Assessing Nonresponse Bias in Estimates of Employment

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1. INTRODUCTION

Response rates often serve as the most visible measure of survey quality, but this may be just a matter of convenience. Although response rates are easy to produce, they do not necessarily provide an accurate measure of survey bias. Low response rates only indicate the possibility of bias. Recent research on household surveys (Haraldsen, Stalnacke, and Fosen 1999; Keeter, Miller, Kohut, Groves, and Presser 2000; Curtin, Presser, and Singer 2000) found little relationship between level of nonresponse and bias. Furthermore, Brick and Bose (2001) showed that adjusting survey weights for nonresponse can reduce bias substantially. While these results are encouraging, the research was confined largely to response rates ranging from forty to seventy percent. It is still unclear what happens when the rates are outside that range.

Of even greater importance here is the fact that this research only looks at the effects of household nonresponse. Differences between responding and nonresponding units in establishment surveys, usually conducted by or for the government, could have a greater effect on bias than in household surveys. Establishments vary much more in terms of size and structure. Tomaskovic-Devey, Leiter, and Thompson (1994) found that certain establishments, such as large ones, those in retail trade, and those establishments in industries with high profits, are less likely to respond. Weighting adjustments, to be effective, must be based on these characteristics. On the other hand, it is especially difficult to adjust weights to account for missing data from a company that makes up a large share of the market in a particular industry or adjustment cell. Most research on establishment nonresponse has focused on characterizing nonresponding establishments (Hidiroglou, Drew, and Gray 1993), adjusting for nonresponse (Sommers, Riesz, and

Kashihara 2004), or trying to understand why establishments do not want to respond (See McCarthy, Johnson, and Ott 1999; McCarthy and Beckler 2000.).

This paper examines the relationship between establishment nonresponse and bias using data from the Current Employment Statistics (CES) Program at the U.S. Bureau of Labor Statistics (BLS). The CES collects employment, hours, and earnings data monthly from a sample of over 300,000 U.S. establishments. The survey tracks monthly gains and losses in number of jobs in various sectors of the economy. Since the CES design became probability based in the late 1990s, interest in the effects of nonresponse on estimates has increased. Copeland (2003) investigated the effects of late responders on early estimates from the survey and developed methods for adjusting for this missing data. The focus here is on estimating bias for establishment subpopulations with different patterns of nonresponse.

2. **THEORY AND** METHOD

2.1 Theory

Developing a theory for identifying relationships between nonresponse and bias requires first considering the mathematical representation of how nonresponse can affect an estimate. The first equation shows the potential effect on an estimate of the population mean, $\bar{Y}_n$**,** from a sample survey with nonresponse, where $\bar{Y}_r$ is the mean of respondents, $\bar{Y}_m$ is the mean of the nonrespondents, **m** is the number of cases missing due to nonresponse, and **n** is the total sample size.

$$\bar{Y}_r = \bar{Y}_n + \left(\frac{m}{n}\right)\left[\bar{Y}_r - \bar{Y}_m\right] \qquad (1)$$

The weighted nonresponse rate (**m**/**n**) just measures the potential effect of nonresponse where that effect is maximized as the nonresponse rate approaches one and is minimized as it approaches zero. In the case of establishment surveys, the nonresponse rate is weighted by the size of the firm. Therefore, the nonresponse measure used here is the proportion of total employees covered by the sample of firms not accounted for as a result of nonresponse.

To know what the actual effect is for a given nonresponse rate, however, one must know how different the two means are at that rate. Figure 1 provides hypothetical examples of two possible relationships between nonresponse rate and the difference between the means of respondents and nonrespondents. Note first the solid line representing the level of potential bias as **m/n** moves from zero to one. The two broken lines assume the difference between the means is zero at either the 30^{th} or 50^{th} percentile on the nonresponse rate axis. At these two points, nonresponse is actually random with respect to its effect on the sample mean.

If these curves were available, another curve relating nonresponse rate and bias could be defined by the product of the differences between the means at various levels of nonresponse and the nonresponse rate itself. Figure 2 illustrates this situation using the two hypothetical examples and the straight line representing potential bias. While small, some bias exists in both cases even when nonresponse is at a low level. We believe that it is likely that true relationship (nature of the curve) will depend on the characteristics of the sample units. Thus, the curves could differ by subpopulation. If subpopulation (typically publication cell) estimates are produced, various levels of bias could exist across these estimates no matter the relationship between bias and nonresponse for the total population.

2.2 Method

2.2.1 The Data

Establishments in the U.S. are required to report total employment to the states each quarter for unemployment insurance purposes. BLS obtains these data from each of the states for use as a sampling frame (the QCEW). In this case, the sample of establishments is all units in the CES sample in quarter 2 of 2003. The selection of the sample units was based on a probability design stratified by industry, geography, and size of firm. The sample size in quarter 2 was 441,961.

The measure of employment is the link relative estimator, which uses a weighted sample trend within an estimation cell, based upon common reporters between the prior and current months, to move forward the prior month's estimate for that cell (Copeland, 2003). Let $\mathbf{Y_t}$ be the estimate for a primary cell for month **t**, then

$$Y_t = R_{t,t-1} * Y_{t-1} \qquad (2)$$

where $\mathbf{R_{t,t-1}}$ is the ratio of the total sample employment in month **t** to the total sample employment in month **t-1** for all sample units reporting data for both months. Using the most recent employment reports in the QCEW (not CES) for both responders and nonresponders, the difference in the link relatives for respondents and nonrespondents is calculated for various subpopulations defined by industry and size within industry. At this point, the link relative of responders is not compared to that for the entire sample, because we are interested in testing the above theory. Results presented are not weighted by probability of selection, but weighted results show similar patterns

The subpopulations studied differ from those defined by CES estimation cells in order to maximize the power of the sample size and focus on just size and industry. The paper also differs from CES estimation in that those estimates are benchmarked annually to the QCEW frame. The combination of the use of benchmarking and estimation cells is thought to remove much of the bias. The conclusions from the present analysis might be helpful in understanding the potential for bias in different groups but isn't intended to estimate the magnitude of the actual bias in the CES.

