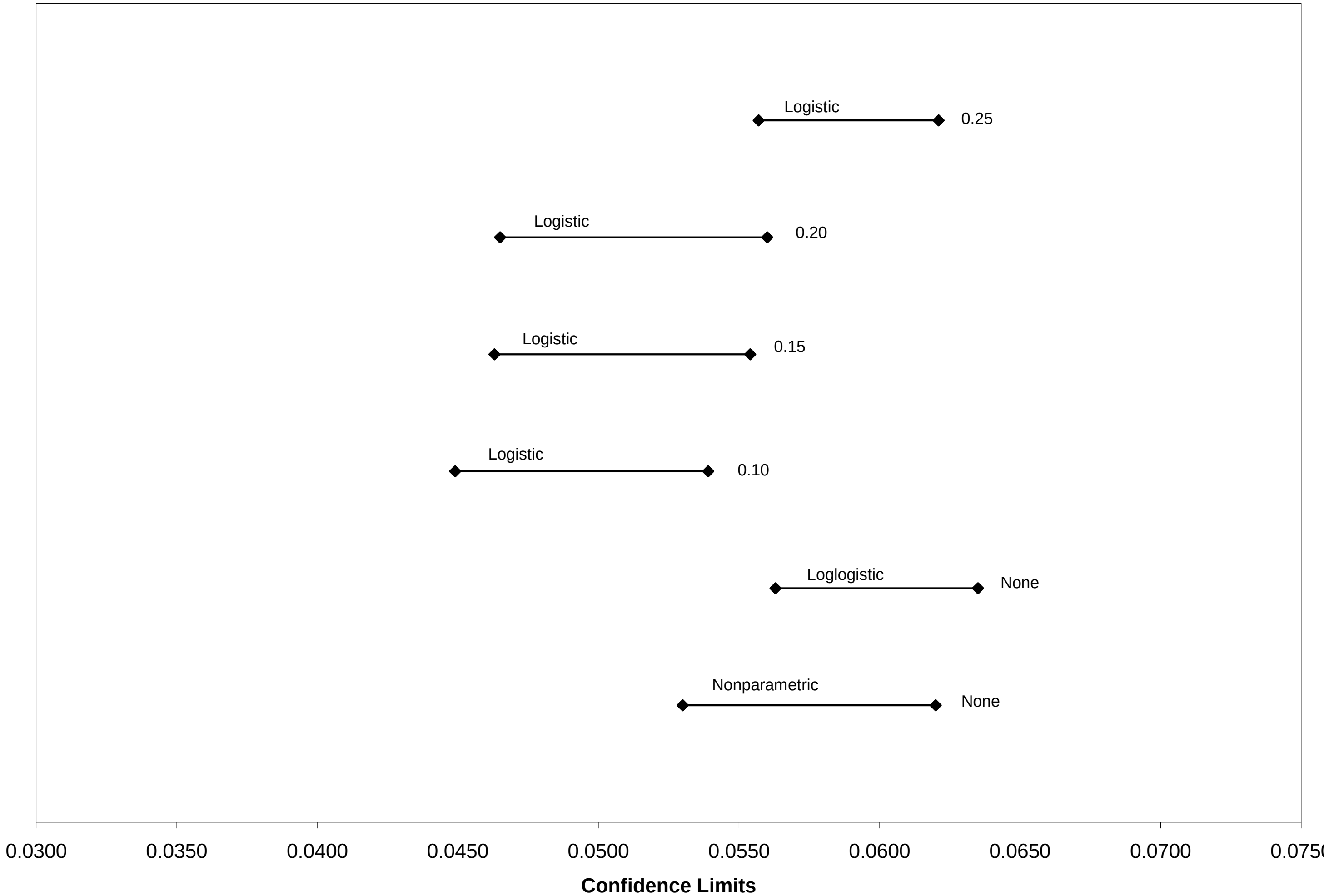


Figure 4.2. Mill A bootstrap confidence intervals based on the percentile method for the 0.95 quantile at various censoring points and based on the distributions assumed at those points.

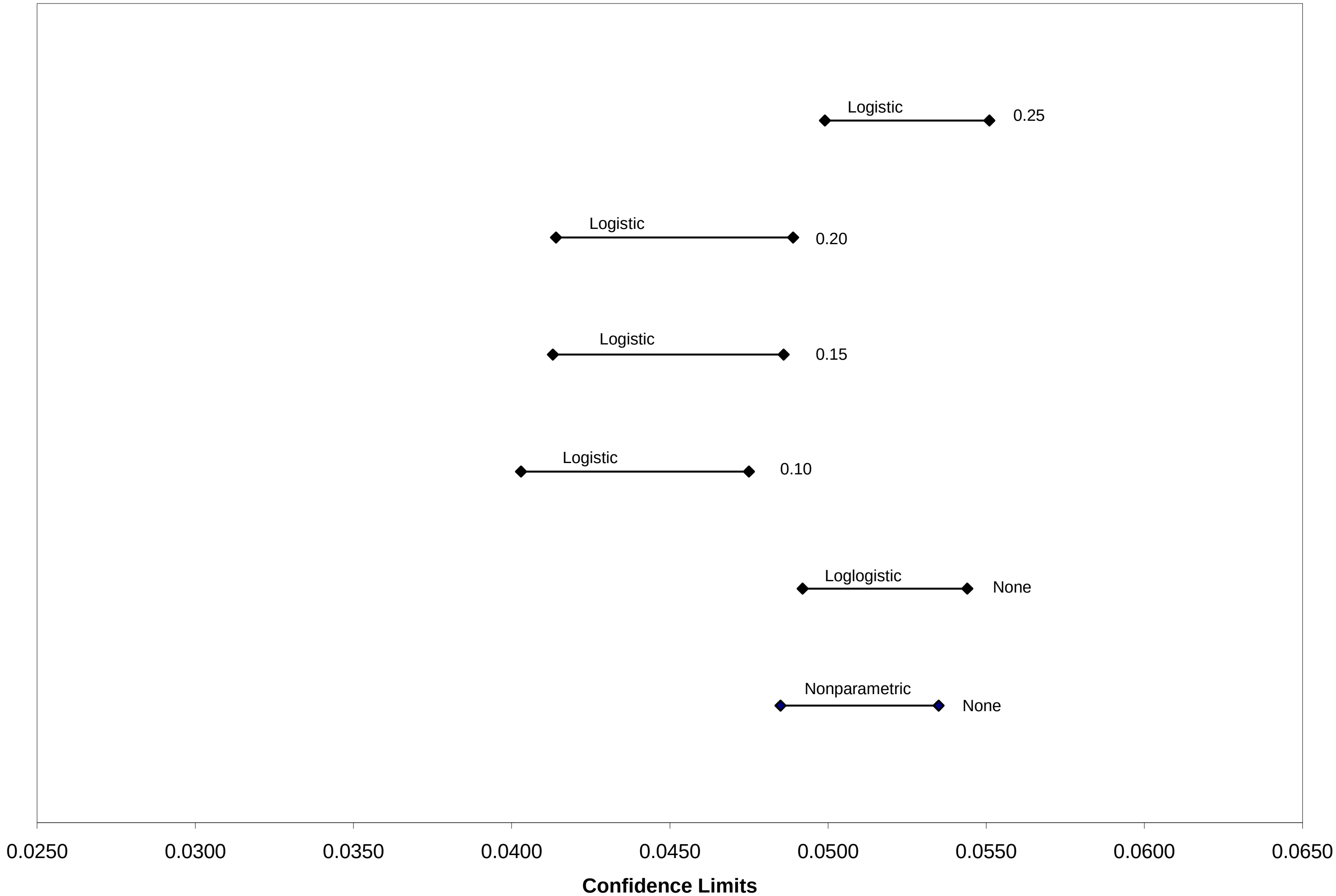


Figure 4.3. Mill A bootstrap confidence intervals based on the percentile method for the 0.90 quantile at various censoring points and based on the distributions assumed at those points.

quantile confidence intervals on a scale that fits the results for Mill A. From Figure 4.2, it can be seen that the confidence intervals jump to the left as the data sets move from no censoring to some censoring. The estimates when censoring between the 0.10 and 0.20 quantiles are fairly similar. However, there is a jump to the right when the censoring occurs at the 0.25 quantile, and this confidence interval is closer to those when no censoring occurs. Censoring at the 0.25 quantile also results in the most precise (narrowest) confidence interval. Thus, for this data set and for estimating the 0.95 quantile, censoring at the 0.25 quantile is recommended. Also, the nonparametric estimates are not as wide as those of the 0.99 quantile. This is expected since the 0.95 quantile is not as extreme as the 0.99 quantile. All confidence intervals fall between approximately 0.045 inches and 0.065 inches for Mill A's 0.95 quantile. In contrast, the intervals for the 0.99 quantile fall between about 0.06 inches and 0.09 inches.

Figure 4.3 shows that the narrowest confidence intervals for the 0.90 quantile are the nonparametric estimate and the estimate when censoring at the 0.25 quantile. The estimates range between about 0.04 inches and 0.06 inches. The intervals for the 0.90 quantile follow the same general pattern as the intervals for the 0.95 quantile. As some censoring occurs, the estimates decrease. Once the censoring reaches the 0.25 quantile, there is an increase in the interval that moves up close to the intervals when no censoring occurs. For this data set and estimating the 0.90 quantile, the best estimates appear to be the nonparametric with no censoring and the interval when censoring occurs at the 0.25 quantile and the Logistic distribution is assumed. Based on the results from all three upper quantile estimates, censoring at the 0.25 quantile appears to be best for Mill A.

4.2. Mill B

Mill B is interesting because the data set is very tight but contains an extreme outlier that is about three times the value of the second-highest data point. After discussion with an expert in the field, it was determined to remove this outlier from the data set. Although it is possible for a strand to be cut to a very thick dimension, process control generally discovers these extremely thick flakes, which are then removed before being pressed into the boards. Removing the extreme outlier also makes it much easier to fit distributions and bootstrap the data set. Mill B is first examined without the outlier in the data set. Without the outlier, Mill B is slightly skewed left. When the data is not censored, the strands follow a Weibull distribution. At all censoring points, the data follows a Smallest Extreme Value distribution.

Figure 4.4 shows the confidence intervals for the 0.99 quantile for Mill B (highest outlier removed) at different censoring points. Please see Figure A.4 in the Appendix for the same graph on a scale to fit the data. As with Mill A, the widest confidence interval is the nonparametric, no censoring bootstrap interval. The ordered statistic 0.99 quantile has a value of 0.0370. Only the nonparametric interval and the confidence interval when censoring at the 0.20 quantile contain this value. The confidence intervals are similar in terms of estimates and width when censoring occurs. Thus, any of these confidence intervals are valuable for this mill. It is also important to note how much more precise the intervals are for Mill B than for Mill A. Mill B's intervals are precise due to the small variability in the data set. In fact, the intervals for Mill B are the most precise of all mills, and this theme will recur later in the thesis.

Figure 4.5 contains confidence intervals for the 0.95 quantile for Mill B with the highest outlier removed. Figure 4.6 shows the intervals for the 0.90 quantile when Mill B's highest

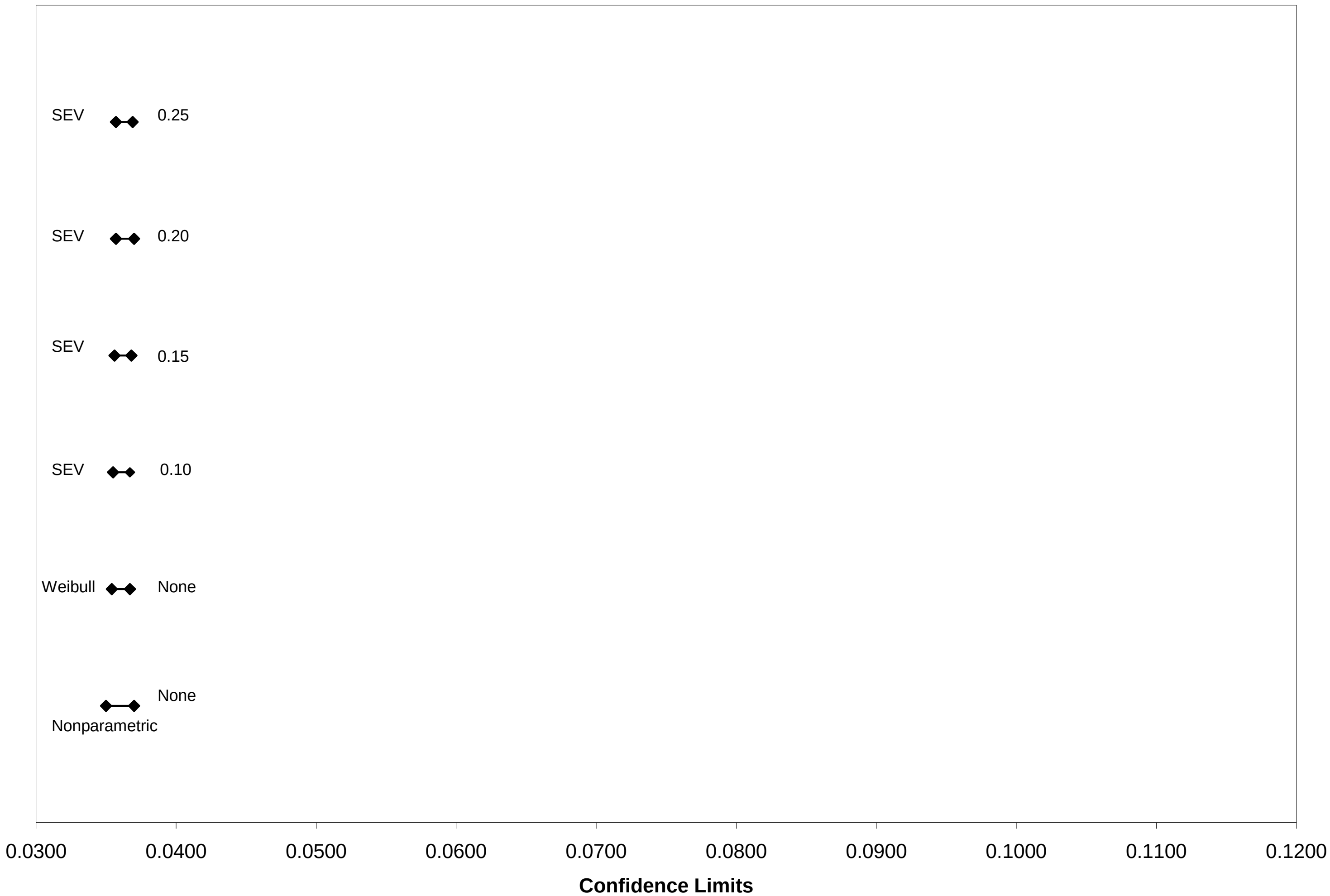


Figure 4.4. Mill B (highest outlier removed) bootstrap confidence intervals based on the percentile method for the 0.99 quantile at various censoring points and based on the distributions assumed at those points.

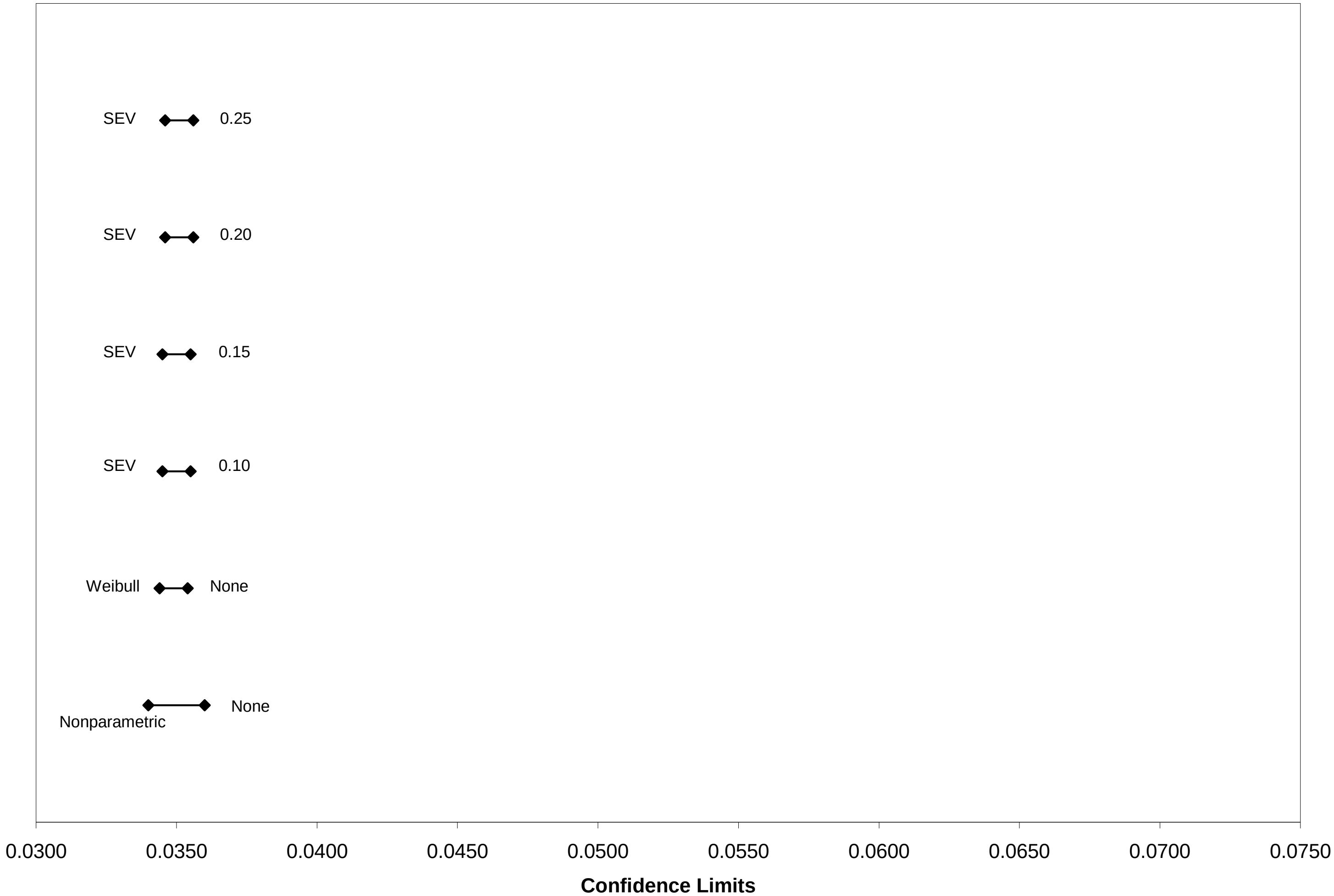


Figure 4.5. Mill B (highest outlier removed) bootstrap confidence intervals based on the percentile method for the 0.95 quantile at various censoring points and based on the distributions assumed at those points.

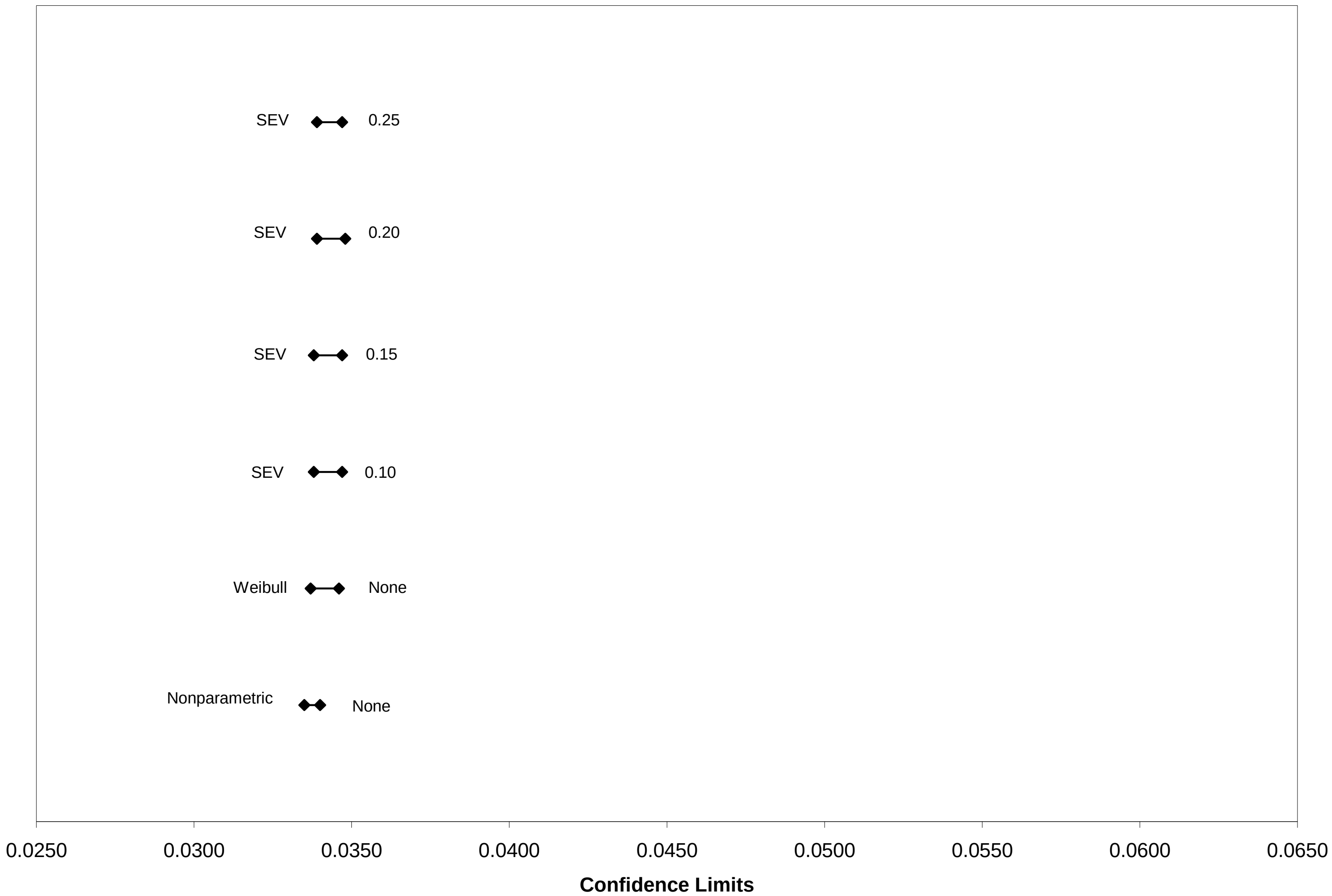


Figure 4.6. Mill B (highest outlier removed) bootstrap confidence intervals based on the percentile method for the 0.90 quantile at various censoring points and based on the distributions assumed at those points.

outlier is removed. Please see Figures A.5 and A.6 in the Appendix for the same graphs on a scale to fit the data. Like the estimates for the 0.99 quantile, the confidence intervals for the 0.90 and 0.95 quantiles are very narrow. In fact, they are the narrowest of all the mills due to Mill B's lack of variability in the data set. These narrow intervals again reinforce the idea of good process control for Mill B. In Figure 4.6, the nonparametric confidence interval for the 0.90 quantile is the most precise of all the intervals. This is likely due to the lack of variability in the data set for Mill B. Additionally, the top ten to twenty percent of data values in Mill B are very similar to one another. Therefore, the nonparametric estimate for the 0.90 quantile is very narrow. For both the 0.90 and 0.95 quantiles, the confidence intervals are similar regardless of the amount of censoring. Like the 0.99 quantile estimates, any of the confidence intervals are valuable. It is clear that assuming a distribution and censoring generally provides more precise intervals (except in the one case of the 0.90 quantile for Mill B). Thus, the practitioner may consider censoring to have more precise results.

Because the upper percentiles are being estimated, the same analysis is performed with the outlier included in the data set as a comparison. Figure 4.7 shows the intervals for Mill B's 0.99 quantile when the outlier is included in the data set. Please see Figure A.7 in the Appendix for the same graph on a scale to fit the data. It is interesting to note that when the outlier is included in the data set, the Loglogistic distribution is the best-fitting regardless of the level of censoring. This indicates that Mill B may have a production process superior to the other mills, even when the outlier is included. In fact, other mills may be able to improve their own processes by examining Mill B. Putting the graphs on the same scale reinforces this idea as it is clear how narrow Mill B's confidence intervals are in relation to those of the other mills.

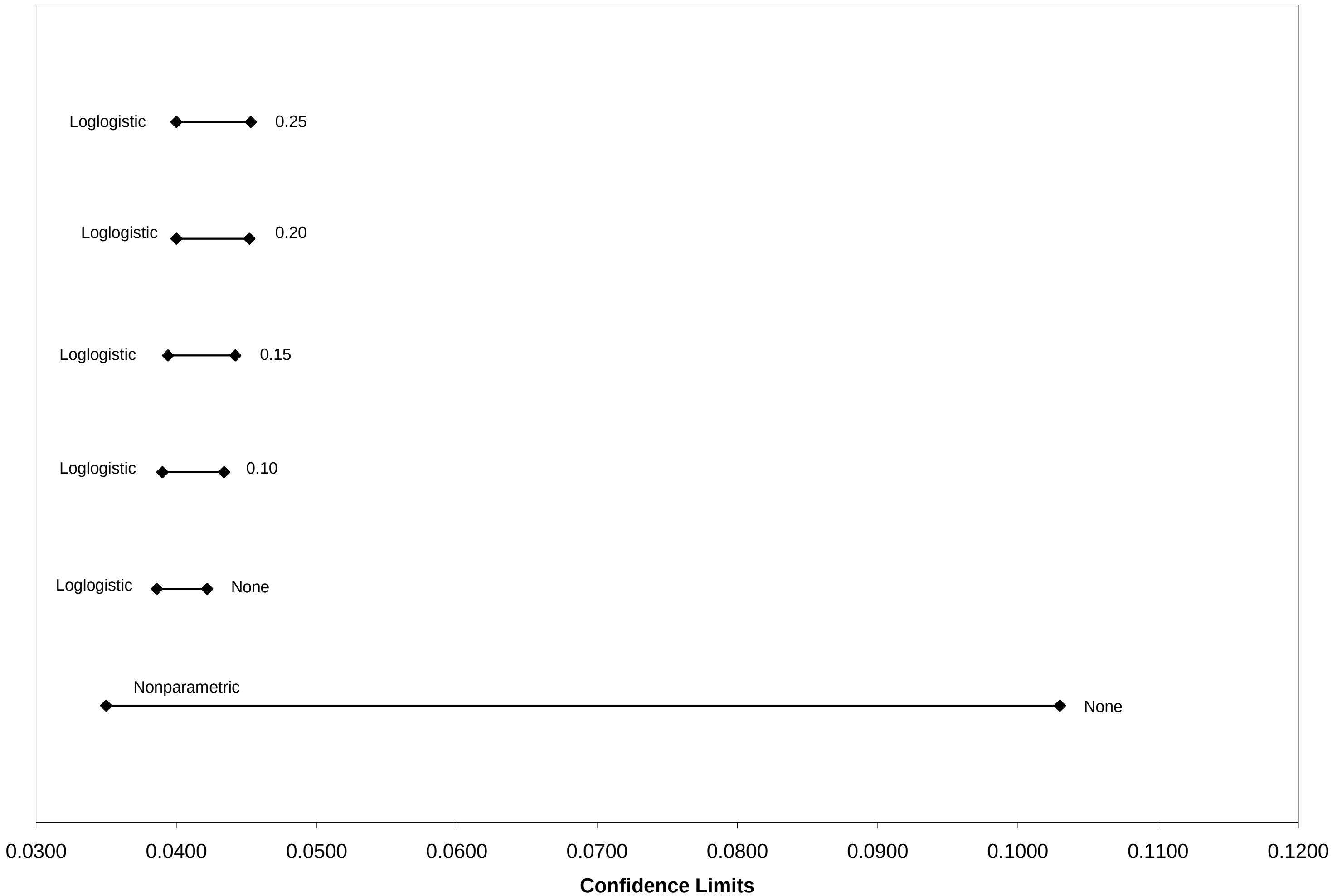


Figure 4.7. Mill B (with outlier) bootstrap confidence intervals based on the percentile method for the 0.99 quantile at various censoring points and based on the distributions assumed at those points.

At first glance, it is obvious that the confidence intervals for Mill B are much wider when the outlier is included in the data set. Clearly, the widest confidence interval when the outlier is included is the nonparametric estimate. This interval is very wide because it contains the outlier as its upper limit. This may come as a surprise to the reader that the nonparametric confidence interval is so much wider than the others. Thus, a binomial analysis was conducted to determine how likely it is that the outlier would be the upper limit for the nonparametric confidence interval. This data set contains 201 total values, and it was desired to find the probability that the outlier appears in one bootstrap resample at least three times. Each data value is equally likely to be chosen for the resample; therefore, the chance of being picked for the resample is $\frac{1}{201}$. Thus, the following binomial model was used to find the chances of getting the outlier in one resample two times or fewer:

$$P(X \le 2) = \sum_{x=0}^{2} {}_{201}C_x \left(\frac{1}{201}\right)^x \left(\frac{200}{201}\right)^{201-x}$$

where

$${}_{201}C_x = \frac{201!}{x!(201-x)!}.$$

After performing the calculations, it is found that $P(X \le 2)$ is approximately equal to 0.92. Thus, the chance that one bootstrap resample will contain the extreme outlier two or fewer times is about 92 percent. Subtracting this result from one, the probability that one bootstrap resample will contain the extreme outlier three or more times is approximately 0.08. This becomes the initial probability for the next part of the binomial analysis.

In the next part of the analysis, it must be determined how likely it is to find three or more bootstrap samples (out of a total 100 samples) that contain the extreme outlier three or more times. As mentioned above, the probability of success (i.e., finding a bootstrap sample containing the outlier three or more times) is 0.08. For this analysis, 100 samples are used. Thus, the following binomial model is used to find the probability that two or fewer samples out of 100 will contain the extreme outlier at least three times:

$$P(Y \leq 2) = \sum_{y=0}^{2} {}_{100}C_y \left(0.08\right)^y \left(0.92\right)^{100-y}$$

where

$${}_{100}C_y = \frac{100!}{y!(100-y)!}.$$

After performing the calculations, it is found that the probability that two or fewer samples out of 100 will contain the extreme outlier at least three times is approximately 0.011. Subtracting this value from one, there is a 0.989 probability that three or more samples out of 100 will contain the extreme outlier at least three times. Thus, the nonparametric confidence interval containing the extreme outlier is a virtual certainty, and the results are expected based on theoretical justification.

Mill B's estimates when censoring occurs are similar in width and value, and the confidence intervals tend to increase only slightly as the level of censoring increases. This graph also shows what assuming a parametric distribution will produce. Here, the nonparametric confidence interval is not very informative because it is so wide and in essence simply captures the entire range of the data set. However, as a distribution is assumed, the confidence intervals become much narrower and lower in value for the upper estimate.

The ordered statistic 0.99 quantile is 0.037 for Mill B with the outlier. Only one of the confidence intervals contains this value: the nonparametric estimate with no censoring. All other confidence intervals have lower limits above the ordered statistic as the outlier pulls up the estimates. If the practitioner is very conservative, he or she may choose to believe the nonparametric confidence interval. However, to have a more informative and useful confidence interval, the practitioner may invoke censoring and assume a distribution. All the other confidence intervals are similar for Mill B with the outlier, so any of these can be valuable.

Figure 4.8 shows the confidence intervals for Mill B's 0.95 quantile when the outlier is included in the dataset. Likewise, Figure 4.9 contains estimates for the 0.90 quantile when Mill B's outlier is not removed. Please see Figures A.8 and A.9 in the Appendix for the same graphs on a scale to fit the data. Again, the confidence intervals are not as narrow when the outlier is included in the data set. The estimates follow the general pattern of increasing as the censoring value increases. For both the 0.90 and the 0.95 quantiles, the narrowest interval occurs when estimating nonparametrically. These results are quite different from those of the 0.99 quantile estimates, where the nonparametric interval is widest. Like the 0.99 quantile, though, assuming a distribution and censoring provides similar confidence intervals regardless of the amount of censoring. Again, this result occurs because of the lack of variability in Mill B's data set. Thus, any level of censoring below the 0.25 quantile is recommended for Mill B.

4.3. Mill C

On the complete data set with no censoring, Mill C follows a Largest Extreme Value distribution. At all censoring values, the data set takes on a Logistic distribution. Figure 4.10

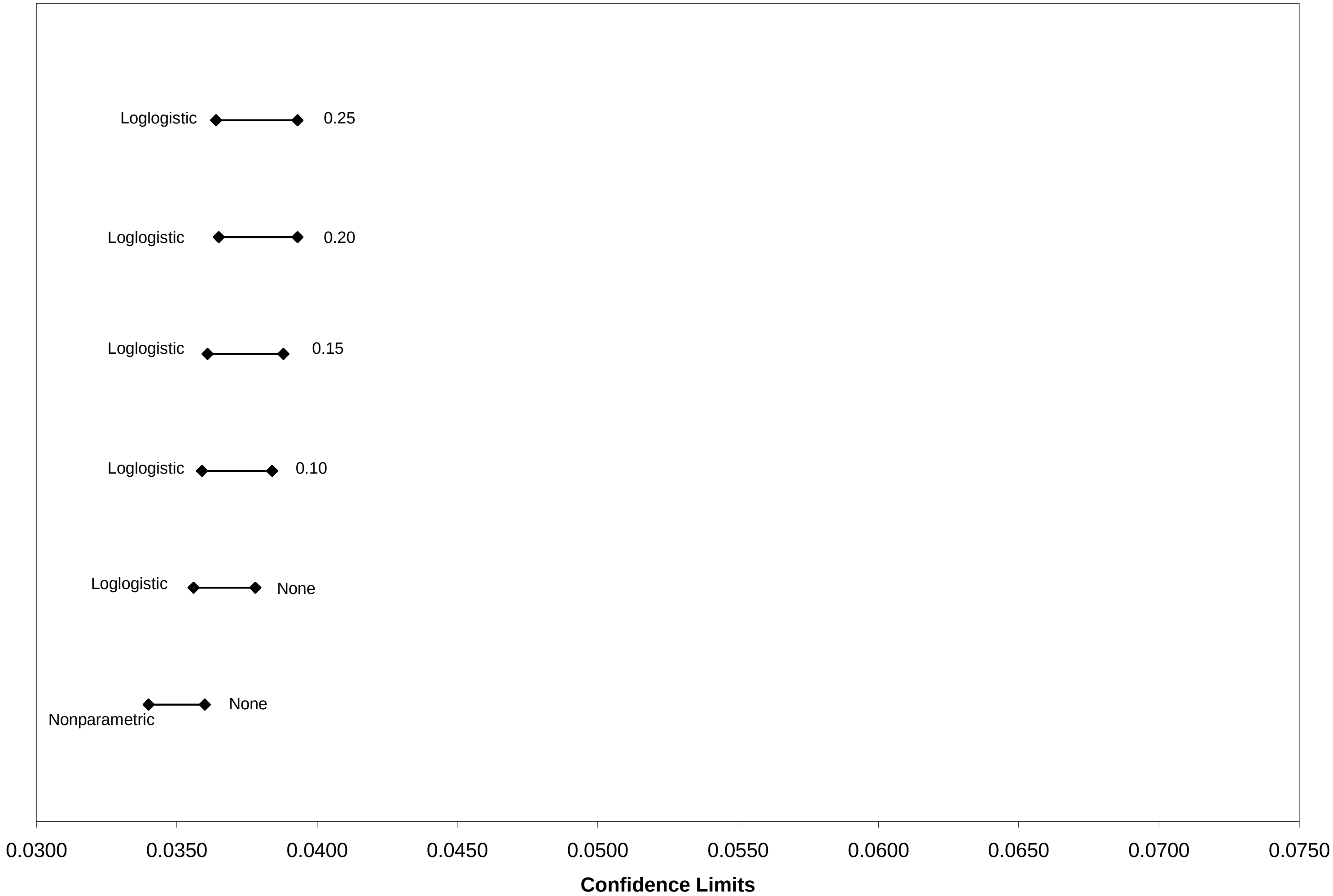


Figure 4.8. Mill B (with outlier) bootstrap confidence intervals based on the percentile method for the 0.95 quantile at various censoring points and based on the distributions assumed at those points.

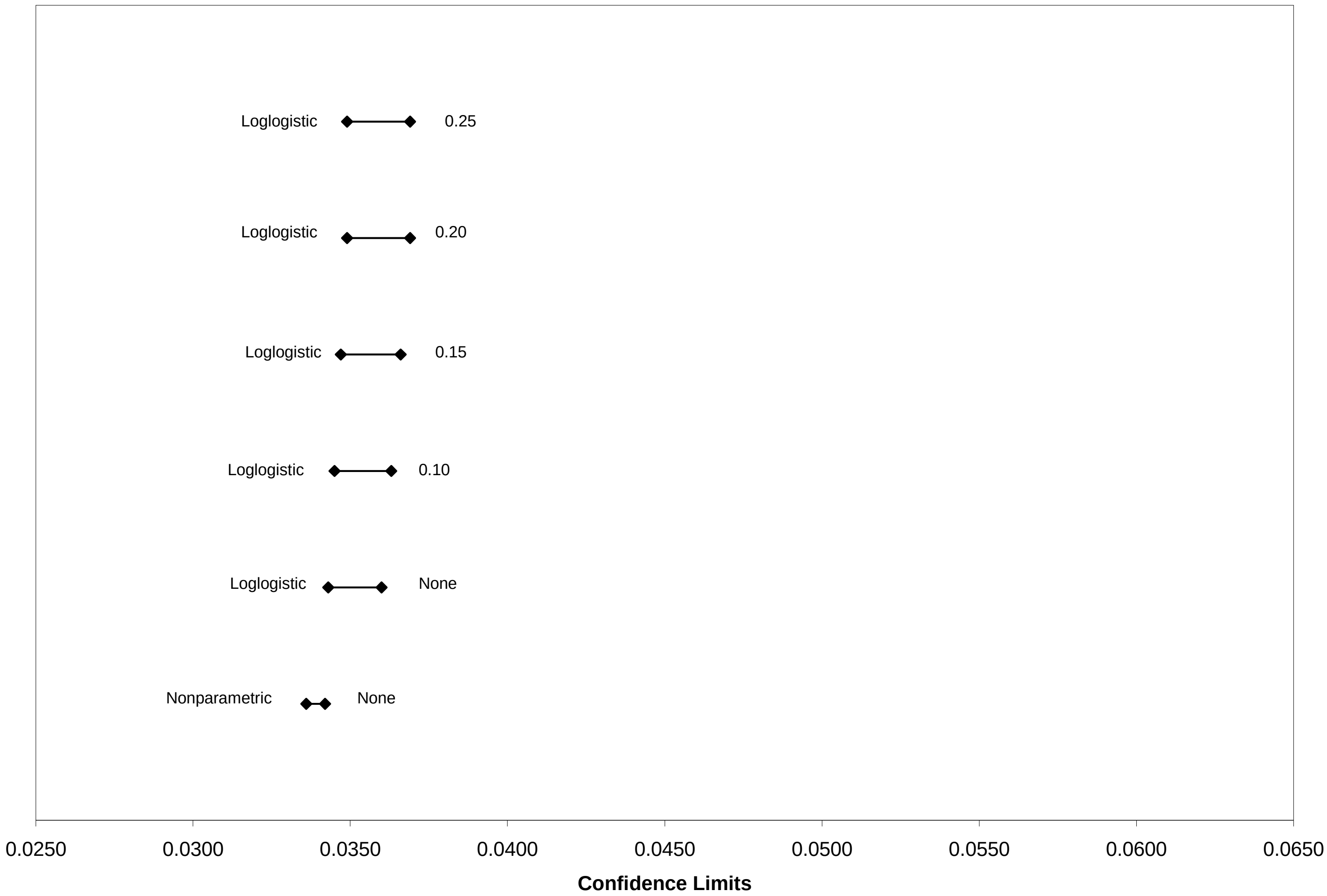


Figure 4.9. Mill B (with outlier) bootstrap confidence intervals based on the percentile method for the 0.90 quantile at various censoring points and based on the distributions assumed at those points.

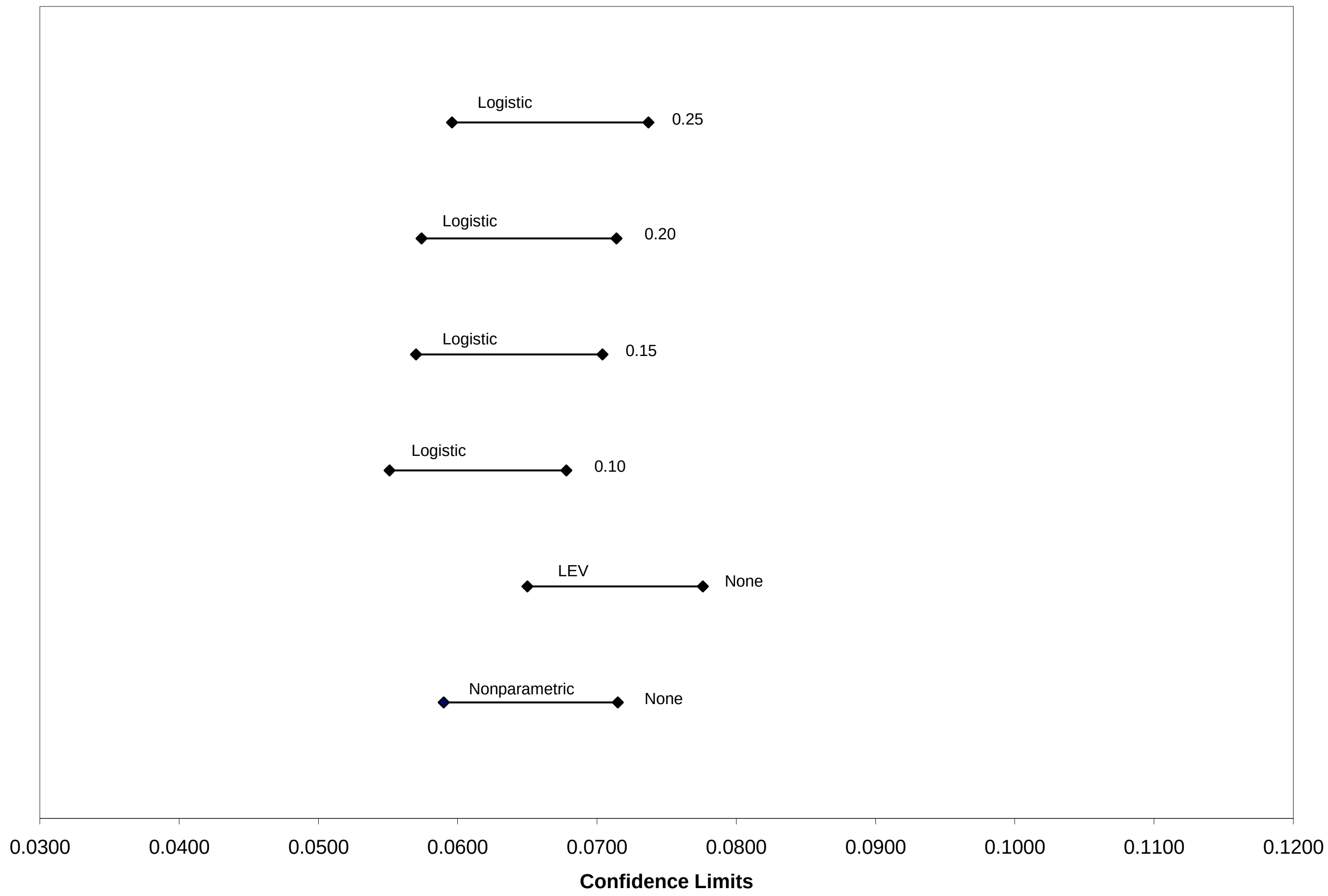


Figure 4.10. Mill C bootstrap confidence intervals based on the percentile method for the 0.99 quantile at various censoring points and based on the distributions assumed at those points.

contains the confidence intervals for the 0.99 quantile for Mill C at various censoring points. Please see Figure A.10 in the Appendix for the same graph on a scale that fits the results. For Mill C, widths of all confidence intervals are very similar with the narrowest confidence interval occurring on the complete data set with no distribution assumed. Mill C follows the same general pattern as Mill A. First, the confidence interval with no censoring but with a distribution assumed results in an interval a bit to the right of the nonparametric estimate. The confidence intervals then move back to the left for the lower censoring values, and slowly increase as the censoring point becomes higher.

The ordered statistic 0.99 quantile for Mill C is 0.0690. All confidence intervals except when censoring at the 0.10 quantile contain this value. Mill C is slightly skewed right. It seems that censoring at least some of the data removes the effect of the thinnest strands as the intervals decrease in value from the complete data to the censored data. Censoring at the 0.25 quantile yields the highest upper limit of the confidence intervals when the data is censored. Thus, this may be the best place to censor for Mill C.

Figure 4.11 shows the confidence intervals for the 0.95 quantile for Mill C. Figure 4.12 contains the intervals for estimating Mill C's 0.90 quantile. Please see Figures A.11 and A.12 in the Appendix for a reproduction of these graphs on a scale to fit the results. Like the pattern with the other data sets, the confidence intervals for Mill C tend to increase in value as the censoring point increases. However, as with Mill B, there is not as large a change in the confidence intervals as the censoring value changes for Mill C. This may indicate that infant mortality is not as big an issue for this mill since the intervals are so similar. The estimates for the 0.90 quantile are slightly smaller than those of the 0.95 quantile, which in turn are slightly smaller than the

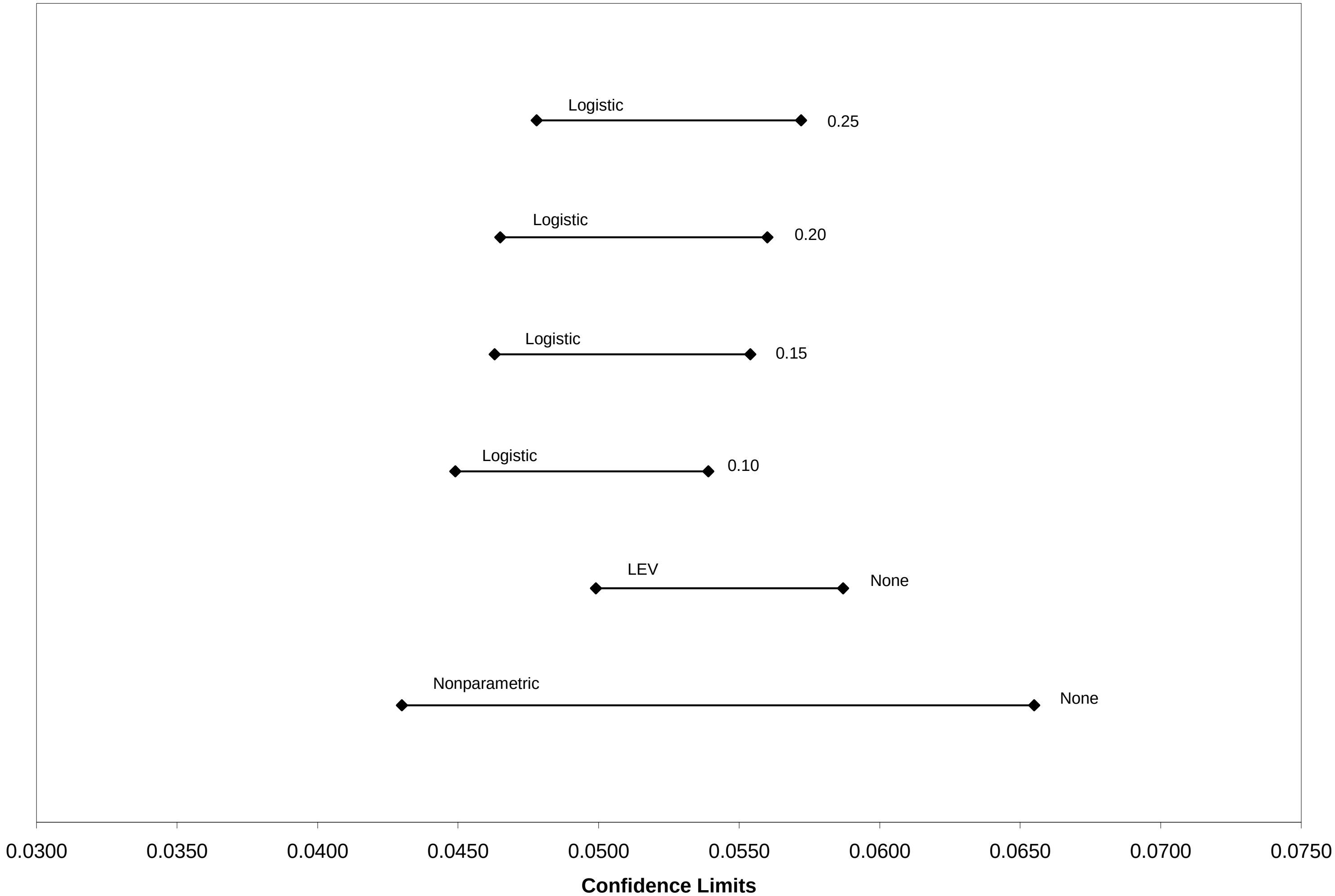


Figure 4.11. Mill C bootstrap confidence intervals based on the percentile method for the 0.95 quantile at various censoring points and based on the distributions assumed at those points.

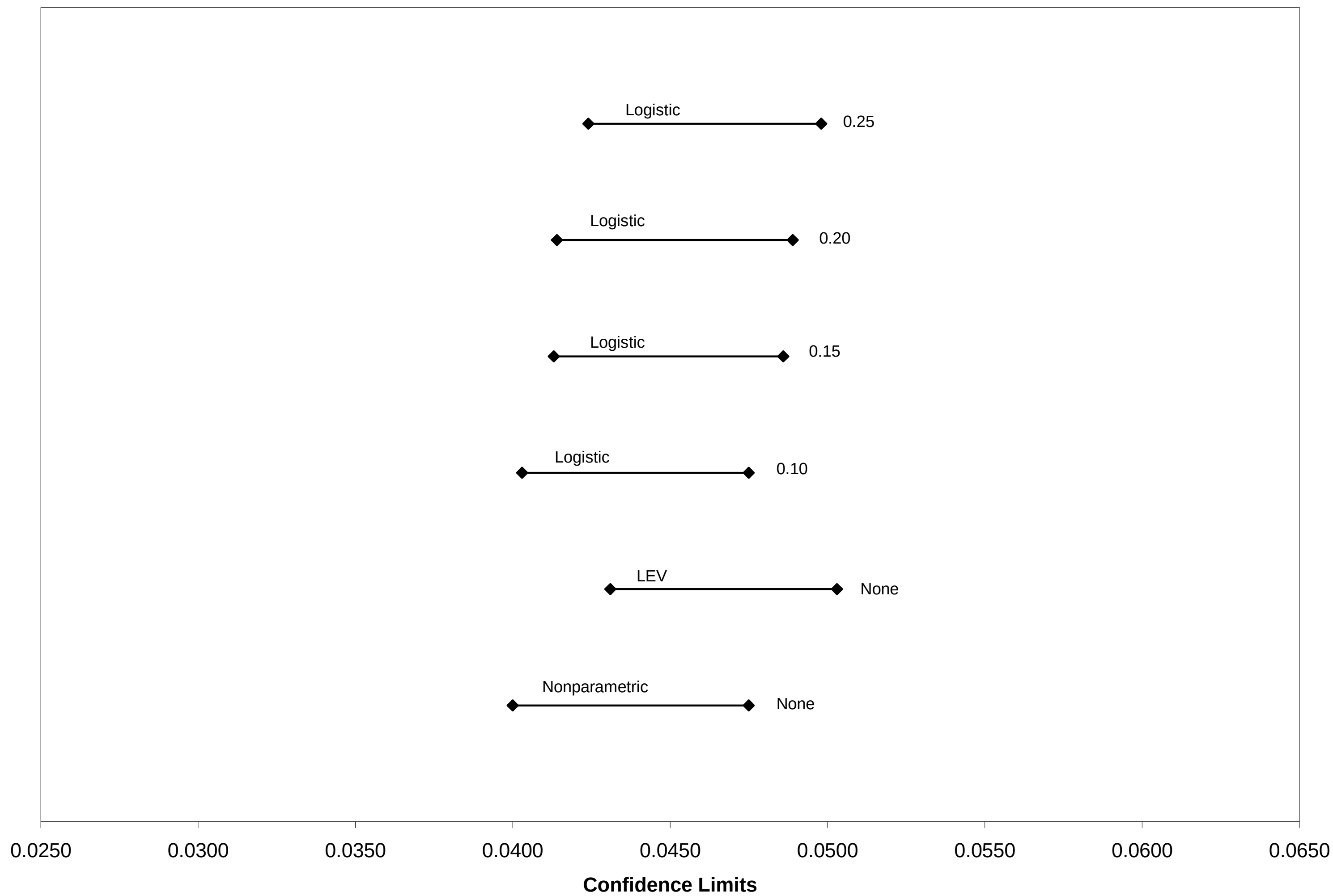


Figure 4.12. Mill C bootstrap confidence intervals based on the percentile method for the 0.90 quantile at various censoring points and based on the distributions assumed at those points.

estimates for the 0.99 quantile. These results are expected. For the 0.95 quantile, the widest confidence interval occurs when no distribution is assumed and no data is censored. Thus, the best confidence interval to use here could be at the 0.25 quantile censoring. This censoring value provides fairly narrow confidence intervals but also yields higher upper estimates than the other censoring values.

4.4. Mill D

Mill D fits a Largest Extreme Value distribution when the data is not censored. As the censoring values move from the 0.10 to the 0.25 quantile, the best distribution is the Logistic. These results are similar to both Mill A and Mill C in that the distribution changes to the Logistic once some censoring is applied.