2.2.2 Quantile Regression

Quantile regression models the relationship between predictors and the conditional quantiles of a response variable. This is useful if the relationship between the predictors and the response variable changes over the conditional distribution of the response variable. The coefficients from a quantile regression can describe the relationship between independent variables over the distribution of the dependent variable. This is especially useful in applications where the extremes are important. The method has been used to study Gross Domestic Product (Koenker and Machado, 1999), job flow and worker skills (Lengermann and Vilhuber, 2002), and wage data (Buchinsky, 1998).

Because size of firm may be related to the propensity to respond, the effects of size of firm on nonresponse bias is examined first. The covariate is whether the firm responded to the Current Employment Statistics survey. The quantile curves show how the relationship between nonresponse and firm size varies by the conditional distribution of firm size. Since industries can be expected to have different patterns, the quantile regressions are done by industry.

The results are based on a test of the difference in employment between CES responders and nonresponders at various points on the distribution of size of firm within industry. $Y=a+Bx+e$ is estimated for different size quantiles, where x is an indicator of nonresponse (essentially a t-test). If size of firm is associated with nonresponse, the coefficients relating nonresponse to the differences in means for employment is likely to change for different size firms, and these patterns of change may be unique by industry. To be more specific, the quantile regression shows the coefficients relating nonresponse (coded 0) to the size of firm. Each point on the curve is a regression relating nonresponse to size conditional on the rest of the distribution.

Because of the skewness in the distribution of firm size (many fewer large firms compared to small ones) affects standard errors, a stabilizing transformation (the log of size) was used in addition to original size. Since the coefficients are based on linear models, the transformation makes the distribution of responders and nonresponders more reasonable. Results for both size and log of size were produced. These results are displayed by industry using both graphs and box and whisker plots.

3. ANALYSIS

Table 1 defines the NAICS 2002 industry categories used in this analysis. Figure 3 contains a chart of the response rates at final closing for these industry categories in the second quarter of 2003. The response rates range between 30 percent and 50 percent. In general, older industries have somewhat higher response rates than a number of industries in the emerging service sector.

Figures 4-24 show pairs of quantile curves for 21 different industry groups. The first curve in each figure is based on the link relative estimator across the distribution of true size, which is positively skewed. The second curve is based on the log transformed values. The vertical axis shows the coefficents for the relationship between nonresponse and establishment size (bias). The horizontal axis shows the quantiles (.1, .15, .2, .25, .4, .5, .75, .8, .9, and .95).

Four patterns emerge from this analysis. The most common is a rapidly increasing positive bias in the untransformed values in the top half of the size distribution. This pattern is typified by Agriculture; Mining; Metal Manufacturing; Transportation and Warehousing; Information; Finance and Insurance; Professional, Scientific and Technical Services; Administrative Services and Waste Management; and Accommodation and Food Services. The upturn is most severe for Transportation and Warehousing; Information; Finance and Insurance; Professional, Scientific and Technical Services; Administrative Services and Waste Management; and Accommodation and Food Services. Because of the large 95 percent confidence bands at the end of the distribution, the bias is not always staistically significant. The log transformed values give a more complete picture, since they have more reasonable confidence intervals. The quantile regression curves using the log of size show smaller firms have proportionately a great deal more bias than larger firms, as can also be seen in the accompanying box & whisker plots.

The next set of industries have a late accelerating bias, like the first set of industries, where the coefficients were fairly flat but accelerate in the upper half of the distribution.

What distinguishes this group is the **increase** in bias at the upper quantiles of the log of size distribution. The Health Care and Social Assistance industry (Figure 21) is a good example of this pattern. Other industries that fit this pattern are Retail Trade; Real Estate, Rental and Leasing; Education Services; and Other Services.

Another common pattern is a more gradually increasing bias reaching an asymptote in the higher quantiles of the distribution of size. For example, in Figure 7 (Construction) the bias increases gradually and tops out at about the 90th percentile. Industries with a similar pattern are Food Manufacturing; Wood and Mineral Manufacturing; Wholesale Trade; and Arts, Entertainment and Recreation. The 95 percent confidence bands show the increasing variance of the parameters at the higher quantiles, probably related to the skewness of the distributions. Since some of the confidence bands include the zero point, it is difficult to say that any bias exists, although the trend for higher estimates for larger firms is expected. Note the distributions for log of size are quite similar to those in the first group of industries.

Two industries, Utilities and Management of Companies and Enterprises, have a bias distribution across log of size that is much like the first and third groups of industries (declining). For the untransformed distribution of size, however, they are both unique. In the case of Utilities (Figure 6), the bias is virtually nonexistent until the very end where it is still quite small and not statistically significant. Management of Companies and Enterprises (Figure 18) has the most unusual bias pattern across the distribution of size. It too is flat at zero bias until near the end, but then the bias becomes noticeably negative.

In order to directly examine the relationship between response rate and bias, the data are aggregated to the MSA level (for MSAs with at least five sample points) and, using quantile regression once again, the level of bias in MSA estimates of employment by industry are observed for varying rates of nonresponse in the MSAs (Figures 25-45). The vertical axis gives the bias coefficients for nonresponse in MSA estimates for various quantiles on the distribution of MSA response rates (horizontal axis) for the particular industry at hand. Keep in mind that the average micro-level response rate for these industries is between 30 and 50 percent. Of course the aggregate response rates can range between zero and 100 percent. For example, there were only 75 MSAs in Agriculture, but the minimum and maximum rates were 0 and 1, with a mean of 0.296. In the case of Retail Trade, the 670 MSAs had minimum and maximum rates of 0.088 and 0.800, with a mean of 0.435. First note that the confidence intervals (at 95 percent) can be quite large, especially at the ends of the distribution where the number of MSAs included may be small. In almost all cases, there is some statistically significant positive bias. The bias tends to be greatest at the low end of the response rate distribution, but it usually exists across the distribution and can even be significant at the upper end. The industries do differ in terms of the shape of their curves. Some slope downward toward zero bias (Agriculture; Metal Manufacturing; Transportation and Warehousing; Professional, Scientific and Technical Services; and Accommodation and Food Services). A few drift upwards (Retail Trade; Education Services; and Health Care and Social Assistance). Utilities and Other Services have U-shaped distributions with greater bias on both ends of the response rate distribution. The curves in the remaining industries have flat distributions in the middle with the bias either up or down on either end. There is some evidence that the bias is greater, as would be expected, for MSAs with low response rates. But the same is true for the upper end in a few cases. Although the variance is larger at each end, there is some indication that the distribution behaves differently on the ends.

4. Discussion

Clearly, quantile regression is a useful technique for studying nonresponse bias in establishment survey (both at the micro and aggregate levels). A number of studies have found that larger firms are more reluctant to respond (Tomaskovic-Devey, Leiter, and Thompson 1994; Phipps, Jones, and Tucker 2007). Perhaps this is because the burden on large firms is greatest; they have more data to gather and they are often certainty units in panel surveys. The analysis in this paper indicates that large firms do contribute more to nonresponse bias. They make up a larger portion of each industry, so if they are missing, it has a greater effect. That is why survey organizations focus their nonresponse followup efforts on large firms (See Hidiroglou, Drew, and Gray 1993.). On the other hand, the results also show that a larger proportion of small firms do not respond. In certain industries (e.g., Retail Trade) and perhaps sparsely populated areas, this nonresponse problem could be significant. Note also that, at least for the time period studied here, even the missing larger firms caused a positive bias indicating these firms may be relatively large but smaller than their responding counterparts.

The patterns of differences between industries did vary, but this variance did not coincide with the differences in industry response rates. Although there are several cases where bias in the middle of the size distribution is significant, the bias problems for many industries are more acute on either end of the distribution of establishment size (either in absolute size or in the proportional effect). Therefore, just based on these results, survey organizations might want to concentrate their nonresponse followup efforts on the smallest and largest firms. Some tailoring of these efforts will, in all likelihood, be needed. What may work for large firms may not be what works for small ones and likely vary by industry. Of course, since there are many more establishments in the center, nonresponse followup techniques also should be developed for them.

Bias in MSA estimates across levels of response rate didn't always conform to the theory, but they did in several cases, even taking into account the wide confidence intervals on either end of the response rate distribution. Certainly, very low response rates cause a problem. At the high end of the response rate distribution, larger biases may occur when may depend on which dominant firms are in or out.

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Figure 1. Hypothetical Relationships Between the Difference in Respondent and Nonrespondent Means and Nonresponse Rate and Overlay of Potential Nonresponse Bias

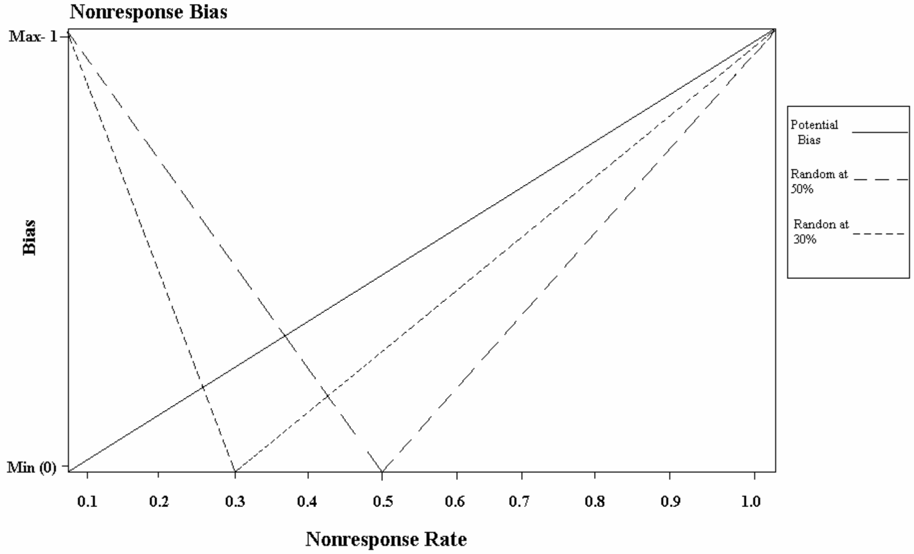


Figure 2. Bias as a Product of Potential Impact and Difference in Means for the Two Hypothetical Relationships Between the Difference and Nonresponse Rate

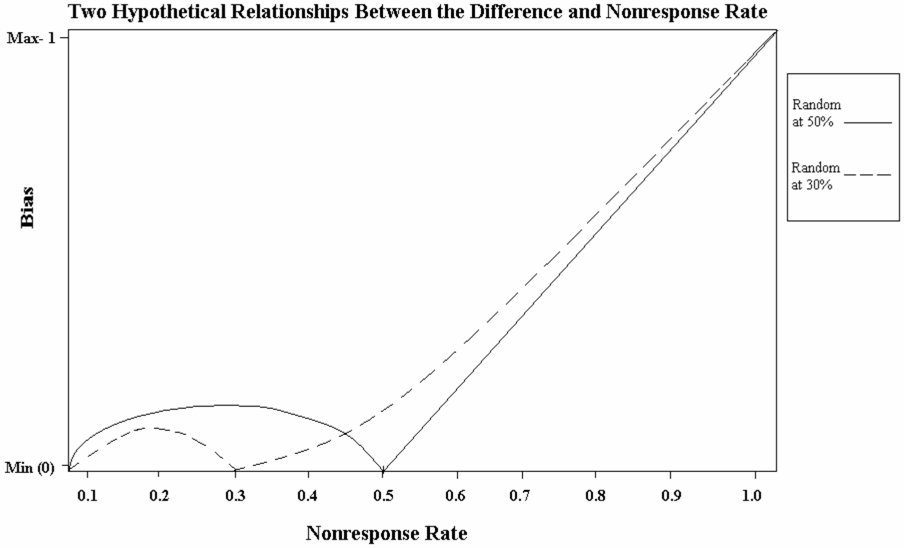


Table 1. NAICS Industry Catergories (Two-Digit Codes) Included in the Analysis

Goods-Producing

Natural resources and mining

Sector 11 (Agriculture, forestry, fishing and hunting)