Figure 4.13 shows the confidence intervals for Mill D's 0.99 quantile. Please see Figure A.13 in the Appendix for a picture of the same graph on a scale to fit the results. The confidence intervals for Mill D follow the same general pattern as Mills A and C. At low censoring points, the estimates tend to increase slightly as the censoring value increases. Additionally, once censoring occurs, the confidence intervals move to the left as compared to the complete data set when a distribution is assumed. In this case, the nonparametric bootstrap confidence interval is very wide. This is likely due to a high outlier contained in this data set. Since this outlier was not as extreme as the one in Mill B when compared to the rest of the data, it was not removed from the data set. The binomial analysis in Mill B's section above could also be applied here to provide theoretical justification for the outlier being the upper limit of the nonparametric interval.

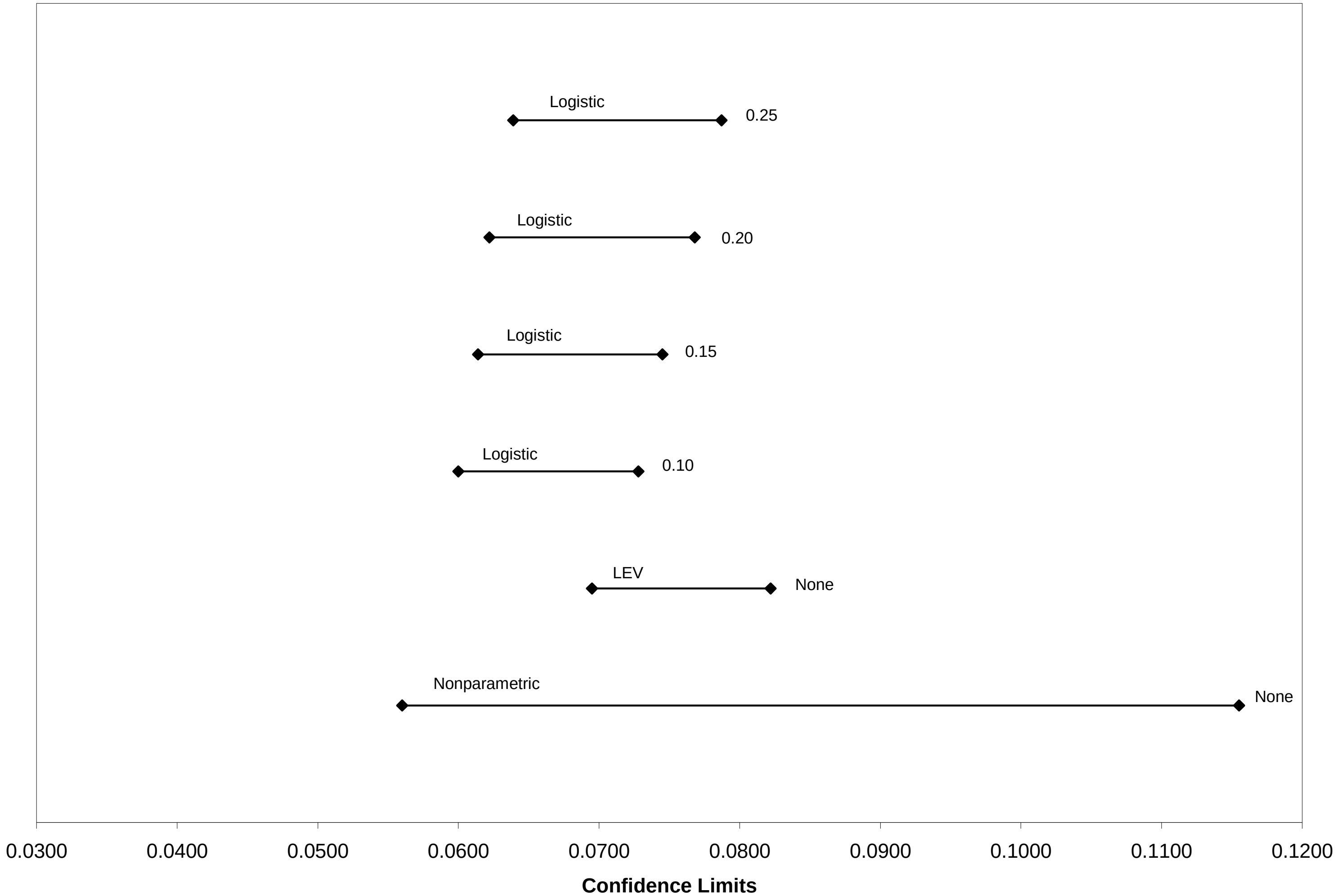


Figure 4.13. Mill D bootstrap confidence intervals based on the percentile method for the 0.99 quantile at various censoring points and based on the distributions assumed at those points.

The ordered statistic 0.99 quantile is 0.0640 for Mill D. All confidence intervals contain this value except when the Largest Extreme Value distribution is assumed and no censoring occurs. For Mill D, it seems that the best confidence interval occurs when some censoring is applied. Specifically, censoring at the 0.25 quantile gets rid of problems with very thin strands and still provides a precise interval.

Figure 4.14 contains the confidence intervals for the 0.95 quantile for Mill D. Figure 4.15 shows the intervals for Mill D's 0.90 quantile. Please see Figures A.14 and A.15 in the Appendix for the same graphs on a scale to fit the results. Both of these quantiles' confidence intervals follow the same general pattern of slightly increasing as the censoring point increases. The practitioner again may choose to censor at the 0.25 quantile as this gets rid of the effect of thin strands but also provides a precise interval.

4.5. Mill E

Without censoring Mill E follows a Weibull distribution. When censoring at the 0.10, 0.15, and 0.20 quantiles, the best distribution is the Logistic. As censoring occurs at the 0.25 quantile, the data set takes on a Smallest Extreme Value distribution. Mill E changes distributions more often than the previous four data sets. Figure 4.16 shows the confidence intervals for estimating Mill E's 0.99 quantile. Please see Figure A.16 in the Appendix for a copy of the same graph on a scale to fit the results. The confidence intervals for this data set follow the same general pattern as Mill A: as the censoring values increase, the intervals tend to become larger up to censoring at the 0.20 quantile. When censoring at the 0.25 quantile, the confidence interval shifts left. This may occur because of the change in distribution from the

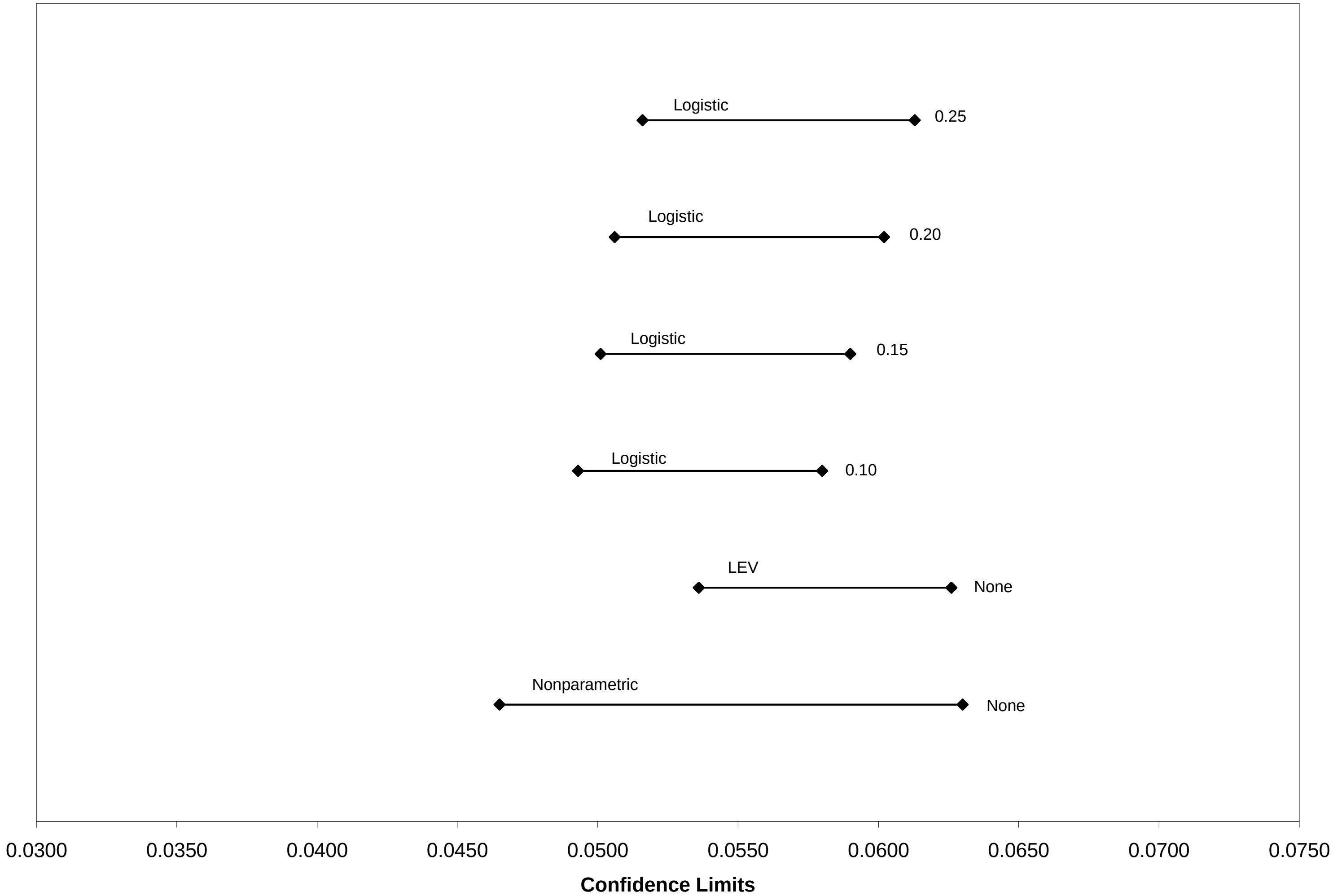


Figure 4.14. Mill D bootstrap confidence intervals based on the percentile method for the 0.95 quantile at various censoring points and based on the distributions assumed at those points.

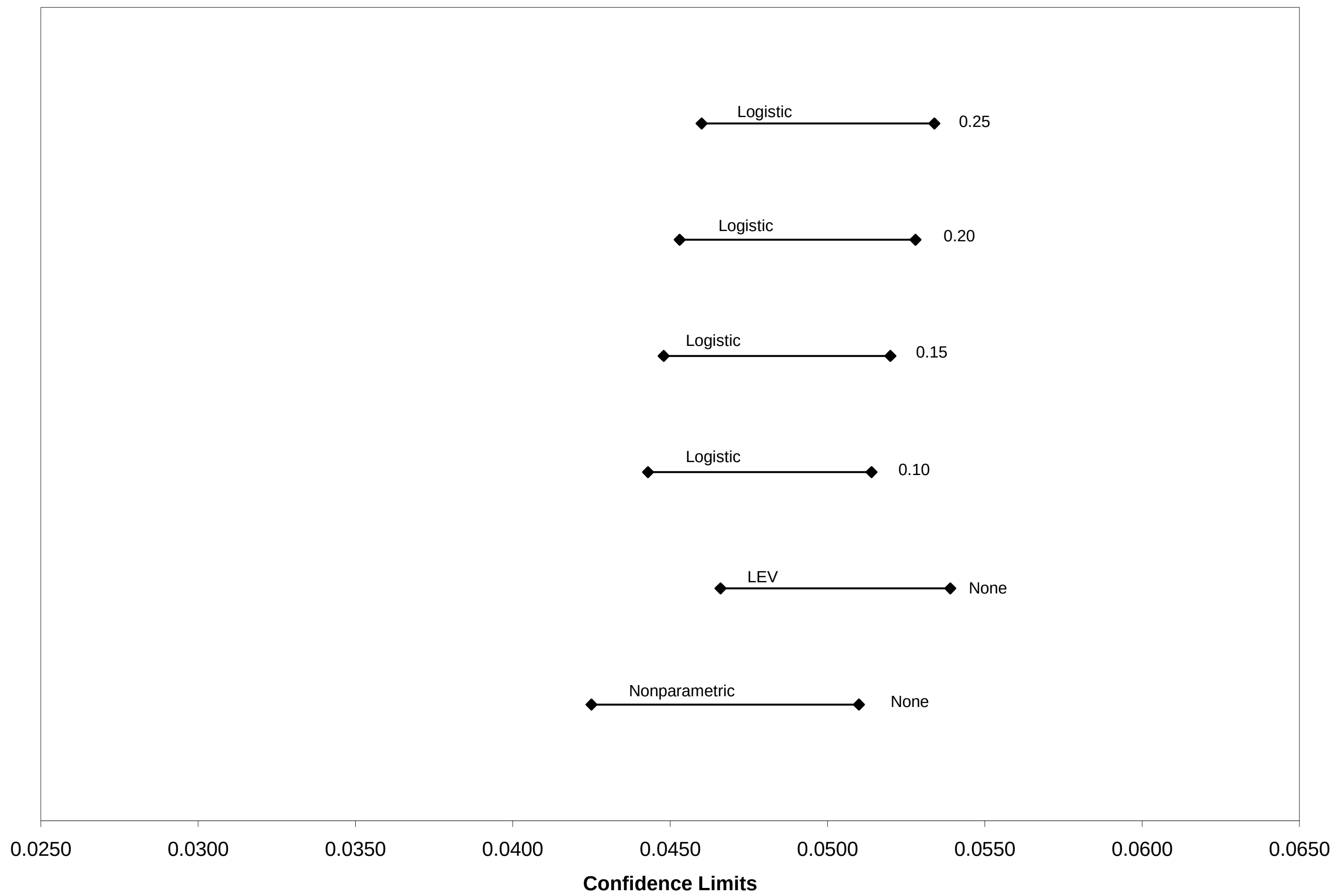


Figure 4.15. Mill D bootstrap confidence intervals based on the percentile method for the 0.90 quantile at various censoring points and based on the distributions assumed at those points.

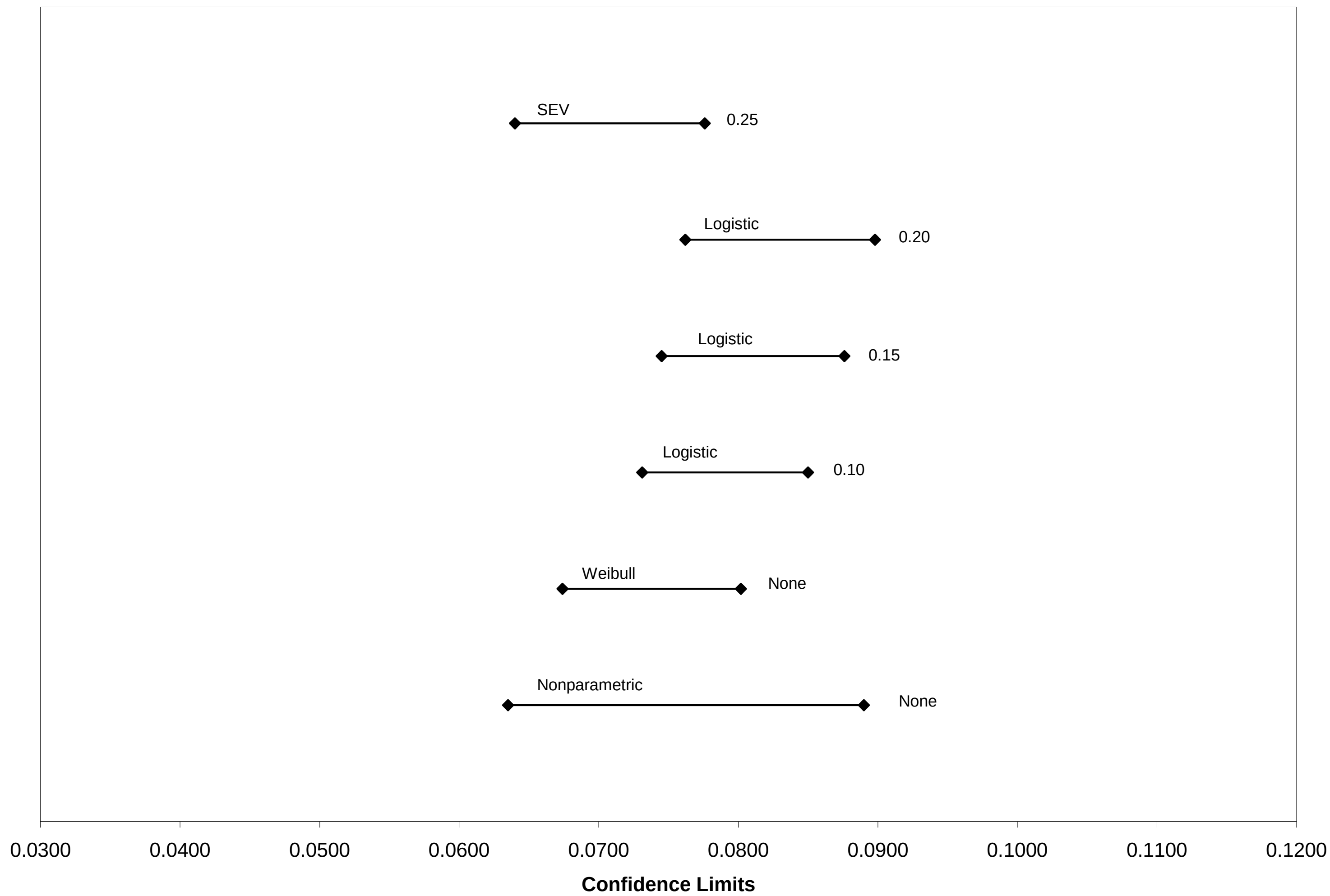


Figure 4.16. Mill E bootstrap confidence intervals based on the percentile method for the 0.99 quantile at various censoring points and based on the distributions assumed at those points.

Logistic to the Smallest Extreme Value. The widest interval occurs when estimating nonparametrically.

The ordered statistic 0.99 quantile for Mill E is 0.0710. All confidence intervals contain this value except when censoring at the 0.10, 0.15, and 0.20 quantiles. Mill E is fairly bell-shaped with the exception of one high outlier. Thus, to have a precise interval that is still conservative in terms of its upper estimate, the best place to censor may be the 0.20 quantile for Mill E.

Figure 4.17 shows the confidence intervals for the 0.95 quantile for Mill E. Figure 4.18 contains the intervals for Mill E's 0.90 quantile. Please see Figures A.17 and A.18 in the Appendix for displays of the same graphs on a scale to fit the results. The confidence intervals for both quantiles tend to increase slightly as the censoring point increases. However, when estimating the 0.95 quantile, there is a small jump to the left as censoring occurs at the 0.25 quantile. This is similar to the results for Mill E when estimating the 0.99 quantile. Thus, censoring at the 0.20 quantile may again be the best for Mill E. The nonparametric estimates are fairly similar to those when a distribution is assumed for estimating both the 0.90 and 0.95 quantiles for Mill E. However, censoring and assuming a distribution provides a generally more precise confidence interval for this mill.

4.6. Mill F

Mill F, like Mill E, fits the widest variety of distributions depending on the censoring point. When the data is complete, the best distribution is the Lognormal. At 0.10 quantile censoring, the distribution changes to the Largest Extreme Value. The distribution changes

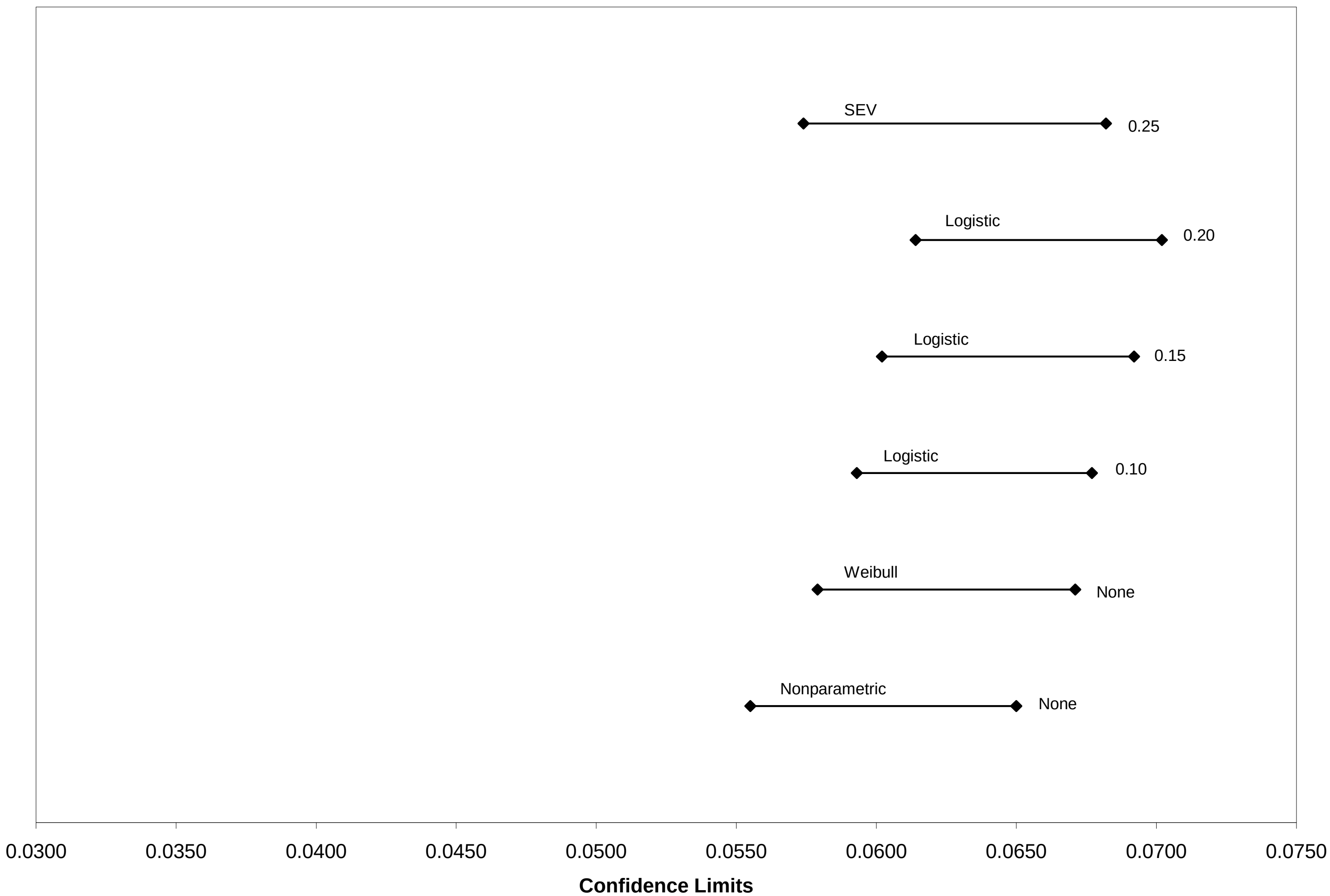


Figure 4.17. Mill E bootstrap confidence intervals based on the percentile method for the 0.95 quantile at various censoring points and based on the distributions assumed at those points.

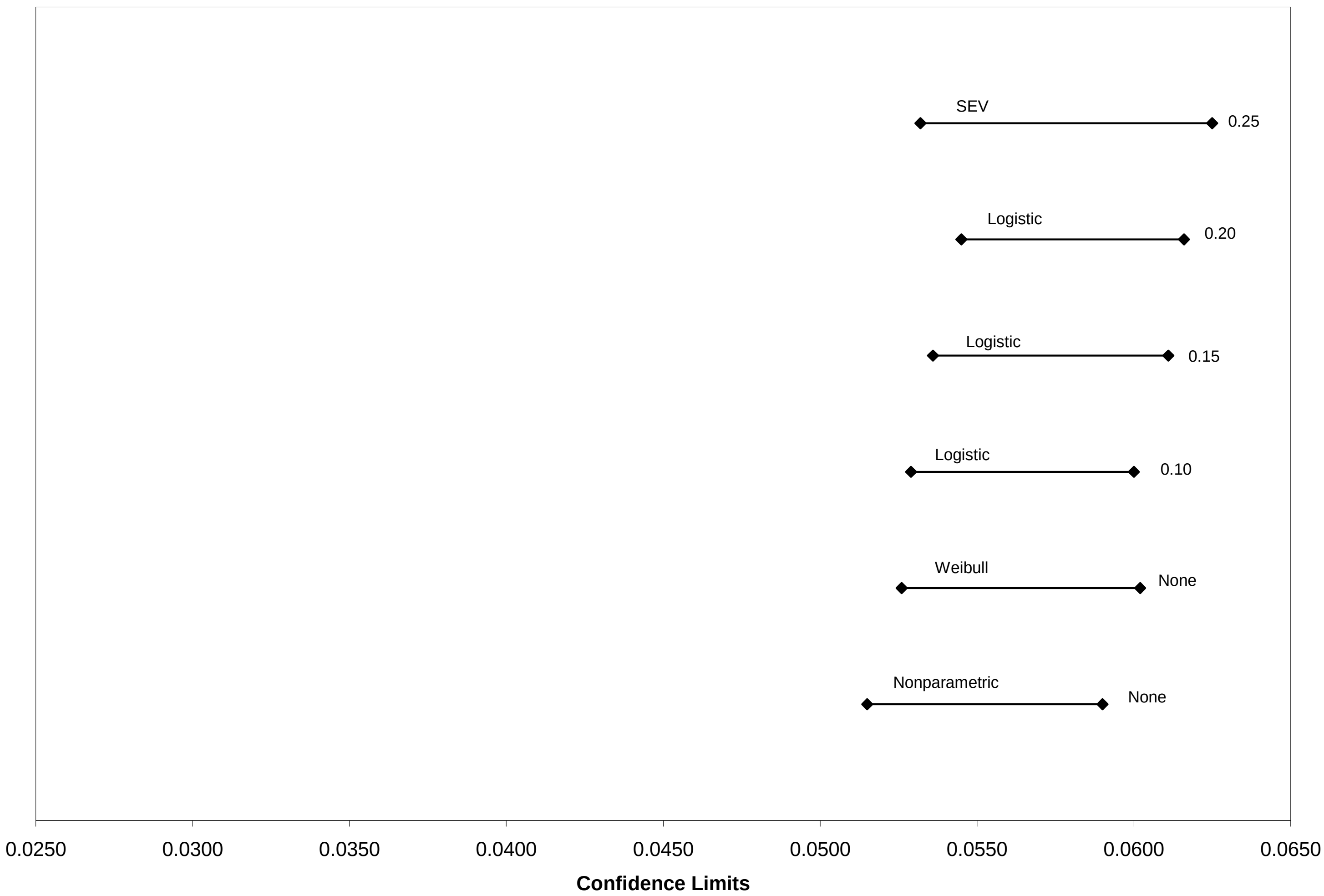


Figure 4.18. Mill E bootstrap confidence intervals based on the percentile method for the 0.90 quantile at various censoring points and based on the distributions assumed at those points.

again to the Logistic at the 0.15 quantile censoring, and this is also the best distribution for the 0.20 and 0.25 quantile censoring. Because the best distribution changes so often for this mill, other sources of variation may be involved that can be investigated to improve the process. This mill can be viewed as the opposite end of the spectrum as Mill B. Where Mill B chose one distribution and was a very tight range of values, Mill F is more variable and chooses multiple distributions depending on the level of censoring. The manufacturers at Mill F may be able to examine the results for Mill B and learn what needs to change in order to improve their process and reduce variability in strand thickness.

Figure 4.19 shows the confidence intervals for the 0.99 quantile for Mill F at various censoring points. Please see Figure A.19 in the Appendix for the same graph on a scale to fit the results. As with many other mills, the widest confidence interval is the nonparametric estimate. The limits for the Largest Extreme Value confidence interval are contained within the Lognormal confidence interval. The confidence intervals then decrease as the distribution changes from the Largest Extreme Value to the Logistic.

The ordered statistic 0.99 quantile for Mill F is 0.0780. This value is contained in all confidence intervals except when censoring at the 0.15, 0.20, and 0.25 quantiles. Mill F is skewed to the right. The best confidence interval for this data set could occur when censoring at the 0.10 quantile. Censoring at the 0.10 quantile appears to get rid of the infant mortality in the data set, as well as provide a precise interval and conservative upper estimate.

Figure 4.20 shows the confidence intervals for estimating Mill F's 0.95 quantile. Figure 4.21 shows the interval estimates for the 0.90 quantile. Please see Figures A.20 and A.21 in the Appendix for the same graphs on a scale to fit the results. Both figures follow the same general

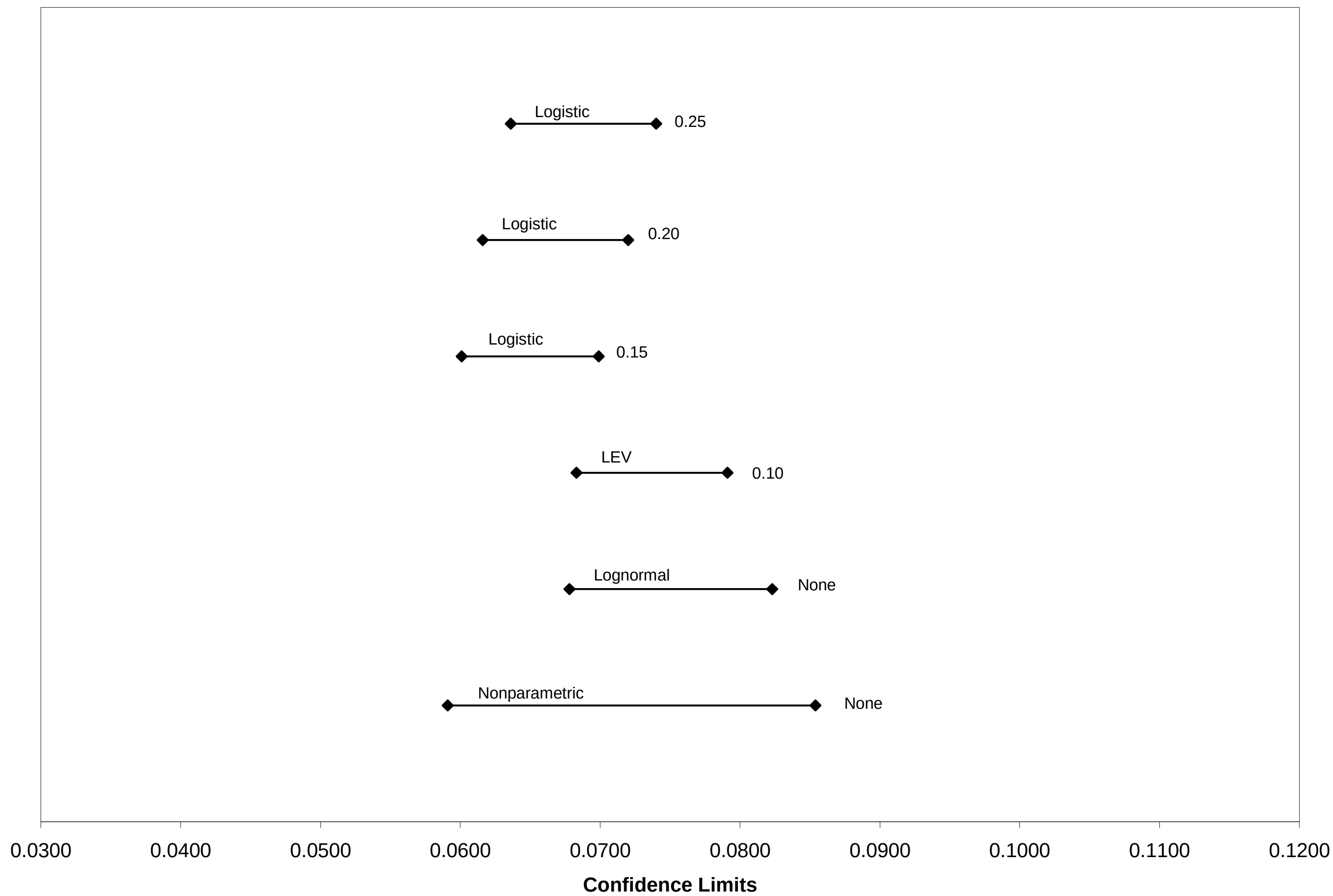


Figure 4.19. Mill F bootstrap confidence intervals based on the percentile method for the 0.99 quantile at various censoring points and based on the distributions assumed at those points.

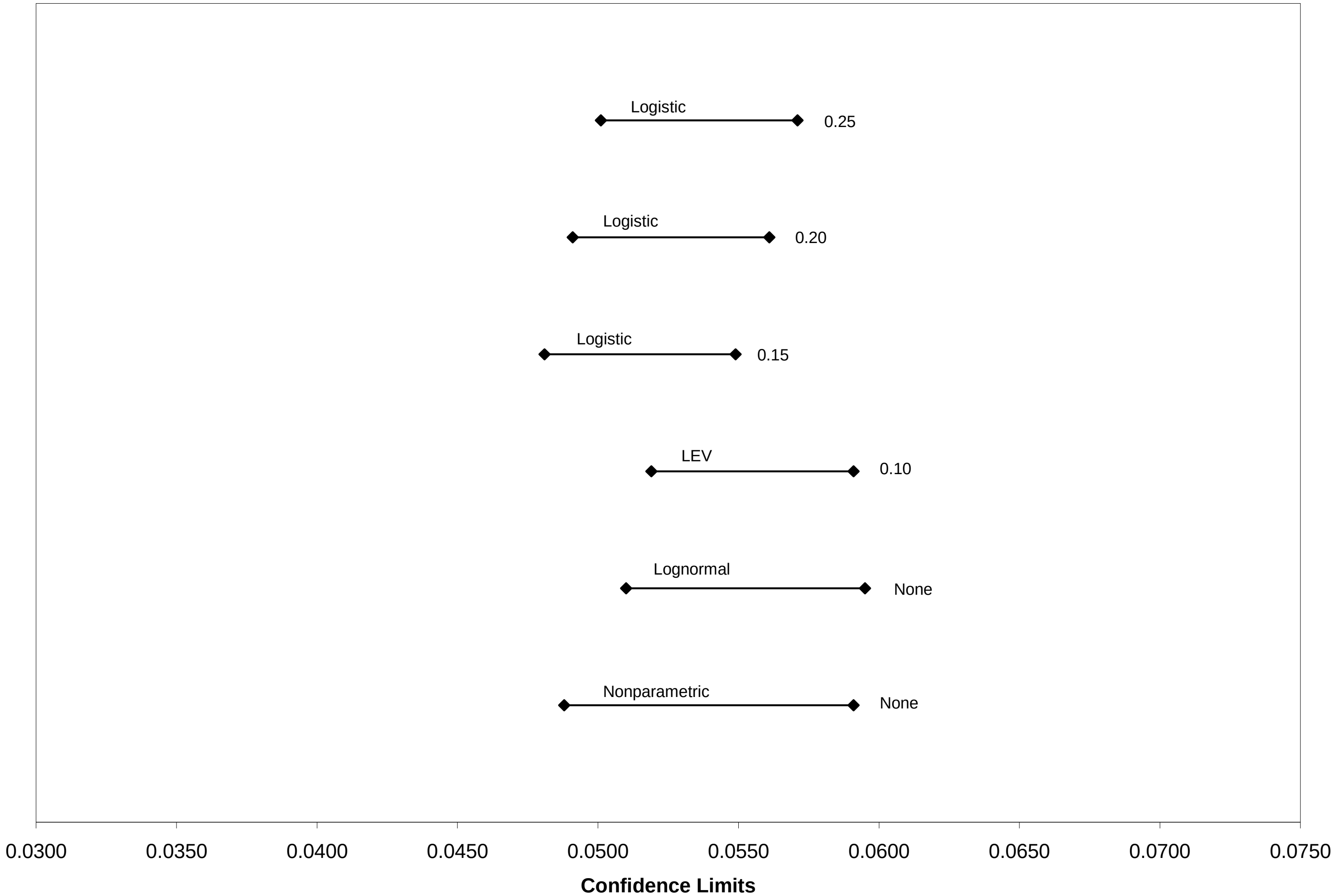


Figure 4.20. Mill F bootstrap confidence intervals based on the percentile method for the 0.95 quantile at various censoring points and based on the distributions assumed at those points.

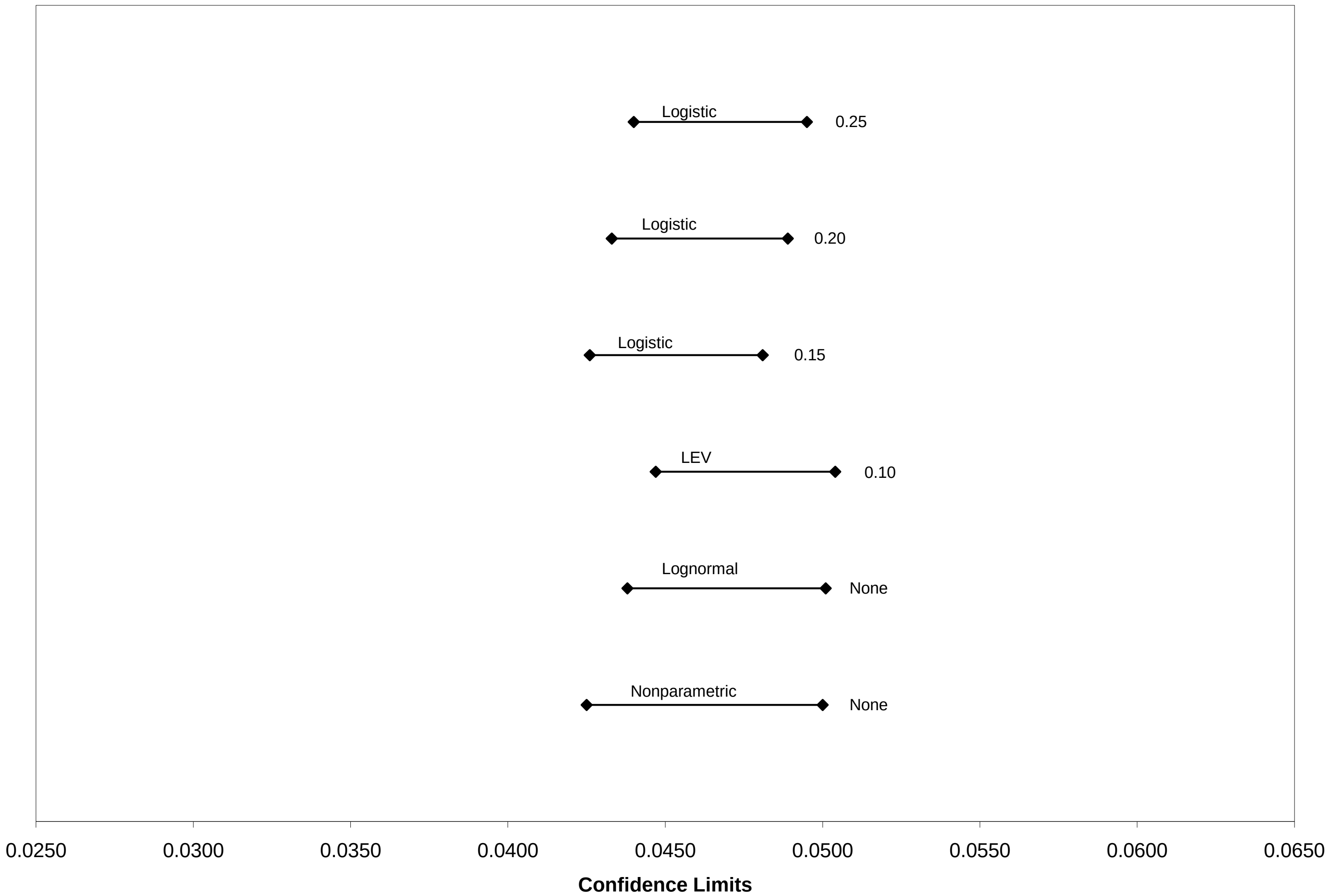


Figure 4.21. Mill F bootstrap confidence intervals based on the percentile method for the 0.90 quantile at various censoring points and based on the distributions assumed at those points.

pattern of slightly increasing as censoring is applied, with a jump to the left at the 0.15 quantile censoring and as the distribution changes to the Logistic. The widest intervals occur when estimating nonparametrically. Of the censored data sets, the interval when censoring at the 0.10 quantile is most conservative in that it has the highest upper limit. Based on results from Mill F's 0.99 quantile, censoring at the 0.10 quantile may be best for this mill.

4.7. Summary

Clearly, the best censoring point depends on the data set and the practitioner's use of the results. If the user wants precise estimates, he or she should apply some censoring to the data set. The user may instead pick the confidence interval with the highest upper limit if he or she wants to be conservative in the estimates. If the practitioner feels that the early infant mortality will have an effect on the distribution chosen for a data set, censoring at the quantiles chosen above is recommended. For instance, censoring anywhere between the 0.10 and 0.25 quantiles is helpful in removing the effect of infant mortality. If only one censoring point must be chosen, the researchers suggest the 0.25 quantile. Censoring at this value seems to be the best overall in terms of providing a precise interval but also having a higher upper limit in case the practitioner is worried about missing the thick flakes.

Mill B clearly has the narrowest confidence intervals, whether the outlier is included or not (with the exception of the nonparametric estimate when the outlier is included in the data set). It appears that Mill B has a very effective process control in place at its manufacturing facilities. There is not much variation in the data set, which was observed in Chapter 3. The other mills are doing a good job of keeping their variation down, but they could improve their processes to save money. The less variation the strands have, the less likely that an outlier occurs that might damage the machines. Less variation can also result in a higher-quality final product and happy customers.

Please see Tables A.1 through A.7 in the Appendix for selected confidence intervals for each mill. The researchers have chosen to include the nonparametric confidence intervals for each mill, as well as those when no censoring occurs but a distribution is assumed, and when censoring at the 0.25 quantile. These values are shown for comparison and as a supplement to the graphs that appear in this chapter. Mill B's confidence intervals are shown when the extreme outlier is both included in and excluded from the data set.

4.8. Validation of Mill B and Mill F Results

Before closing this chapter, a validation of the results for Mills B and F is examined. Each of the two data sets was divided into two parts: 75 percent used as a training data set and the remaining 25 percent used as a validation data set. The thickness measurements were assigned random numbers and sorted to determine in which category they would be classified. On the training data sets, nine distributions were fit and the AIC was scored to determine the best-fitting model. Then, bootstrap confidence intervals were found in SPLIDA for the 0.90, 0.95, and 0.99 quantiles, just like the results for the previous parts of this chapter. On the validation data sets, nonparametric bootstrap confidence intervals were found using MATLAB for the 0.90, 0.95, and 0.99 quantiles. These two types of confidence intervals were found on the complete data sets as well as the data sets censored between the 0.10 and 0.25 quantiles.

Mill B's outlier was included in this analysis, and it was randomly assigned to the training data set. Figure 4.22 shows the results for Mill B's 0.90 quantile. Figure 4.23 plots the confidence intervals for Mill B's 0.95 quantile. Figure 4.24 depicts the intervals for Mill B's 0.99 quantile. The nonparametric confidence intervals are generally lower than the intervals when assuming a distribution. This is likely due to the outlier being included in the training data set where models were fit before bootstrapping. For the 0.90 and 0.95 quantiles, there is some overlap in the confidence intervals for the training and validation data sets. On the 0.99 quantile, however, there is no overlap in the intervals. The nonparametric intervals on the validation data sets tend to move slightly left as the censoring increases. On the other hand, the parametric intervals on the training data sets tend to move slightly right as the censoring increases. As mentioned previously, this is likely due to the lack of variability in Mill B's data set and the outlier being included in the training data set.

Mill F did not have an extreme outlier like Mill B, so its results appear more stable. Figure 4.25 plots the confidence intervals for the training and validation data sets for Mill F's 0.90 quantile. Likewise, Figures 4.26 and 4.27 plot the intervals for Mill F's 0.95 and 0.99 quantiles, respectively. Unlike Mill B, Mill F's confidence intervals when assuming a distribution tend to fall within or at least overlap the nonparametric intervals. This result is promising in that it shows the training intervals fall close to the validation intervals. The nonparametric intervals also tend to be wider than the intervals when assuming a distribution.

By holding out a validation data set, the results can be confirmed. Because there is generally at least some overlap in the intervals for the training and validation data sets, the results are a little more believable. Mill B's intervals were more erratic than Mill F's, likely due

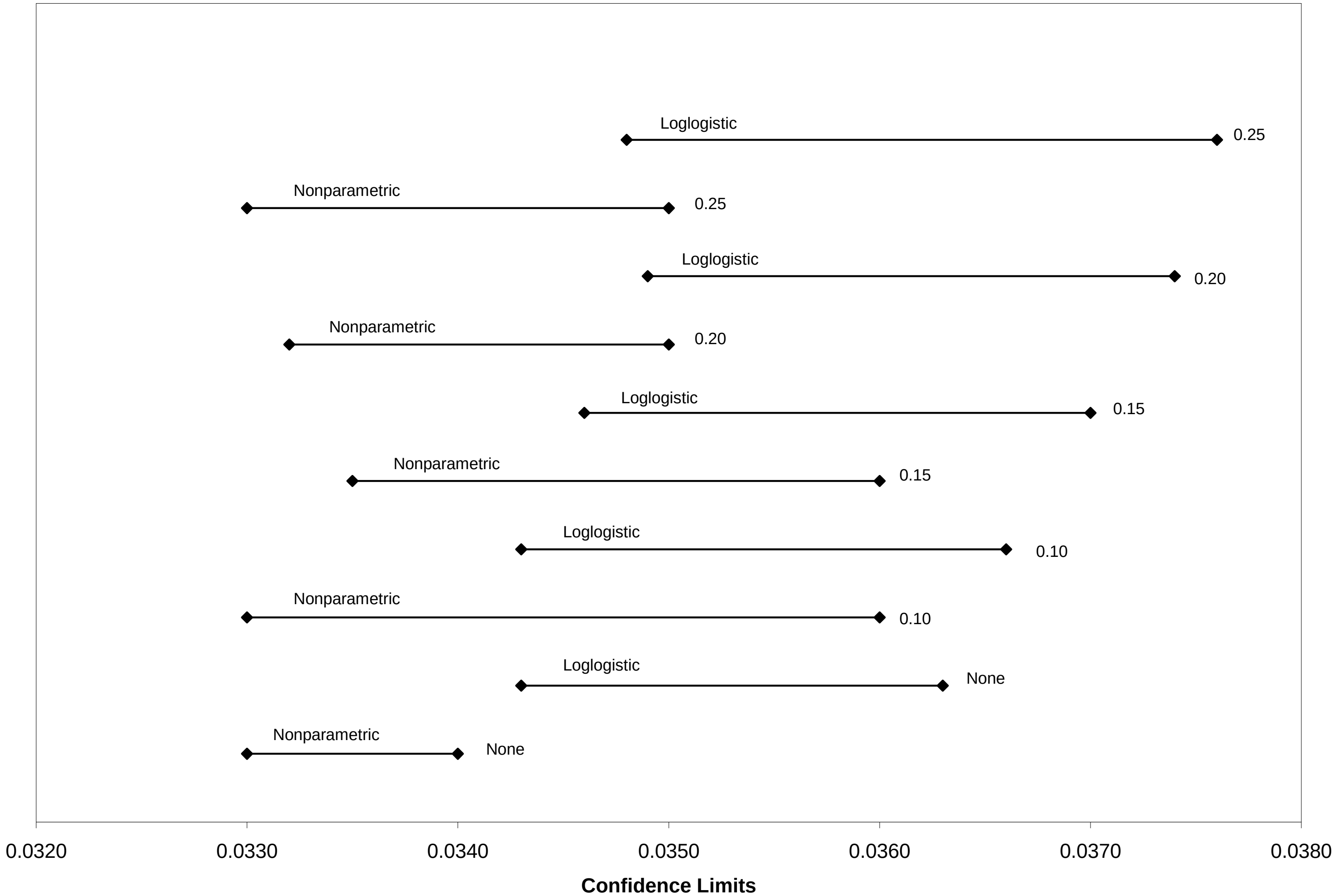


Figure 4.22. Mill B (with outlier) bootstrap confidence intervals based on the percentile method for the 0.90 quantile at various censoring points and based on the distributions assumed at those points for training and validation sets.

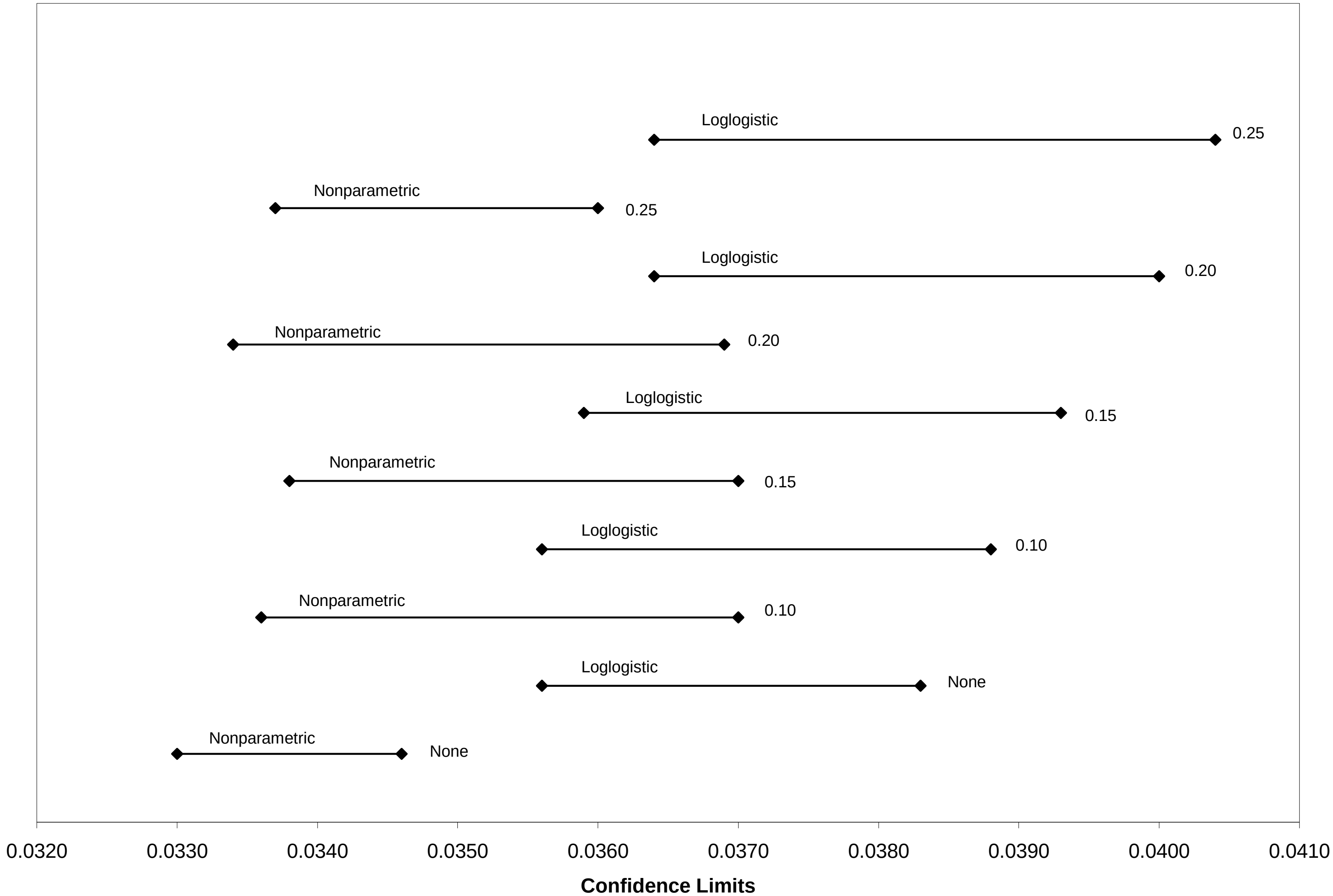


Figure 4.23. Mill B (with outlier) bootstrap confidence intervals based on the percentile method for the 0.95 quantile at various censoring points and based on the distributions assumed at those points for training and validation sets.