Sector 21 (Mining)

Construction

Sector 23 (Construction)

Manufacturing

Sector 31 (Food Manufacturing)
Sector 32 (Wood and Mineral Manufacturing)
Sector 33 (Metal Manufacturing)

Service-Providing

Trade, transportation, and utilities

Sector 42 (Wholesale trade)

Sector 44-45 (Retail trade)

Sector 48 (Transportation)
Sector 49 (Warehousing)

Sector 22 (Utilities)

Information

Sector 51 (Information)

Financial activities

Sector 52 (Finance and insurance)

Sector 53 (Real estate and rental and leasing)

Professional and business services

Sector 54 (Professional, scientific, and technical services)

Sector 55 (Management of companies and enterprises)

Sector 56 (Administrative and support and waste management and remediation services)

Education and health services

Sector 61 (Education services)

Sector 62 (Health care and social assistance)

Leisure and hospitality

Sector 71 (Arts, entertainment, and recreation)

Sector 72 (Accommodation and food services)

Other services

Sector 81 (Other services, except public administration)

Figure 3

CES Response Rates by NAICS Categories

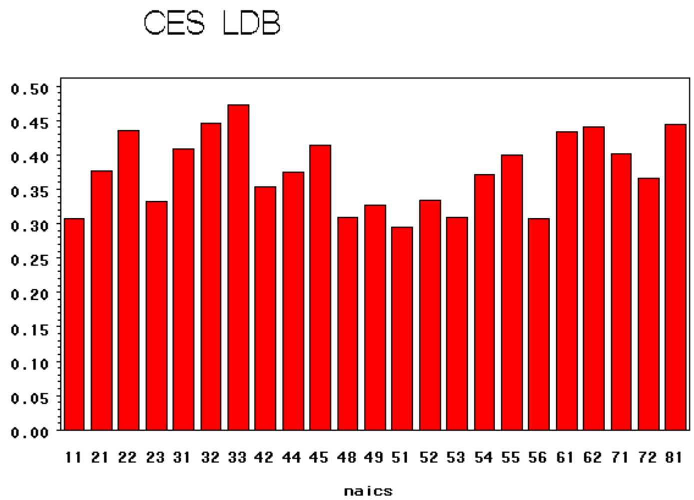


Figure 4: Agriculture, Forestry, Fishing and Hunting