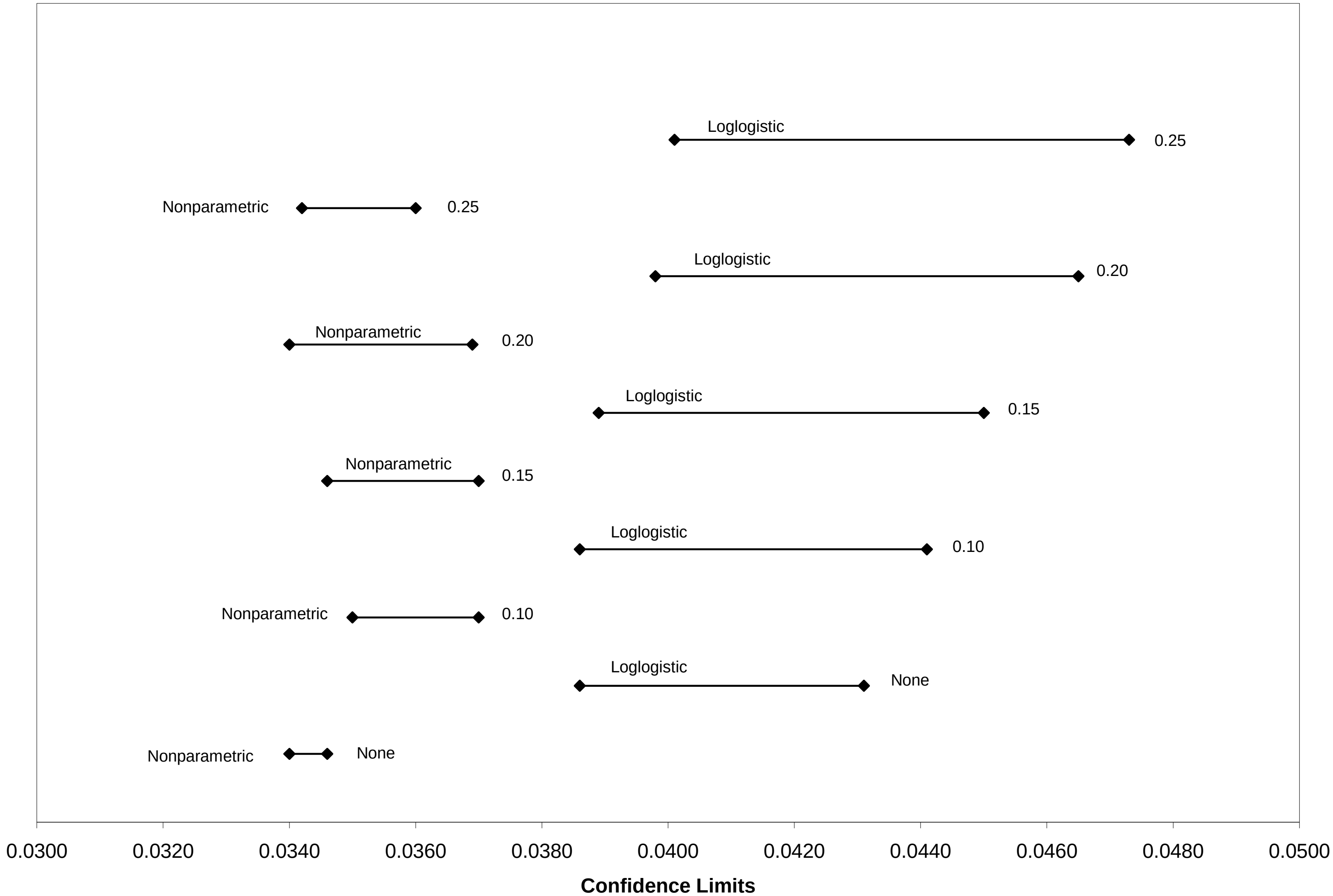


Figure 4.24. Mill B (with outlier) bootstrap confidence intervals based on the percentile method for the 0.99 quantile at various censoring points and based on the distributions assumed at those points for training and validation sets.

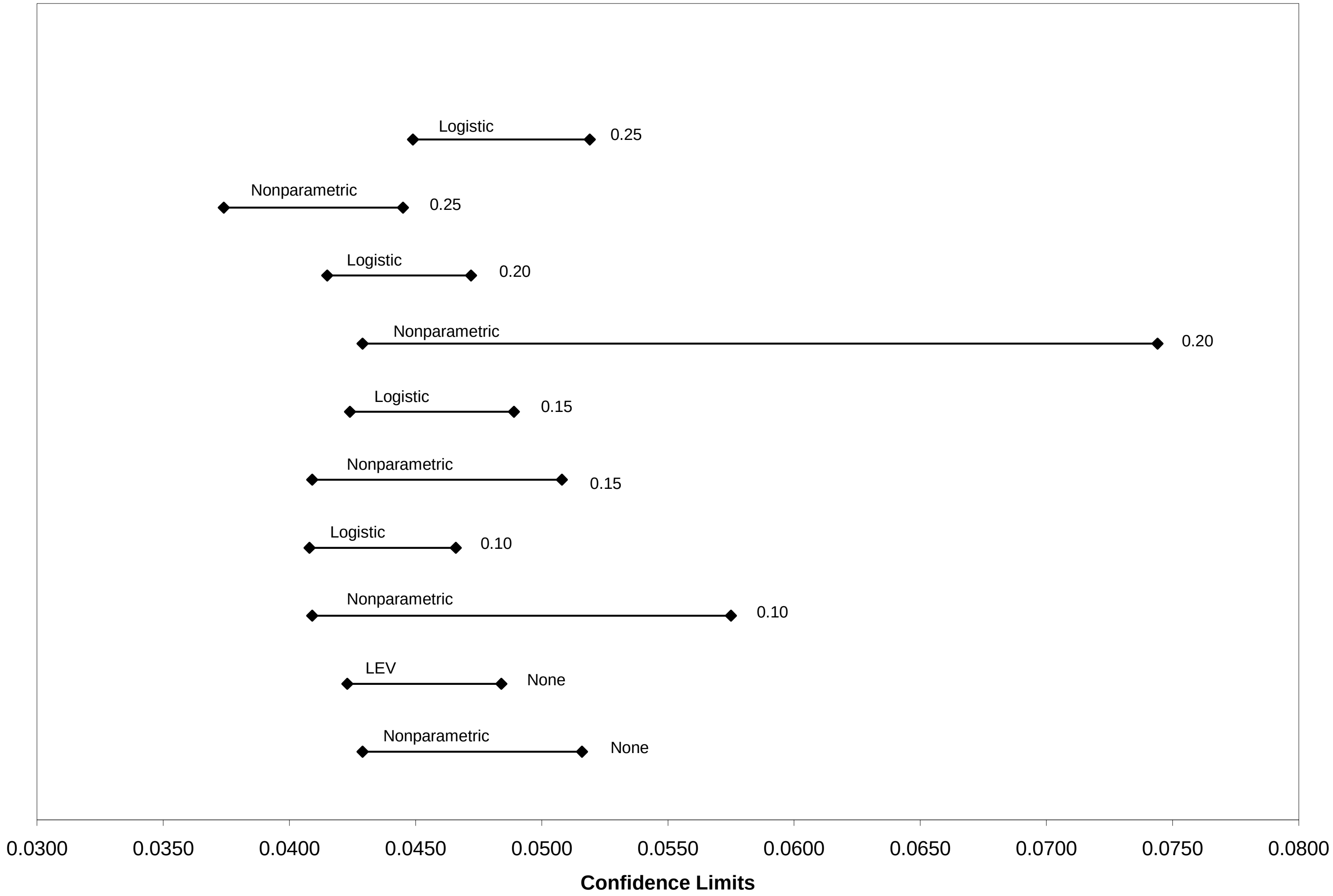


Figure 4.25. Mill F bootstrap confidence intervals based on the percentile method for the 0.90 quantile at various censoring points and based on the distributions assumed at those points for training and validation sets.

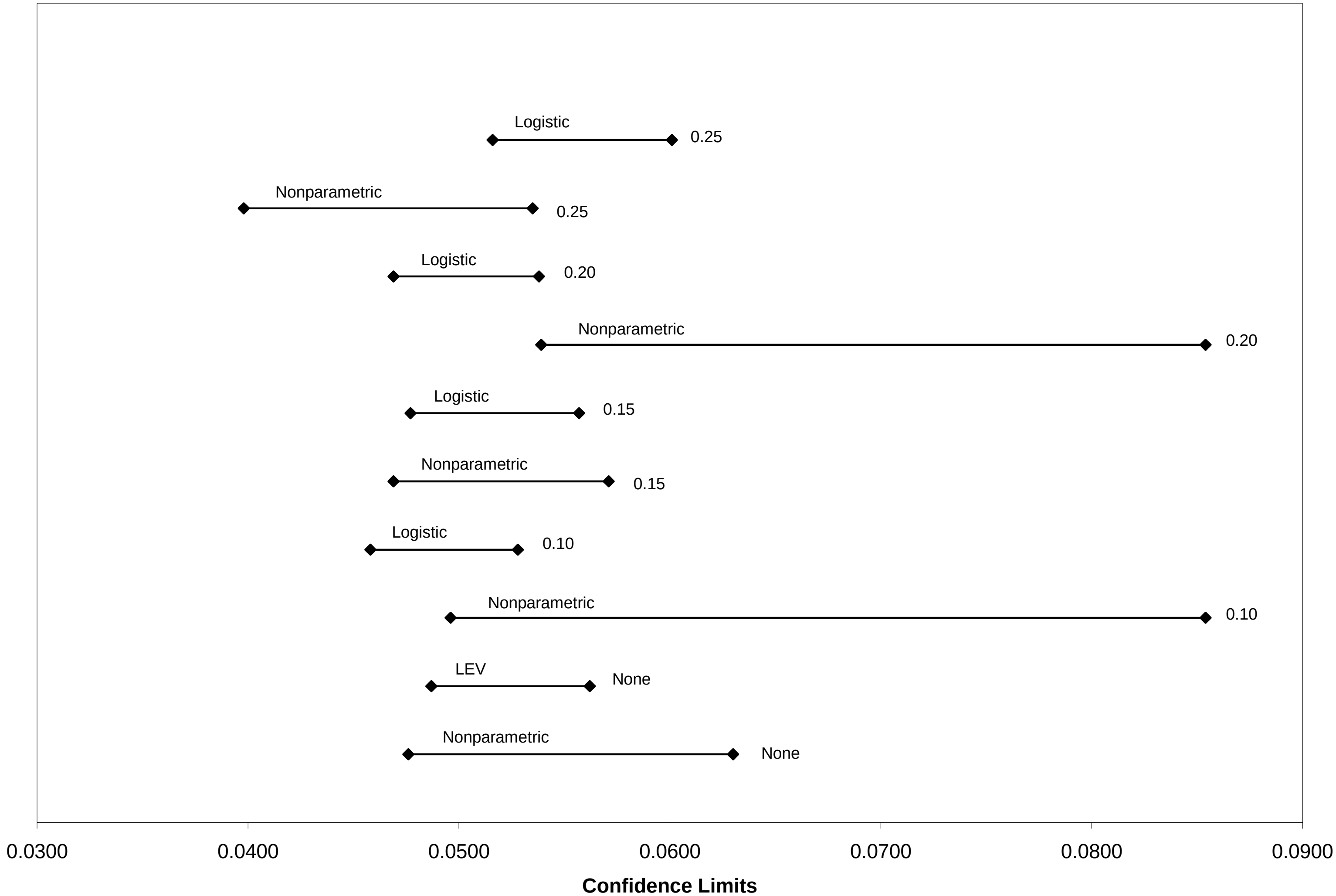


Figure 4.26. Mill F bootstrap confidence intervals based on the percentile method for the 0.95 quantile at various censoring points and based on the distributions assumed at those points for training and validation sets.

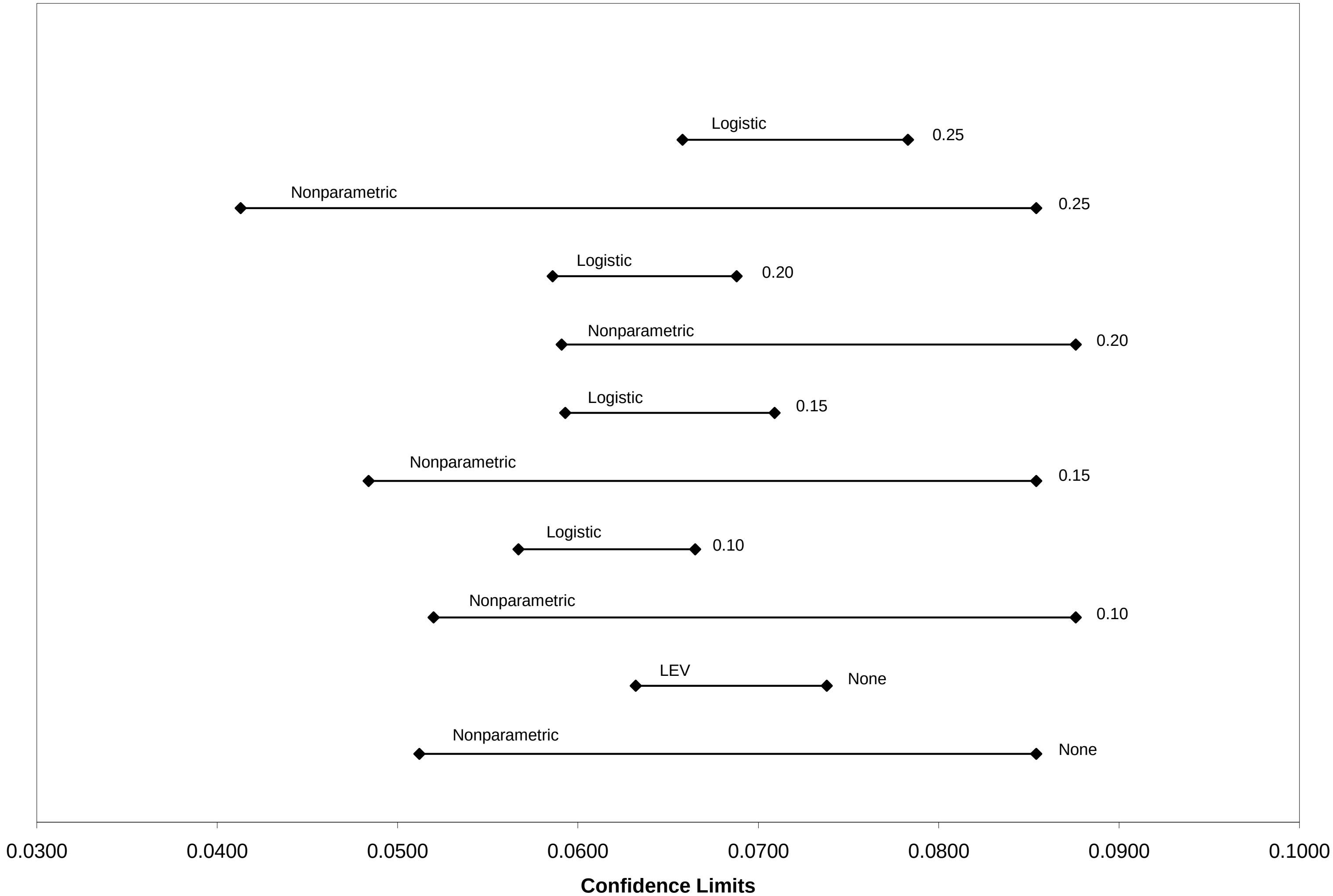


Figure 4.27. Mill F bootstrap confidence intervals based on the percentile method for the 0.99 quantile at various censoring points and based on the distributions assumed at those points for training and validation sets.

to the extreme outlier in the data set for Mill B. Without the outlier, Mill B's results may have overlapped more for the training and validation sets. This could be an area of future research for another student.

Chapter 5

Conclusions

This thesis has focused on determining the best distribution for each data set (or mill), plotting survival curves, and estimating the upper percentiles through bootstrapping. The researchers found that the most popular distributions for the complete data sets are the Loglogistic, Largest Extreme Value, and Weibull, whether the highest outlier in the data is removed or not. The story changes, however, when forced censoring is used. When censoring at the lower quantiles, such as the 0.10 up to the 0.25 quantile, the most popular distribution is clearly the Logistic. The exception to this generalization occurs when fitting a distribution to Mill B including the outlier. In this case, Mill B with the outlier always chooses the Loglogistic distribution as best. These results are contrary to what was originally expected as the researchers thought they would see the Weibull distribution appear much more often. However, the absence of the Weibull distribution did not pose a problem, and the researchers were still able to estimate the upper percentiles. Additionally, the changes in the choice of distribution with the various levels of censoring show the impact of thin strands. As mentioned in Chapters 2 and 4, infant mortality in this case refers to thinner strands. When these values are censored, the choice of distribution changes from the best when the complete data set is used.

Bootstrapping in Chapter 4 revealed the various censoring to estimate the upper percentiles. Specifically, the most conservative confidence interval is the widest for each data set. In many cases, the widest estimate is the nonparametric interval. However, the most conservative interval depends on the data set itself and so may occur when a distribution is assumed, and even possibly when censoring occurs. Often, the nonparametric confidence interval coincided with other intervals when censoring and distributional assumptions were made. If the practitioner is concerned with infant mortality, or early failures impacting the choice of distribution, censoring at lower quantiles is recommended. Specifically, censoring at the 0.10 up to the 0.25 quantiles removes the effect of the earliest failures and focuses on estimating the upper values. Since the research has shown that percentile censoring does provide better estimates for the upper percentiles, mill owners may consider using this technique when analyzing their data. With improved estimates, they can better predict what the thickest values may be and thus protect their capital investment.

The nonparametric confidence intervals are also useful since they are based on no distributional assumptions and come straight from the data. However, censoring and assuming an underlying distribution generally yields a narrower confidence interval. Thus, both methods of bootstrapping are important and should be used to compare to each other. However, if no distribution fits the data well, the nonparametric estimates can always be used as a measure based completely on the data itself. Thus, the lack of a well-fit distribution does not pose a problem when estimating the upper percentiles.

A recurring theme throughout this thesis involved Mill B and its very tight data set in terms of variability. Mill B contained one very extreme outlier without which the data set had a range of only about 0.016 inches. This was by far the least variable mill of the six. As mentioned in Chapter 4, removal of the outlier for Mill B occurred since it was such an unusual value and would be removed from the pressing process in normal manufacturing conditions. Other mills could possibly examine Mill B's data set as well as its production process to see what the manufacturer is doing to produce such a tight range of strand thickness values. In fact, the other mills may be able to improve their own processes by determining what Mill B does so well. If they can determine sources of variation, these manufacturers may be able to reduce costs and increase efficiency. Improving the process leads to saving money, producing a better product, and staying in business longer.

The techniques used in this thesis may also be applied to other characteristics of OSB, such as internal bond strength and thickness swell. Forced right censoring at the upper percentiles can be performed to then estimate the lower percentiles where the board is weak. Manufacturers may also be interested in the upper percentiles where the board is very strong. Thus, censoring at lower percentiles can be completed to better estimate the upper values. Further investigation of the upper values may reveal panel strength, which can then be used to improve the process and prevent low strength panels.

This thesis began with an analysis to understand the data sets and determine parametric models. The research involved bootstrapping of the upper percentiles to improve confidence interval estimates obtained through standard statistical inference. The research progressed with an exploration of forced censoring at various values to further improve the interval estimates. The results can be used by scientists and practitioners. Students may also gain insight on reliability analysis and bootstrapping from this thesis.

Chapter 6

Future Research

This chapter provides future research ideas. An important area of future research for this data involves Bayesian analysis. Specifically, researchers may consider finding a posterior distribution for one mill based on a diffuse prior and the data set itself. Once this posterior distribution is obtained for one mill, it can be used as the prior distribution for the other mills. Then, the posterior distributions can be calculated and compared to the results found in Chapter 3 of this thesis. Confidence intervals for the upper percentiles may also be calculated based on the posterior distribution and compared to the results in Chapter 4 of this thesis. The Bayesian approach has numerous advantages despite the criticisms it receives, and exploring this area of statistical inference would be interesting for these data sets. Bayesian analysis may also assist in determining the sample size needed for valid inference. Please see also Insua and Ruggeri (2000) and Ghosh, Delampady, and Samanta (2006) for further information on Bayesian analysis.

Another possible area of future research involves the relationship of flake thickness to internal bond strength or thickness swell. Correlation of these variables may be important. A model that predicts the internal bond strength of the final OSB panel based on the distribution for the thickness of the individual strands may be explored. Brochmann, Edwardson, et al. (2004) is a useful article that may be examined when considering this future area of study. If there is a quantifiable model for strand thickness and final board properties, this finding would be both practical and crucial for scientists and practitioners.

Other co-variables should also be studied. A researcher may be interested in the wood species and strand thickness. Geographic location of wood may be important, i.e., is there a difference in the strength of the trees used in the Southeast as compared to the Northwest due to climate or soil differences? Finally, examining the data sets by manufacturing shift or operator may reveal possible sources of variation in the strand thickness. When the co-variables are included in the data set, quantile regression may be explored. Additionally, a Proportional Hazard (PH) model may be used with this data when co-variables are considered. According to Meeker and Escobar (1998), "The main area for potential application of PH models would appear to be in the analysis of field reliability data for which it is necessary to adjust for covariates like operating environment, use-rate, and so on." The Cox Proportional Hazard model is a semiparametric version of the PH model (Meeker and Escobar 1998). Please see Gertsbakh (1989) for the theory behind the PH model, as well as Meeker and Escobar (1998) for areas of application and further references.

The recurring theme of Mill B having the least variability may be considered further. The researchers here suggest that Mill B has a manufacturing process superior to the other five mills due to its tightness in range when the outlier is removed. Mill B also has one distribution selected, regardless of the censoring point, when the outlier is included in the data set. When the outlier is removed, the distribution changes only once and this occurs when moving from no censoring to some censoring. Thus, it would be interesting to determine whether it helps to have only one distribution for the data set regardless of how much censoring is done. The one distribution for Mill B is no doubt due to its lack of variability, but does this have an effect on how valid the percentile estimates are? Also, since Mill B has less variation, the amount of resin needed when pressing the flakes together to form the board would likely be less variable than that of other mills. Thus, it may be interesting to determine resin usage by mills with greater variability in strand thickness. A study to determine the relationship between strand thickness variability and resin use variability could be very beneficial to mills across the United States.

Finally, thickness swell is a very important subject in the study of OSB. How good the final board is can be measured by its strength, as well as other characteristics like thickness swell or modulus of elasticity. Thickness swell may have tighter confidence interval bands and less variation from one censoring value to another. Thus, it may be easier to perform this analysis, and it would be very practical for manufacturers.

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Appendix

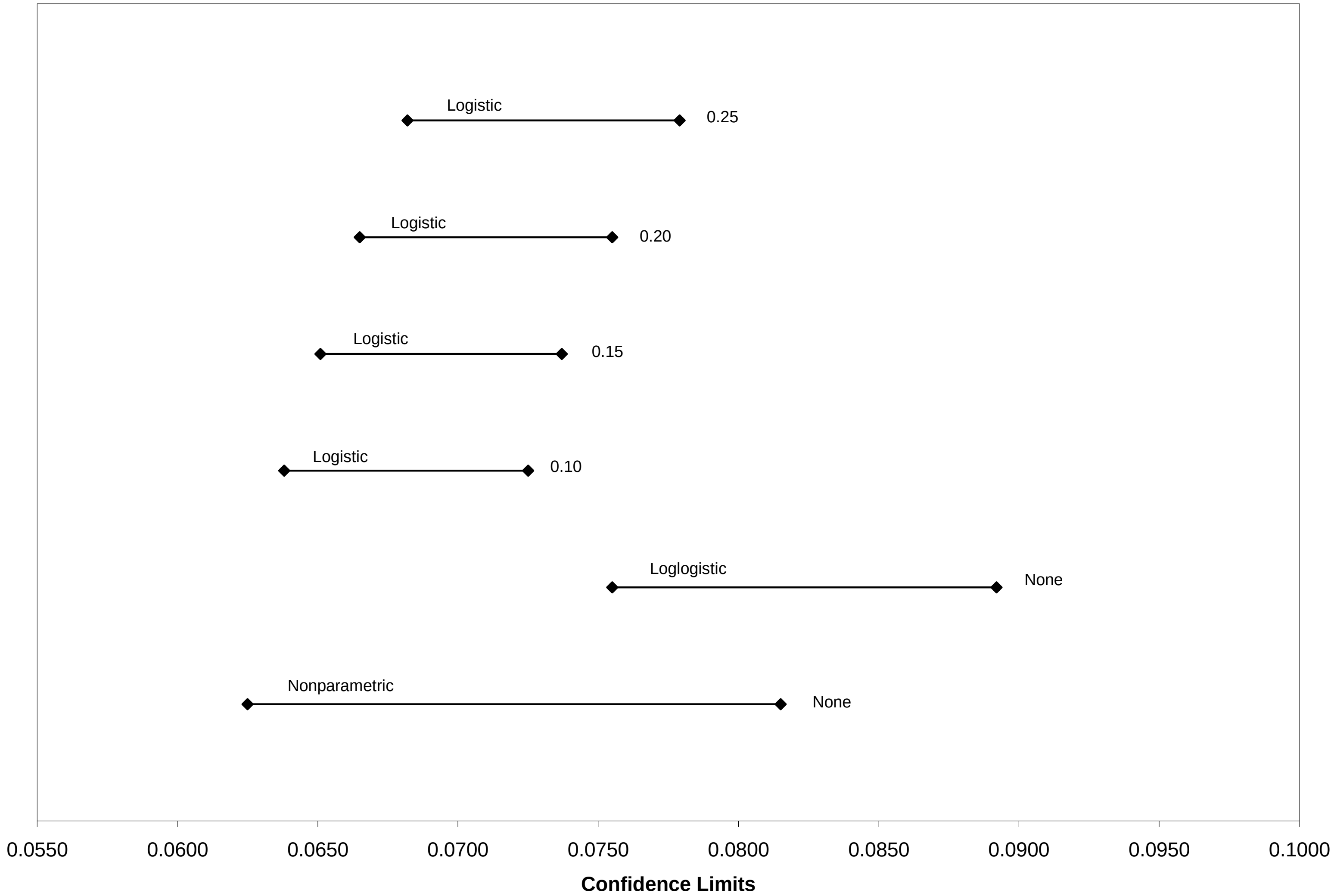

Figure A.1. Mill A bootstrap confidence intervals based on the percentile method for the 0.99 quantile at various censoring points and based on the distributions assumed at those points (scaled).

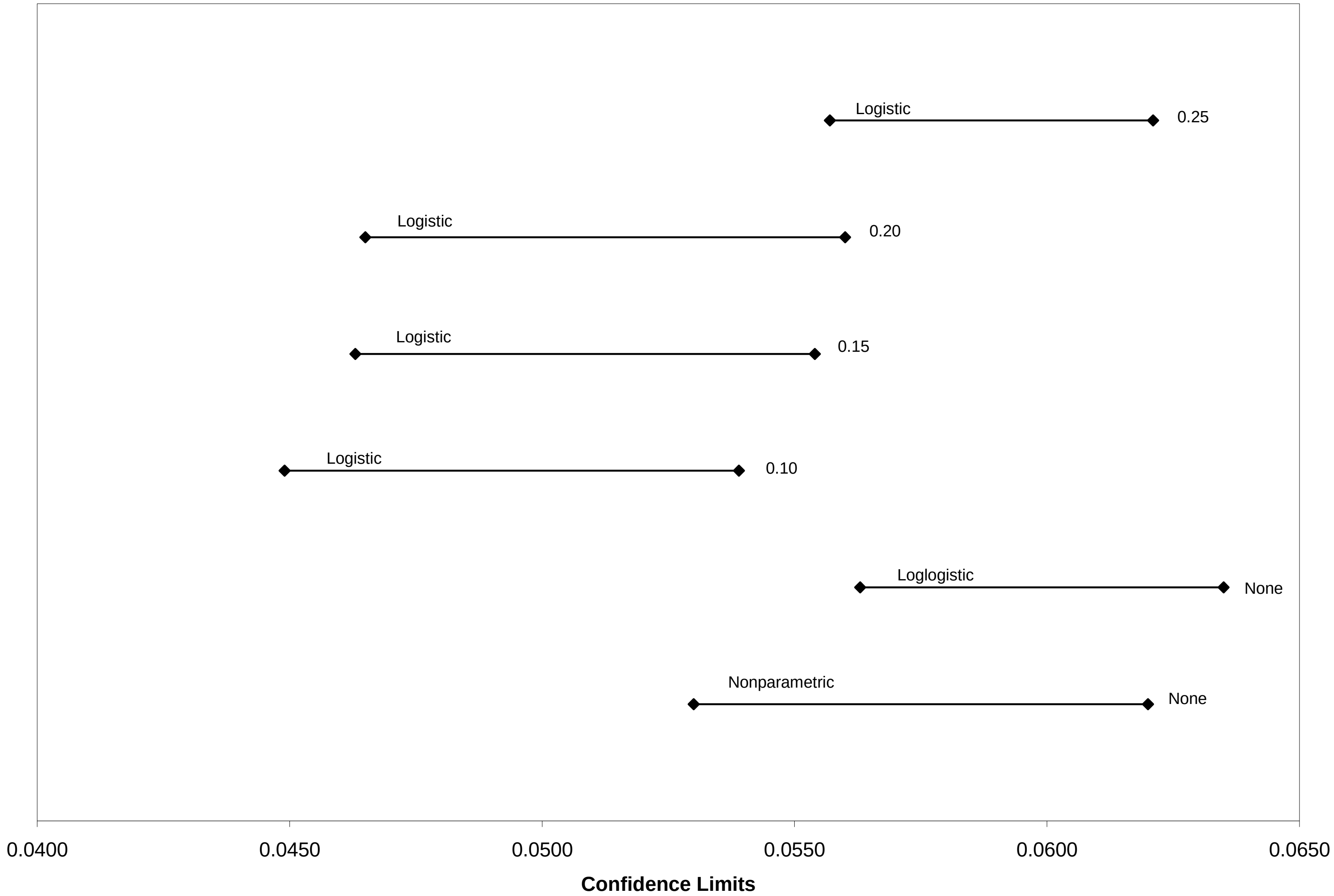

Figure A.2. Mill A bootstrap confidence intervals based on the percentile method for the 0.95 quantile at various censoring points and based on the distributions assumed at those points (scaled).

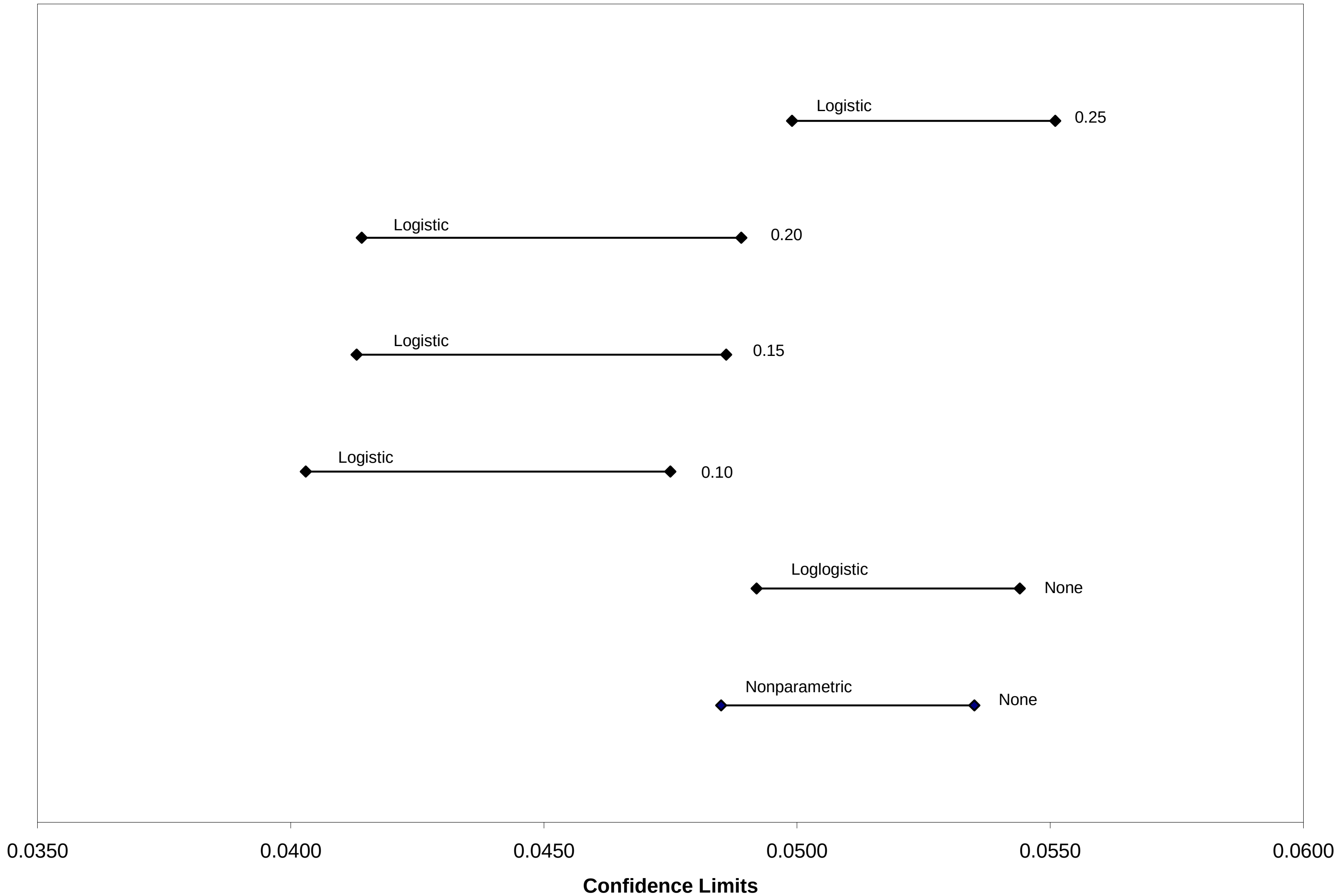

Figure A.3. Mill A bootstrap confidence intervals based on the percentile method for the 0.90 quantile at various censoring points and based on the distributions assumed at those points (scaled).

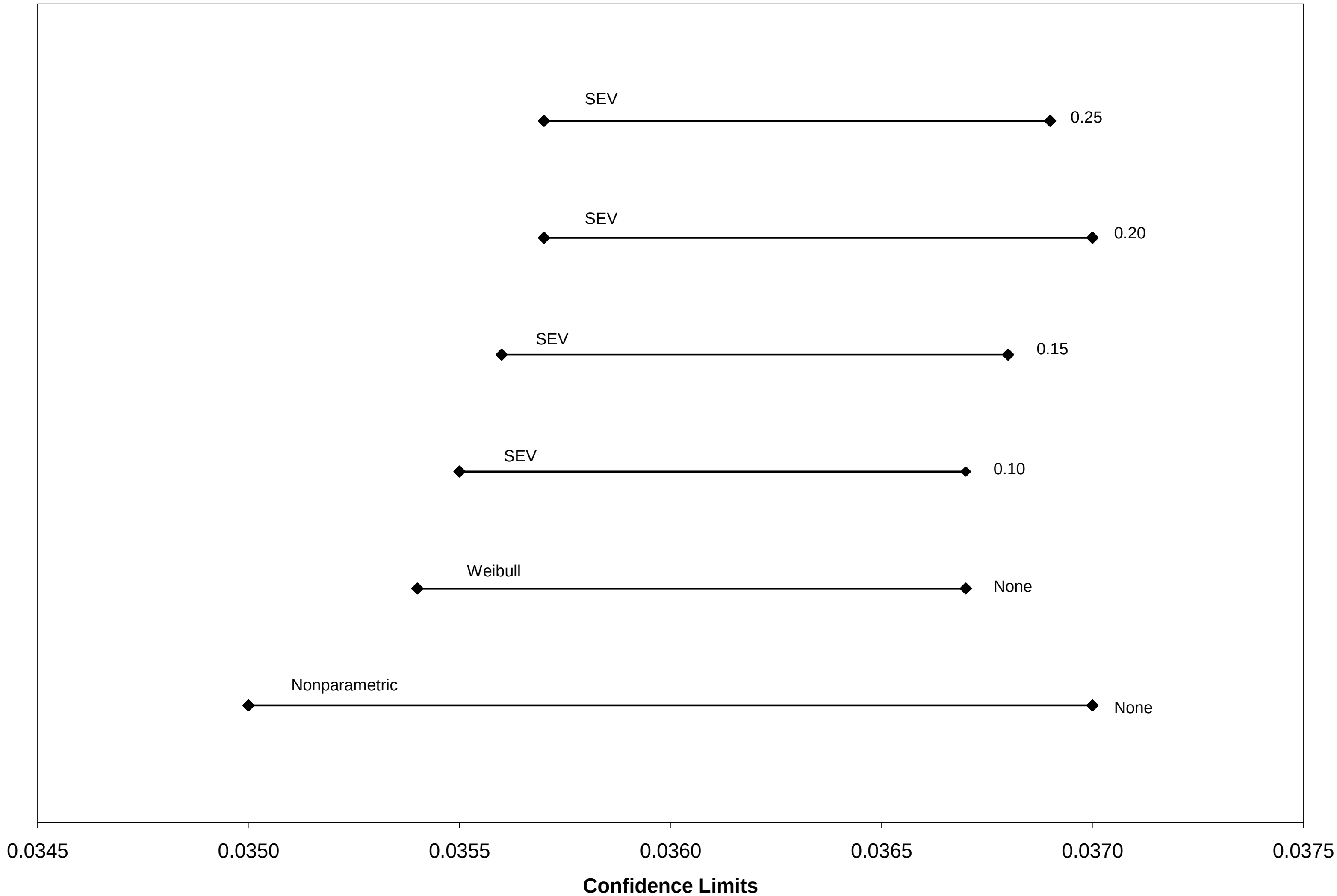

Figure A.4. Mill B (highest outlier removed) bootstrap confidence intervals based on the percentile method for the 0.99 quantile at various censoring points and based on the distributions assumed at those points (scaled).

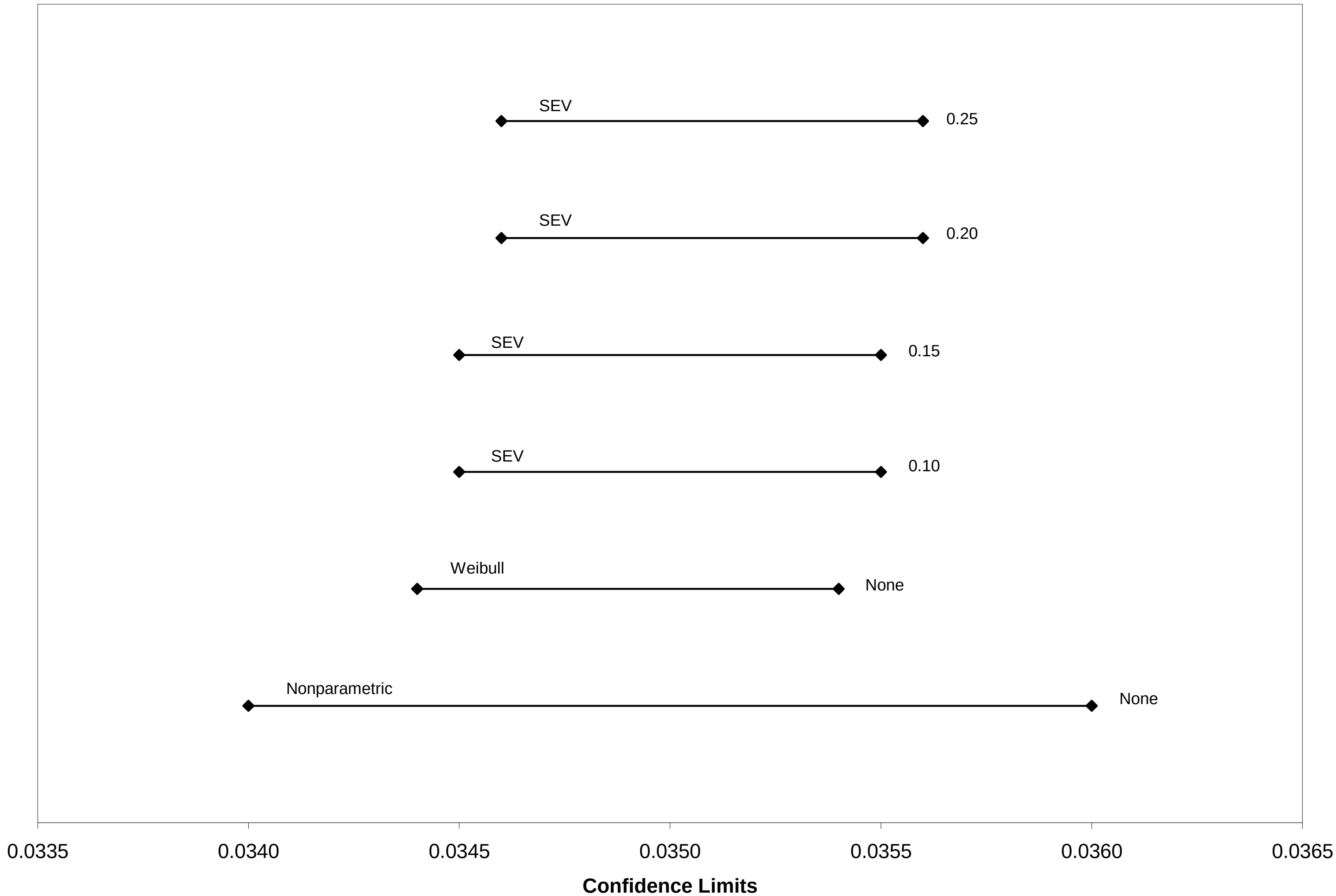

Figure A.5. Mill B (highest outlier removed) bootstrap confidence intervals based on the percentile method for the 0.95 quantile at various censoring points and based on the distributions assumed at those points (scaled).

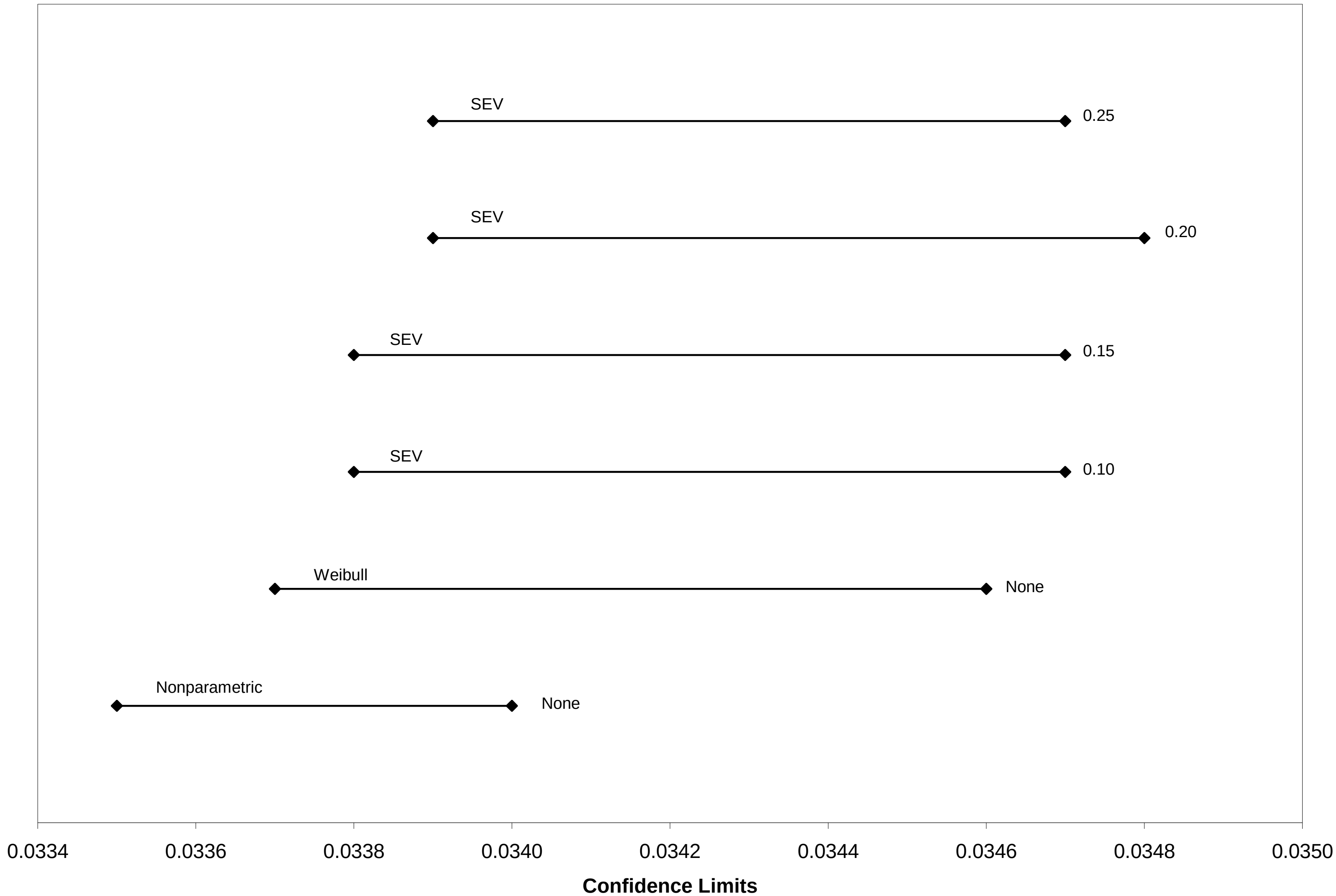

Figure A.6. Mill B (highest outlier removed) bootstrap confidence intervals based on the percentile method for the 0.90 quantile at various censoring points and based on the distributions assumed at those points (scaled).

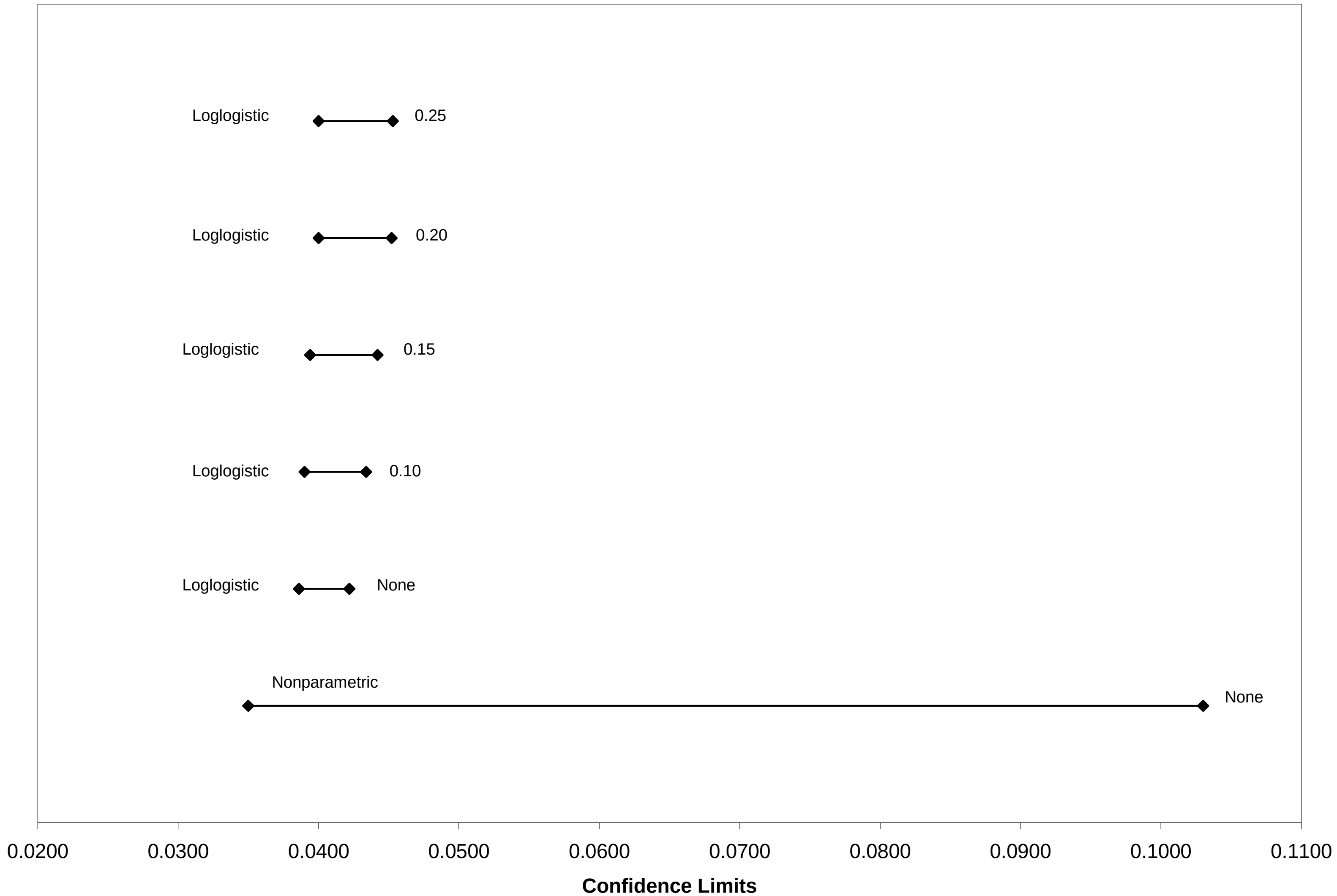

Figure A.7. Mill B (with outlier) bootstrap confidence intervals based on the percentile method for the 0.99 quantile at various censoring points and based on the distributions assumed at those points (scaled).

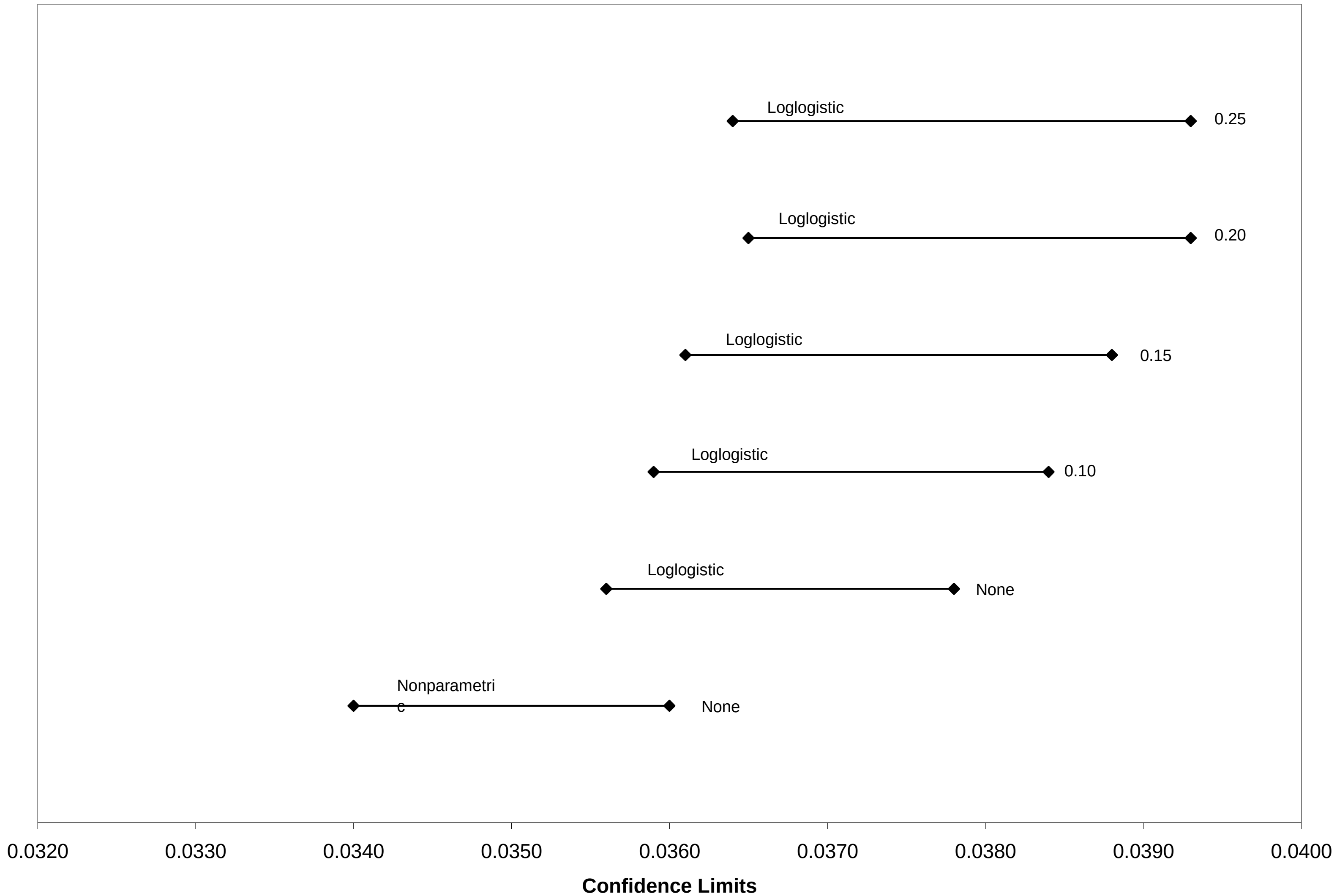

Figure A.8. Mill B (with outlier) bootstrap confidence intervals based on the percentile method for the 0.95 quantile at various censoring points and based on the distributions assumed at those points (scaled).