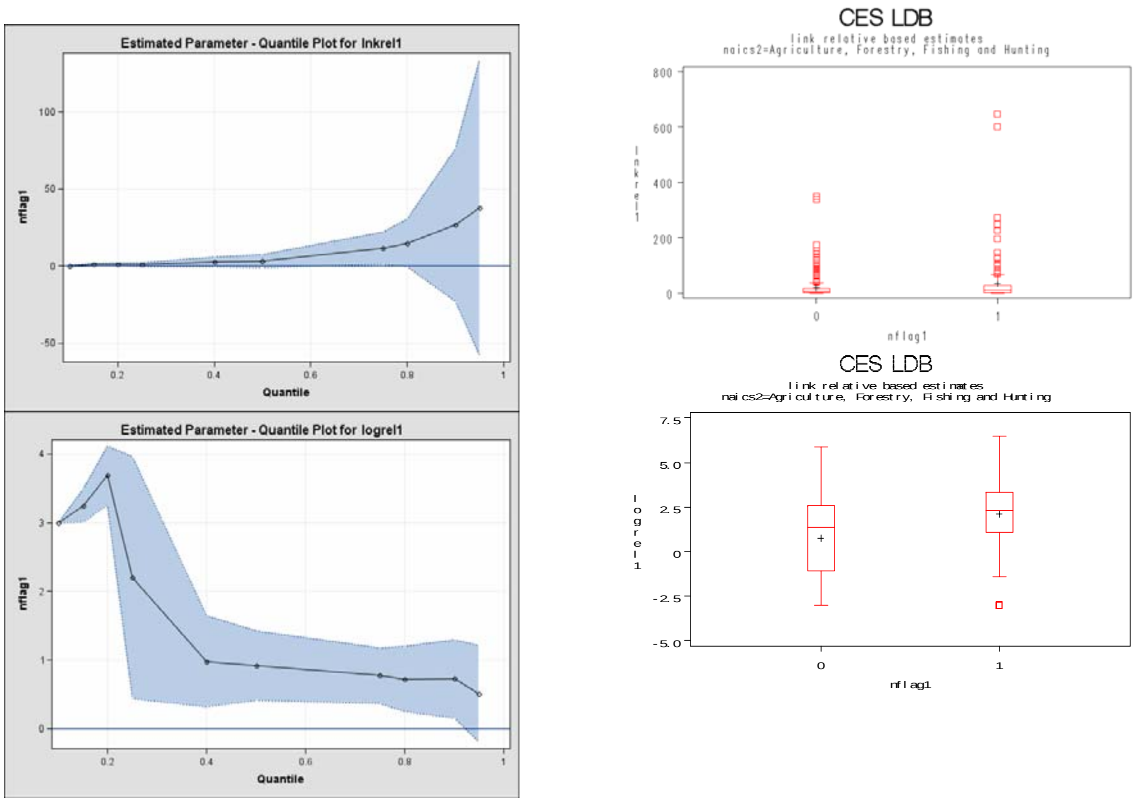


Figure 5: Mining

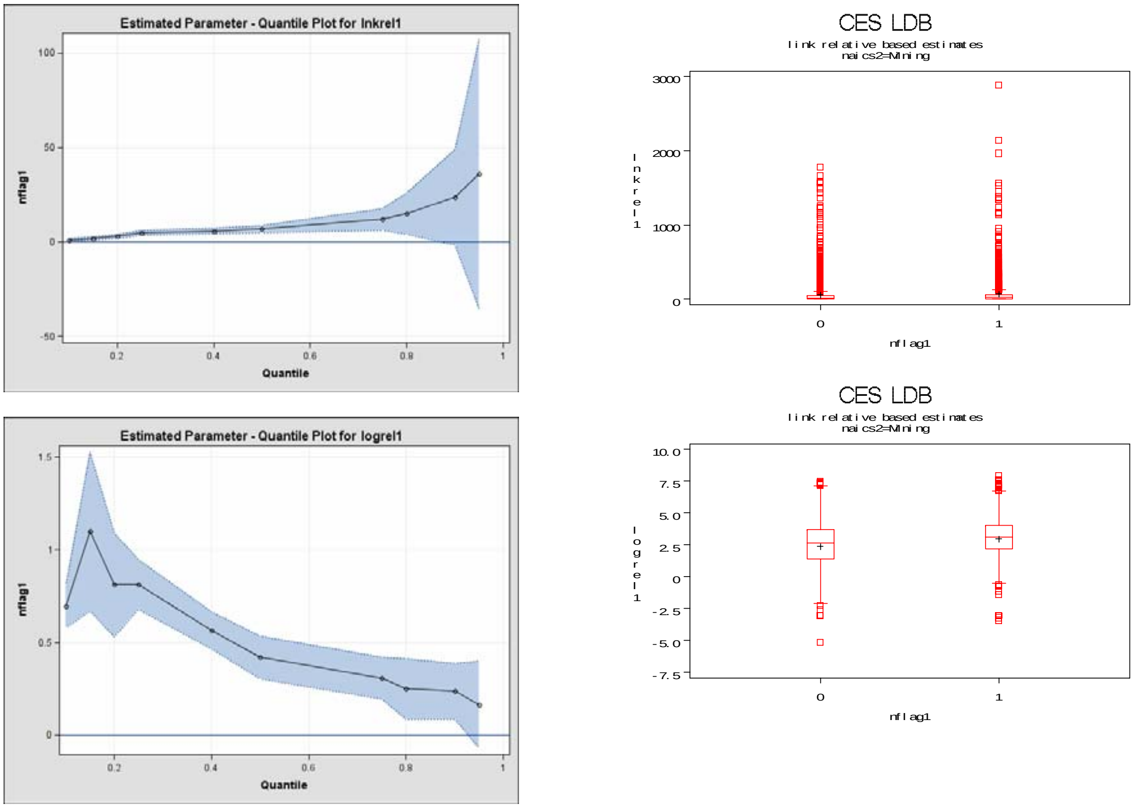


Figure 6: Construction

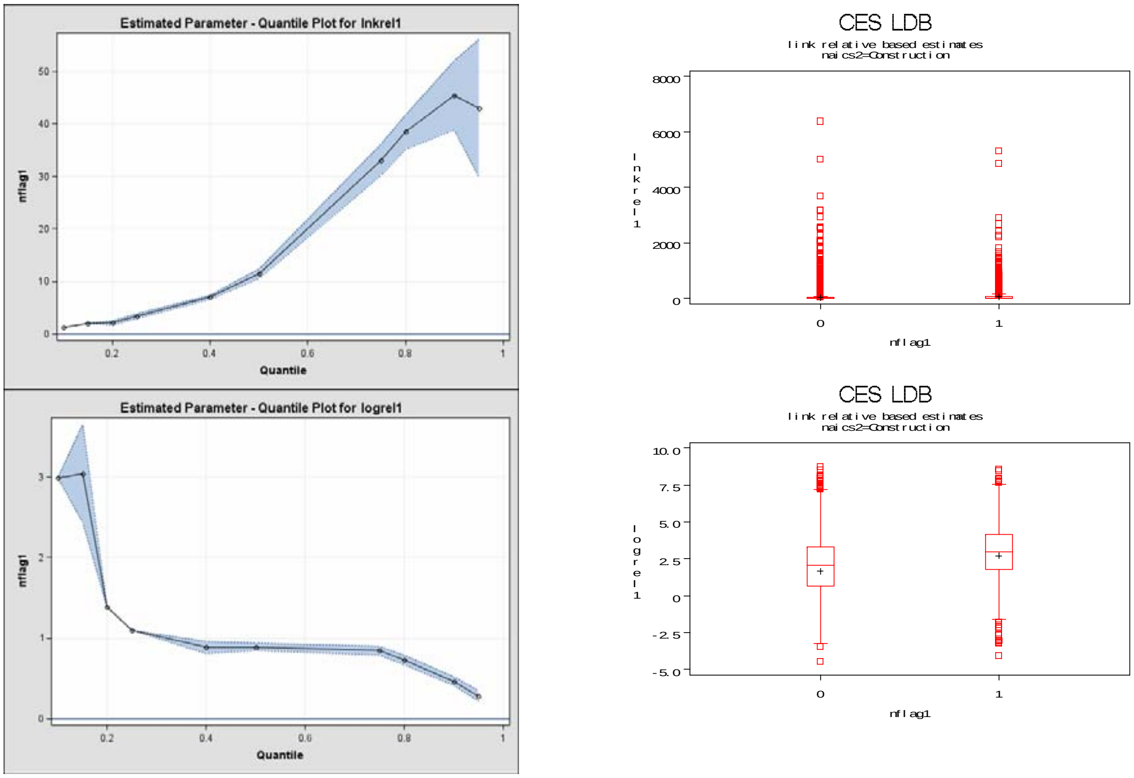


Figure 7: Food Manufacturing

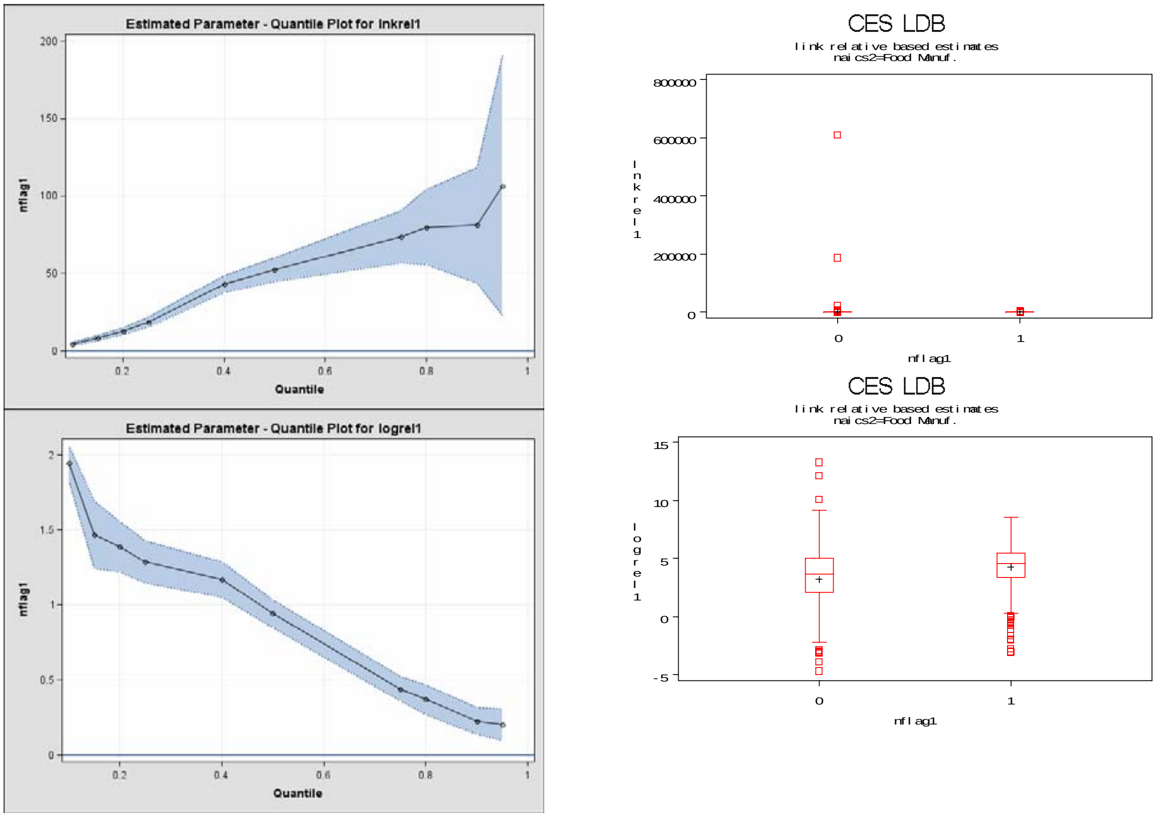


Figure 8: Wood and mineral Manufacturing

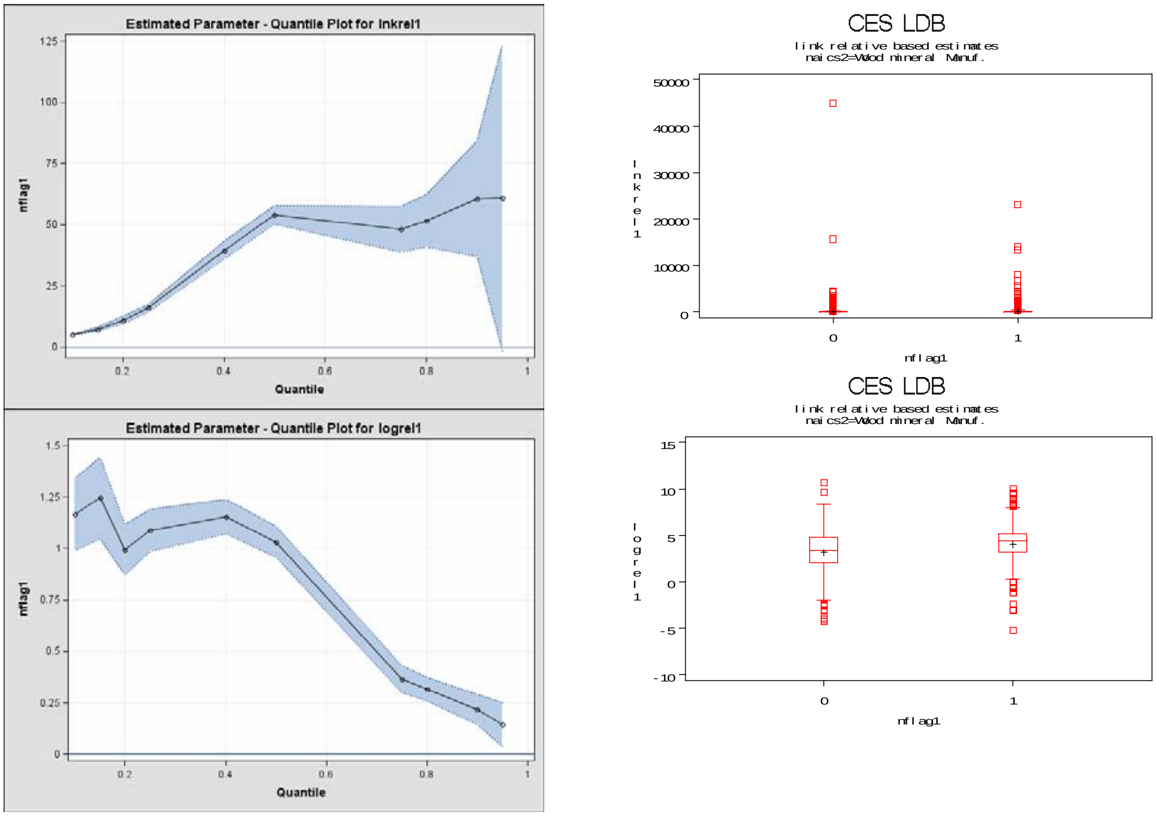


Figure 9: Metal Manufacturing

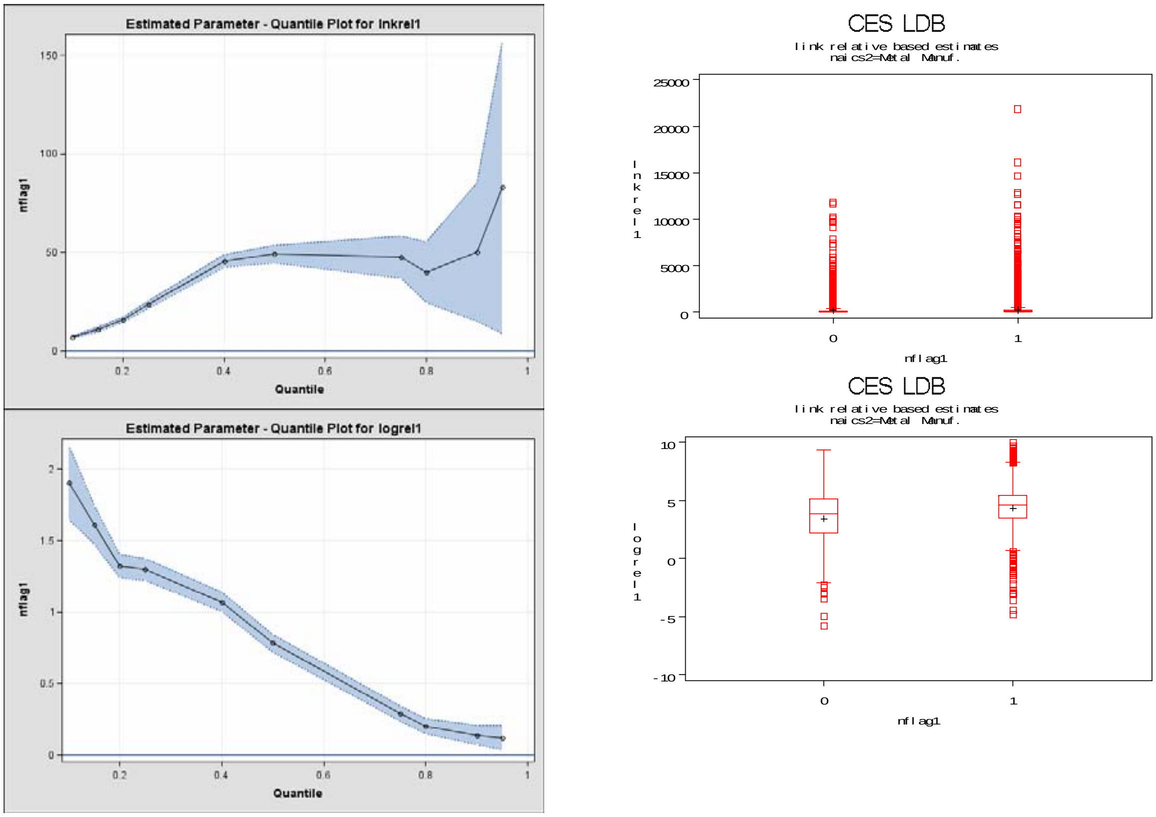