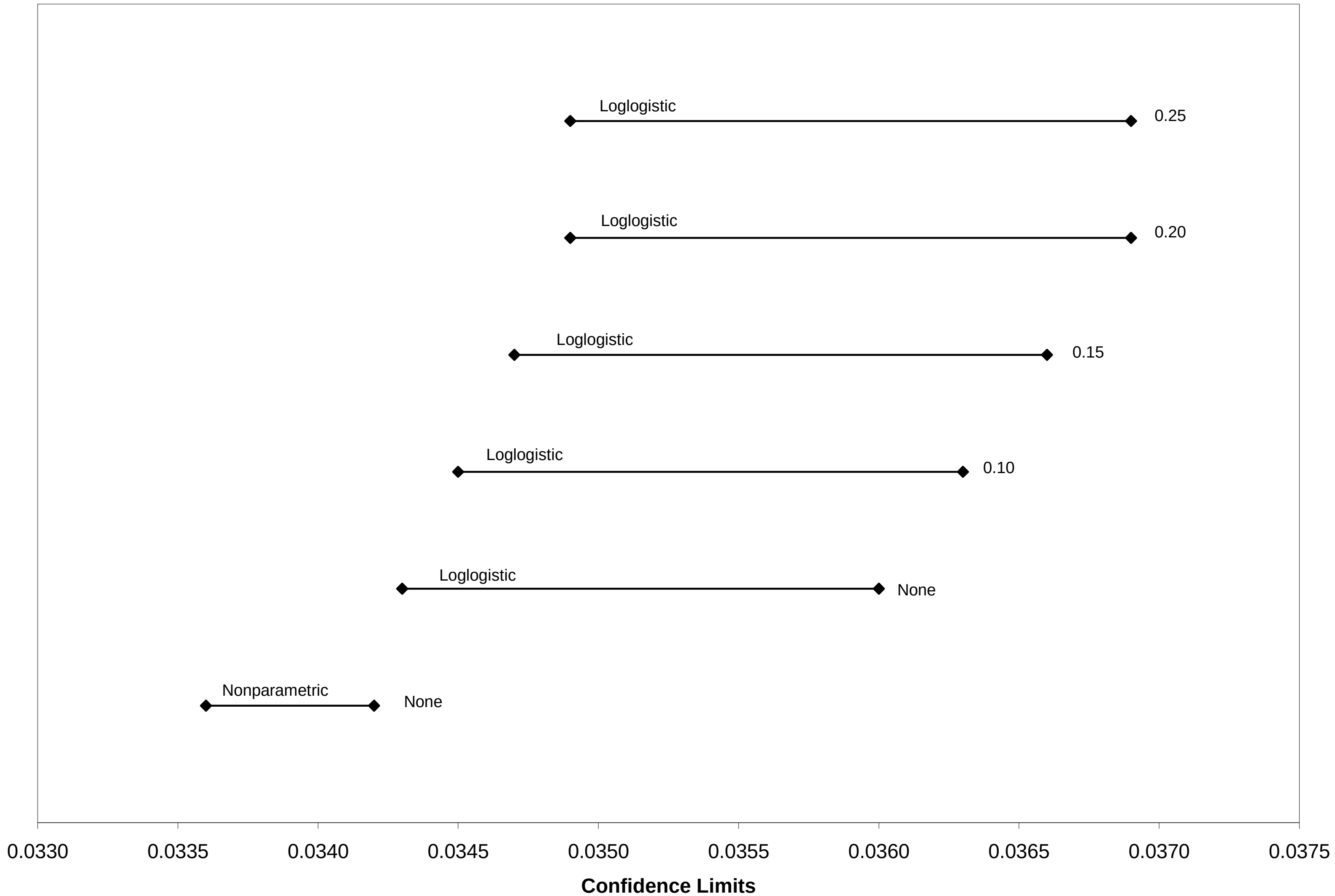

Figure A.9. Mill B (with outlier) bootstrap confidence intervals based on the percentile method for the 0.90 quantile at various censoring points and based on the distributions assumed at those points (scaled).

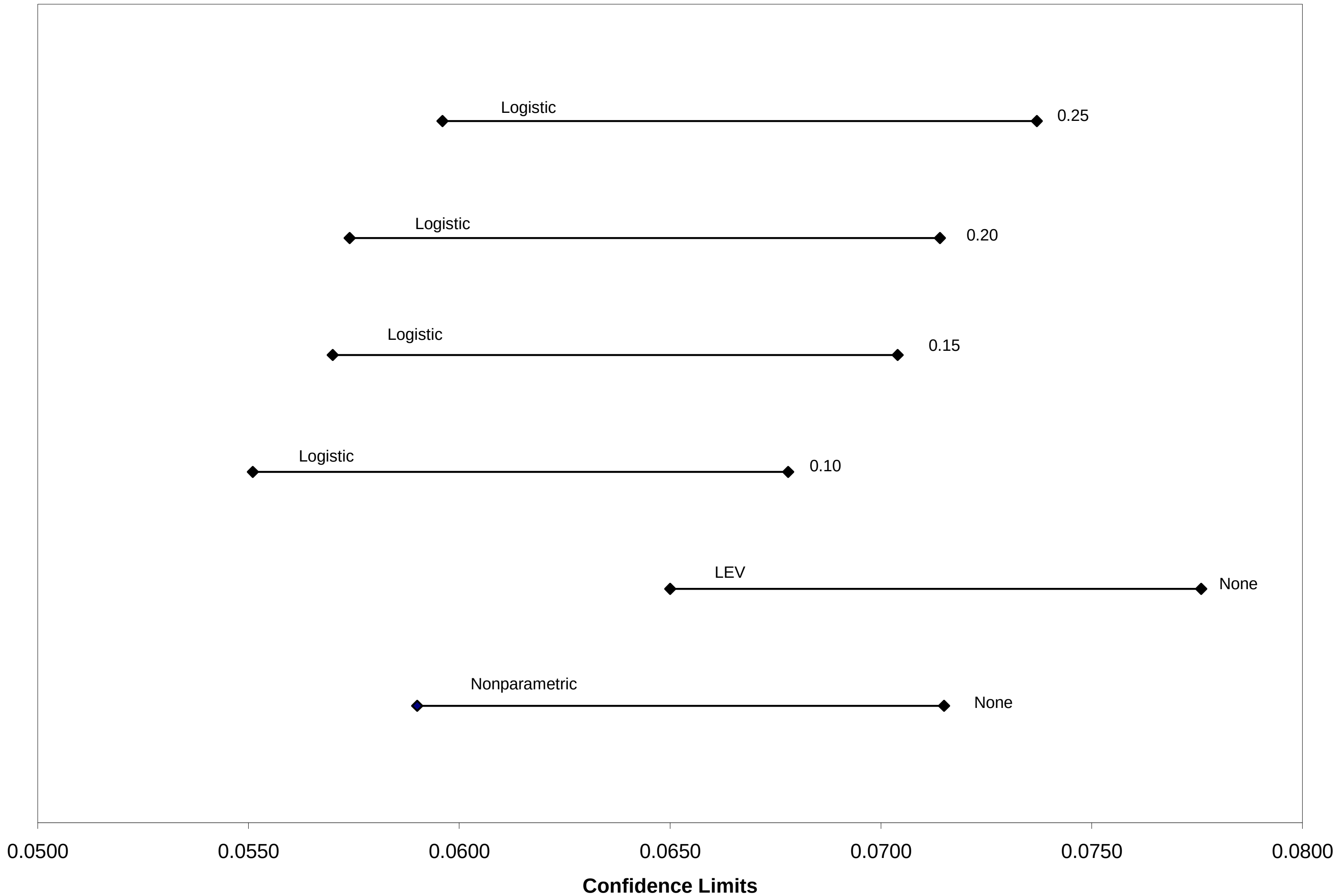

Figure A.10. Mill C bootstrap confidence intervals based on the percentile method for the 0.99 quantile at various censoring points and based on the distributions assumed at those points (scaled).

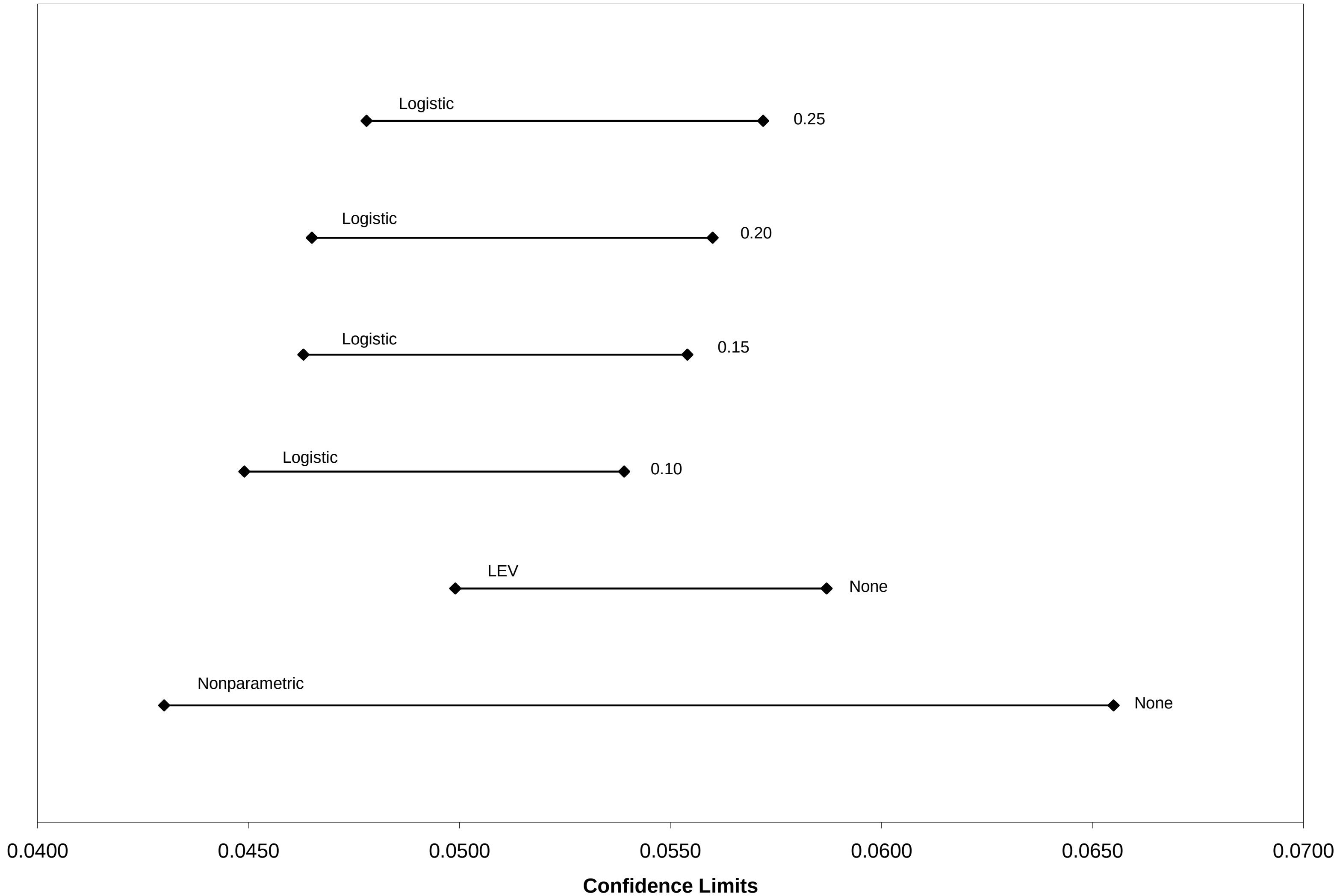

Figure A.11. Mill C bootstrap confidence intervals based on the percentile method for the 0.95 quantile at various censoring points and based on the distributions assumed at those points (scaled).

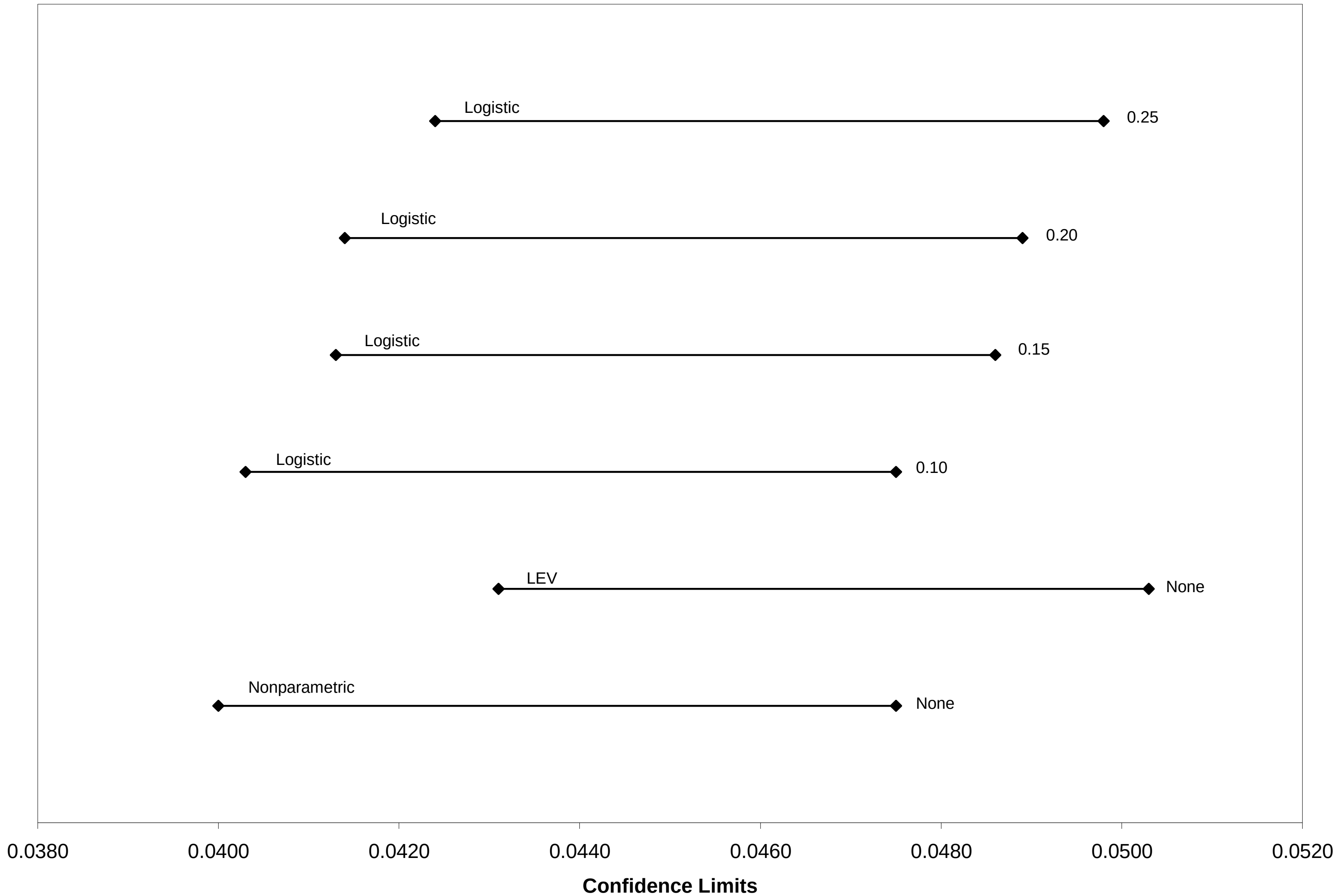

Figure A.12. Mill C bootstrap confidence intervals based on the percentile method for the 0.90 quantile at various censoring points and based on the distributions assumed at those points (scaled).

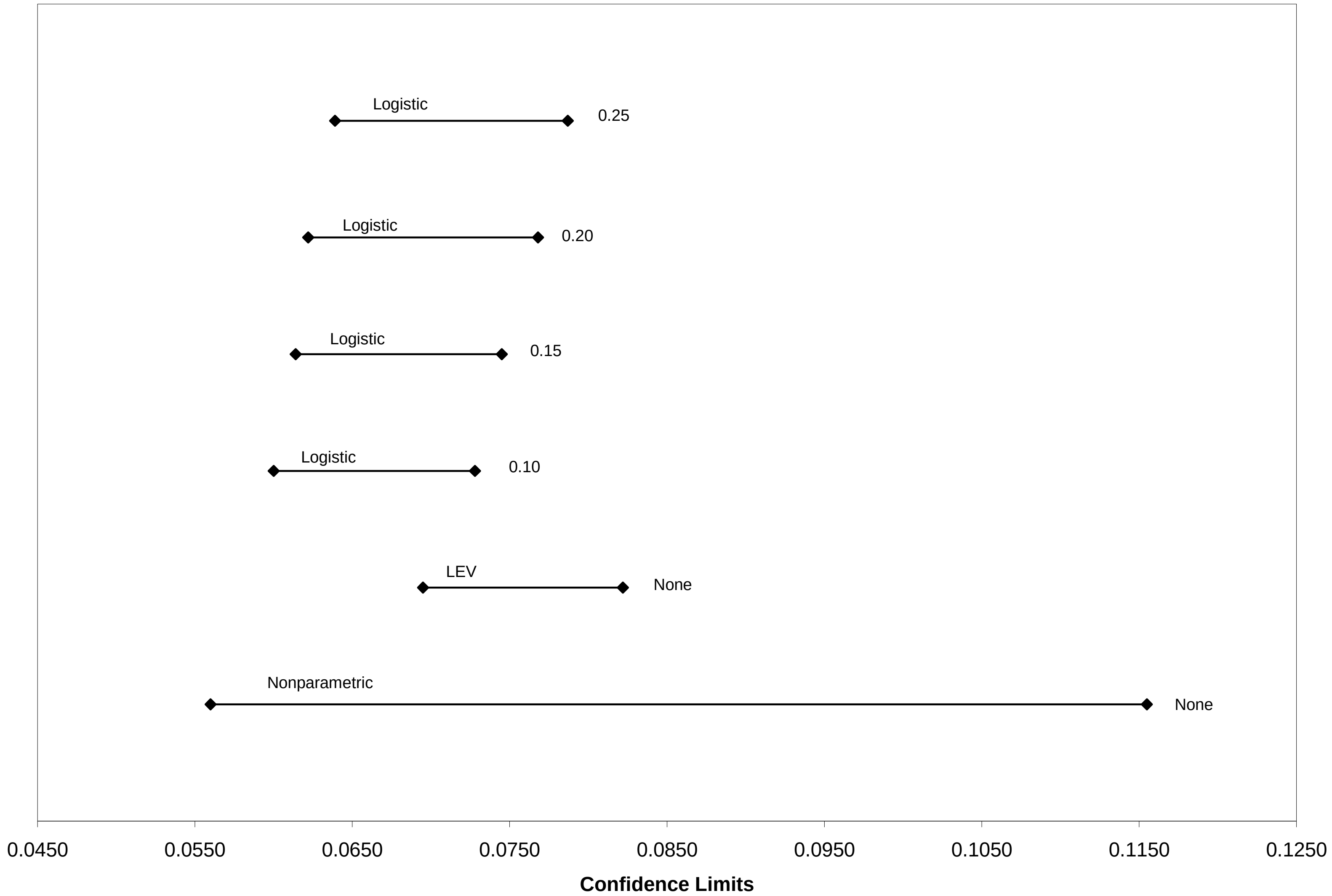

Figure A.13. Mill D bootstrap confidence intervals based on the percentile method for the 0.99 quantile at various censoring points and based on the distributions assumed at those points (scaled).

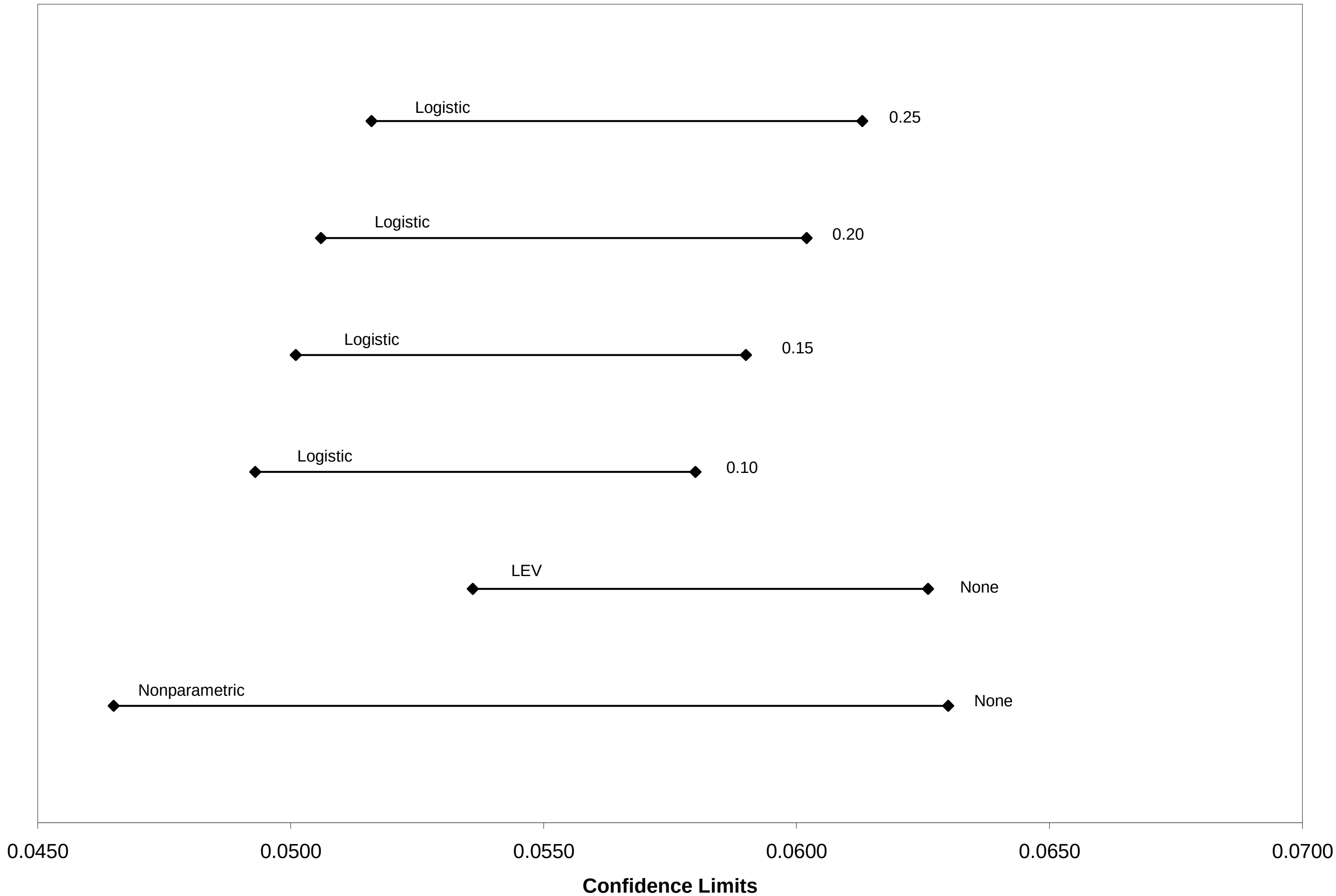

Figure A.14. Mill D bootstrap confidence intervals based on the percentile method for the 0.95 quantile at various censoring points and based on the distributions assumed at those points (scaled).

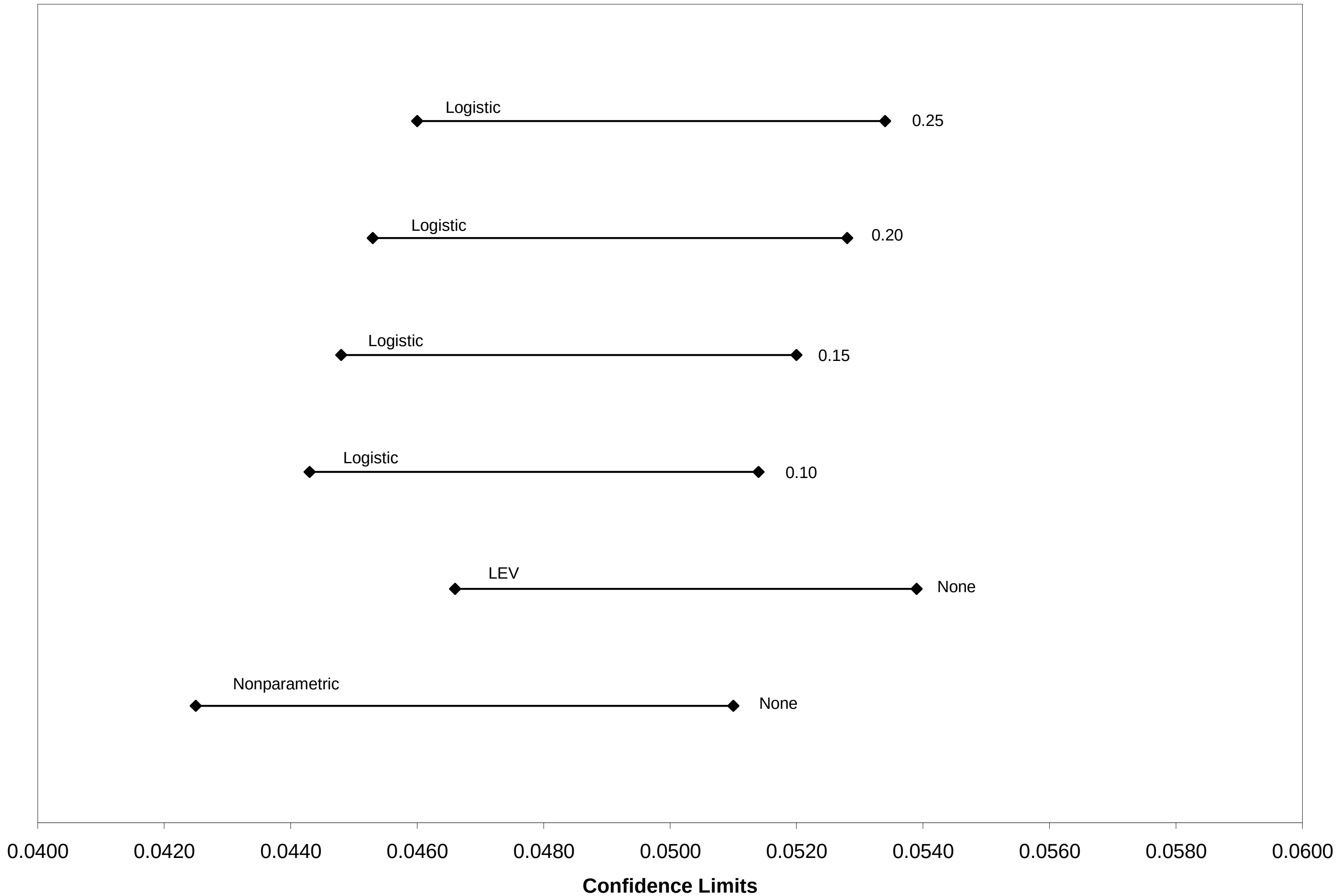

Figure A.15. Mill D bootstrap confidence intervals based on the percentile method for the 0.90 quantile at various censoring points and based on the distributions assumed at those points (scaled).

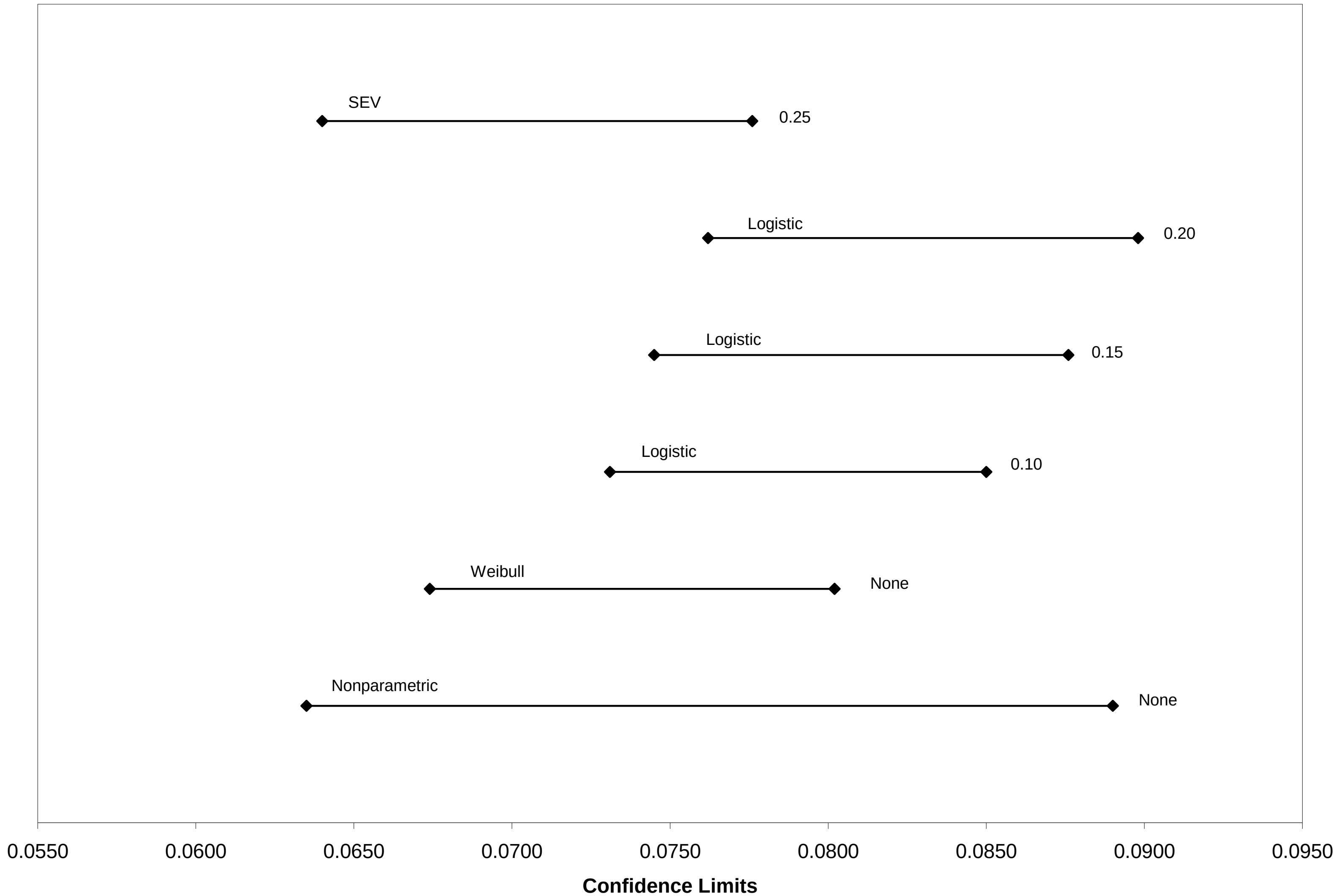

Figure A.16. Mill E bootstrap confidence intervals based on the percentile method for the 0.99 quantile at various censoring points and based on the distributions assumed at those points (scaled).

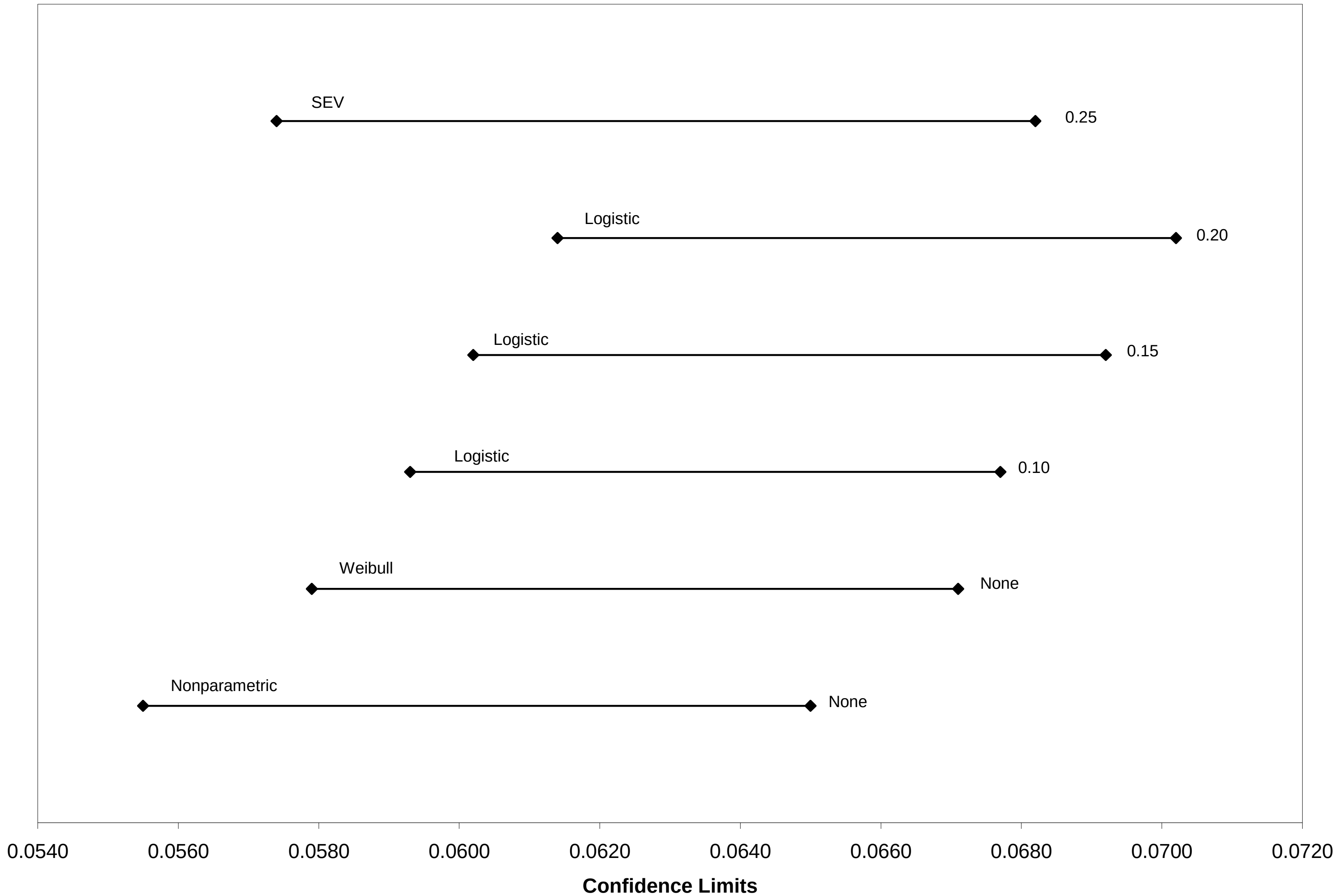

Figure A.17. Mill E bootstrap confidence intervals based on the percentile method for the 0.95 quantile at various censoring points and based on the distributions assumed at those points (scaled).

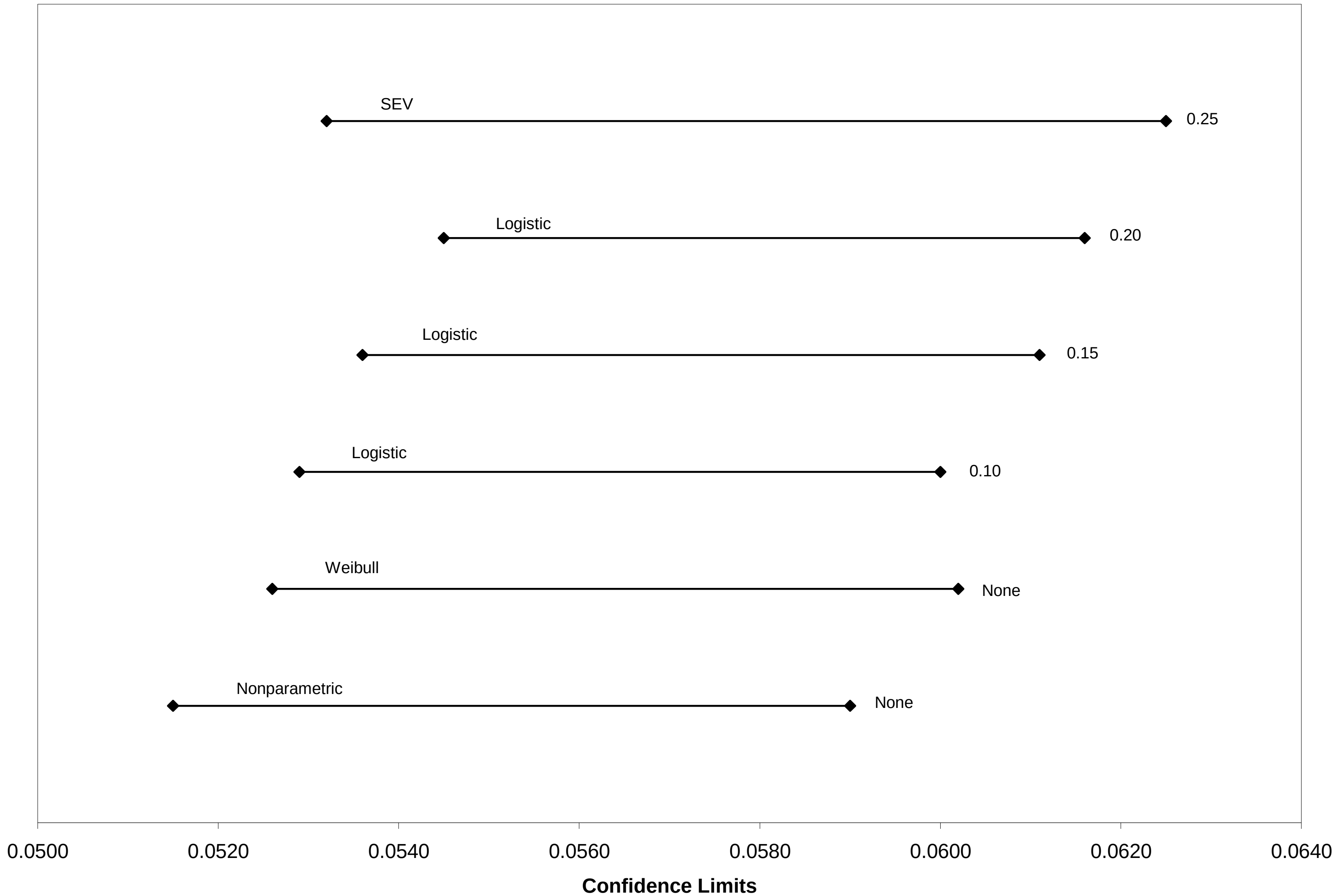

Figure A.18. Mill E bootstrap confidence intervals based on the percentile method for the 0.90 quantile at various censoring points and based on the distributions assumed at those points (scaled).

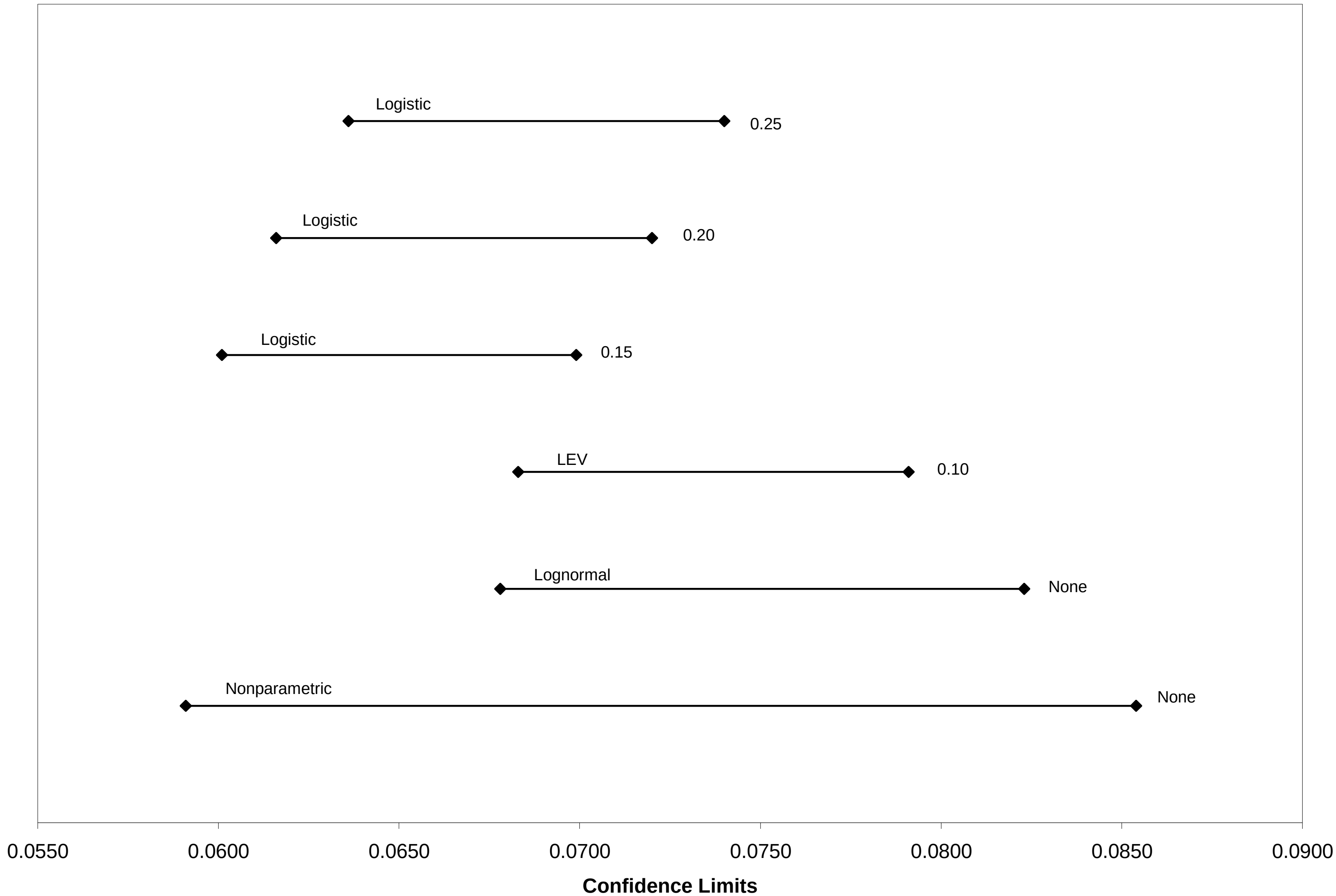

Figure A.19. Mill F bootstrap confidence intervals based on the percentile method for the 0.99 quantile at various censoring points and based on the distributions assumed at those points (scaled).

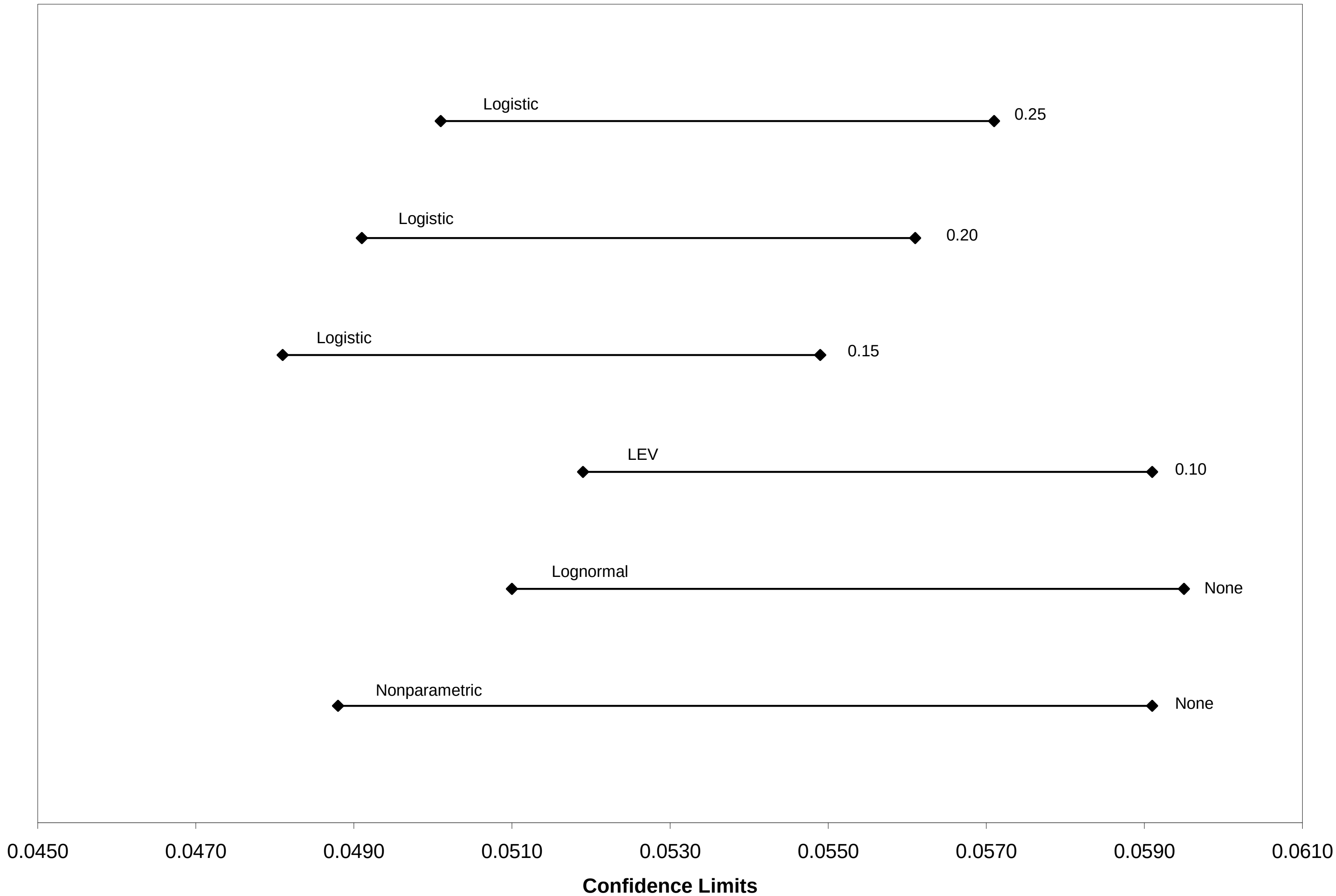

Figure A.20. Mill F bootstrap confidence intervals based on the percentile method for the 0.95 quantile at various censoring points and based on the distributions assumed at those points (scaled).

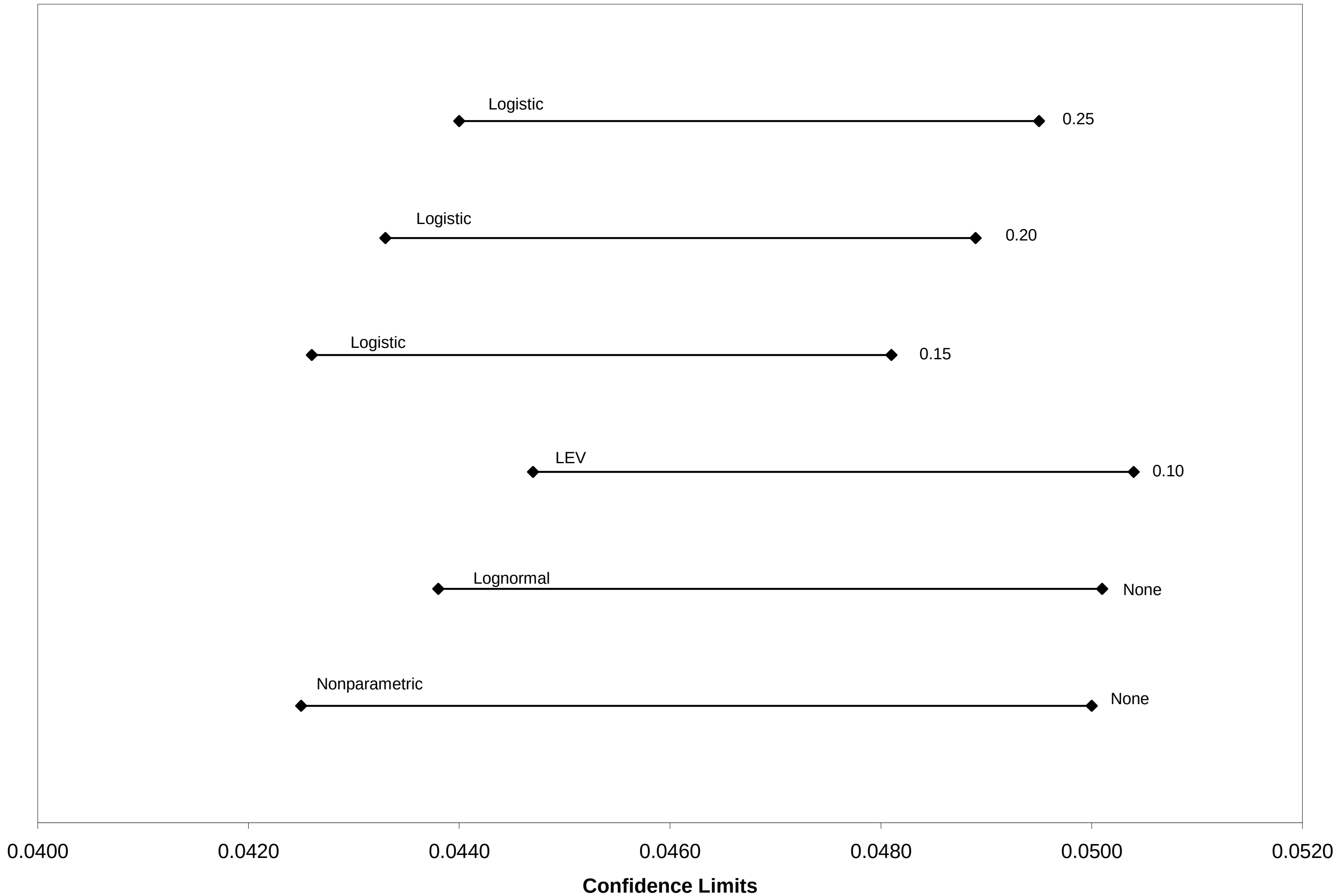

Figure A.21. Mill F bootstrap confidence intervals based on the percentile method for the 0.90 quantile at various censoring points and based on the distributions assumed at those points (scaled).

Table A.1. Mill A confidence limits for the 0.90, 0.95, and 0.99 quantiles with no censoring and censoring at the 0.25 quantile.

	Quantile		
Method	0.90	0.95	0.99
Nonparametric	[0.0485, 0.0535]	[0.0530, 0.0620]	[0.0625, 0.0815]
No Censoring	[0.0492, 0.0544]	[0.0563, 0.0635]	[0.0755, 0.0892]
0.25 Censoring	[0.0499, 0.0551]	[0.0557, 0.0621]	[0.0682, 0.0779]

Table A.2. Mill B (highest outlier removed) confidence limits for the 0.90, 0.95, and 0.99 quantiles with no censoring and censoring at the 0.25 quantile.

	Quantile		
Method	0.90	0.95	0.99
Nonparametric	[0.0335, 0.0340]	[0.0340, 0.0360]	[0.0350, 0.0370]
No Censoring	[0.0337, 0.0346]	[0.0344, 0.0354]	[0.0354, 0.0367]
0.25 Censoring	[0.0339, 0.0347]	[0.0346, 0.0356]	[0.0357, 0.0369]

Table A.3. Mill B (with outlier) confidence limits for the 0.90, 0.95, and 0.99 quantiles with no censoring and censoring at the 0.25 quantile.

	Quantile		
Method	0.90	0.95	0.99
Nonparametric	[0.0336, 0.0342]	[0.0340, 0.0360]	[0.0350, 0.1030]
No Censoring	[0.0343, 0.0360]	[0.0356, 0.0378]	[0.0386, 0.0422]
0.25 Censoring	[0.0349, 0.0369]	[0.0364, 0.0393]	[0.0400, 0.0453]

Table A.4. Mill C confidence limits for the 0.90, 0.95, and 0.99 quantiles with no censoring and censoring at the 0.25 quantile.

	Quantile		
Method	0.90	0.95	0.99
Nonparametric	[0.0400, 0.0475]	[0.0430, 0.0655]	[0.0590, 0.0715]
No Censoring	[0.0431, 0.0503]	[0.0499, 0.0587]	[0.0650, 0.0776]
0.25 Censoring	[0.0424, 0.0498]	[0.0478, 0.0572]	[0.0596, 0.0737]

Table A.5. Mill D confidence limits for the 0.90, 0.95, and 0.99 quantiles with no censoring and censoring at the 0.25 quantile.

	Quantile		
Method	0.90	0.95	0.99
Nonparametric	[0.0425, 0.0510]	[0.0465, 0.0630]	[0.0560, 0.1155]
No Censoring	[0.0466, 0.0539]	[0.0536, 0.0626]	[0.0695, 0.0822]
0.25 Censoring	[0.0460, 0.0534]	[0.0516, 0.0613]	[0.0639, 0.0787]

Table A.6. Mill E confidence limits for the 0.90, 0.95, and 0.99 quantiles with no censoring and censoring at the 0.25 quantile.

	Quantile		
Method	0.90	0.95	0.99
Nonparametric	[0.0515, 0.0590]	[0.0555, 0.0650]	[0.0635, 0.0890]
No Censoring	[0.0526, 0.0602]	[0.0579, 0.0671]	[0.0674, 0.0802]
0.25 Censoring	[0.0532, 0.0625]	[0.0574, 0.0682]	[0.0640, 0.0776]

Table A.7. Mill F confidence limits for the 0.90, 0.95, and 0.99 quantiles with no censoring and censoring at the 0.25 quantile.

	Quantile		
Method	0.90	0.95	0.99
Nonparametric	[0.0425, 0.0500]	[0.0488, 0.0591]	[0.0591, 0.0854]
No Censoring	[0.0438, 0.0501]	[0.0510, 0.0595]	[0.0678, 0.0823]
0.25 Censoring	[0.0440, 0.0495]	[0.0501, 0.0571]	[0.0636, 0.0740]

Vita

Jennifer S. Chastain is a graduate research assistant under Dr. Timothy M. Young at the Forest Products Center at the University of Tennessee, Knoxville. She plans to graduate from the University of Tennessee with a Master of Science degree in Statistics in May 2009. Jennifer received a Bachelor of Science degree in Business Administration with a major in Finance and a minor in Mathematics from the University of Tennessee, Chattanooga, where she graduated Summa Cum Laude. After completing her undergraduate studies, Jennifer worked for Beacon Verification Services in Chattanooga, a company for which she had been an intern prior to graduating from UTC. She stayed with Beacon until she moved to Knoxville to pursue her graduate degree. During her first year in graduate school, Jennifer worked as both a graduate research assistant and a graduate teaching assistant. She returned to Beacon Verification during the summer between her first and second years in graduate school. In her second year of graduate school, Jennifer worked as a graduate research assistant only, focusing mainly on the research of this thesis and paper development. She is a member of Beta Gamma Sigma and the Alpha Society for economics.