Figure 10: Wholesale Trade

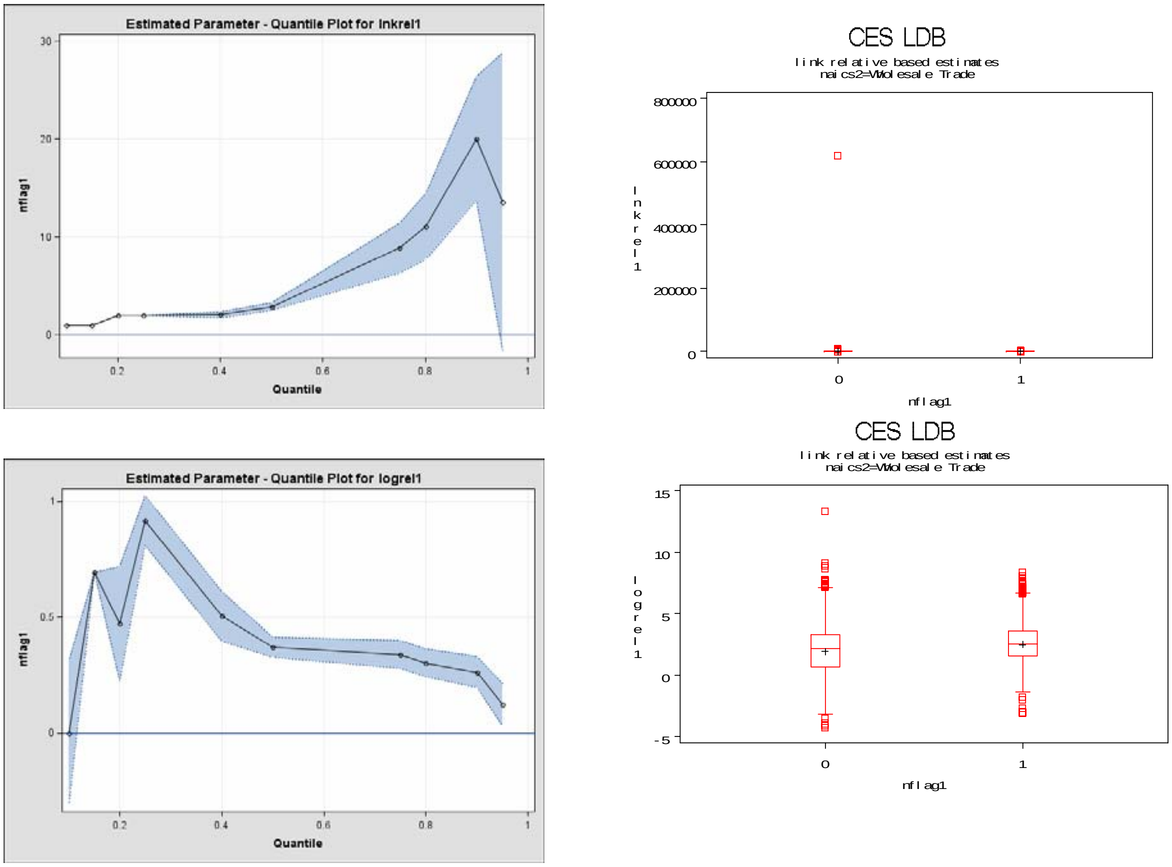


Figure 11: Retail Trade

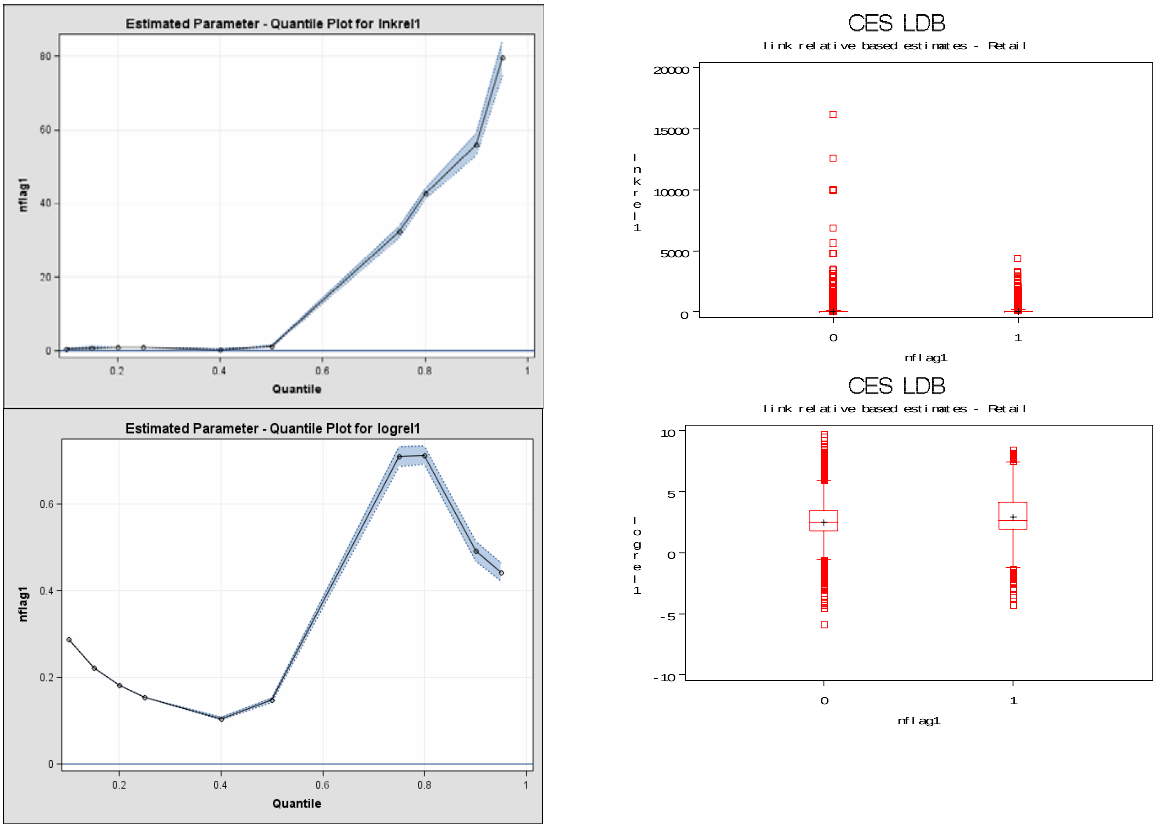
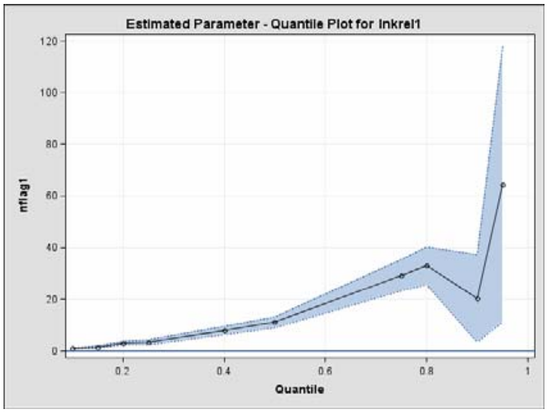
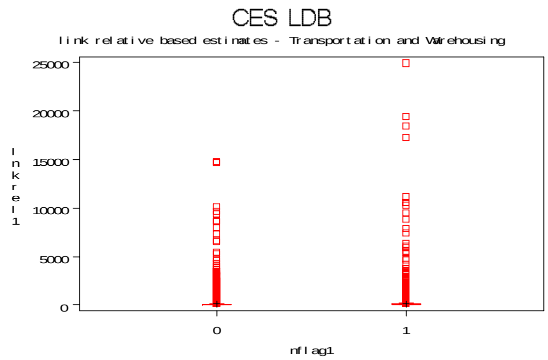
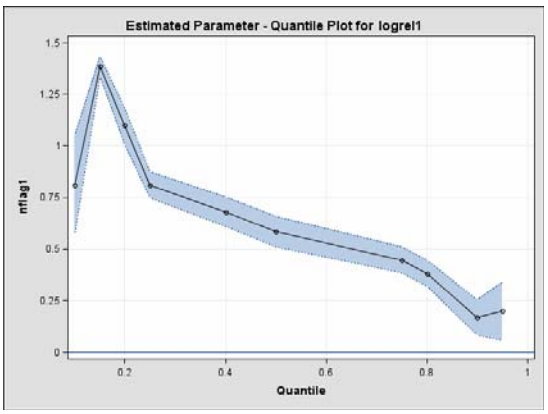


Figure 12: Transportation and Warehousing







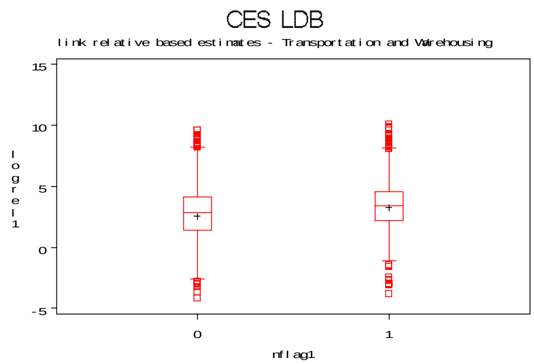


Figure 13: Utilities

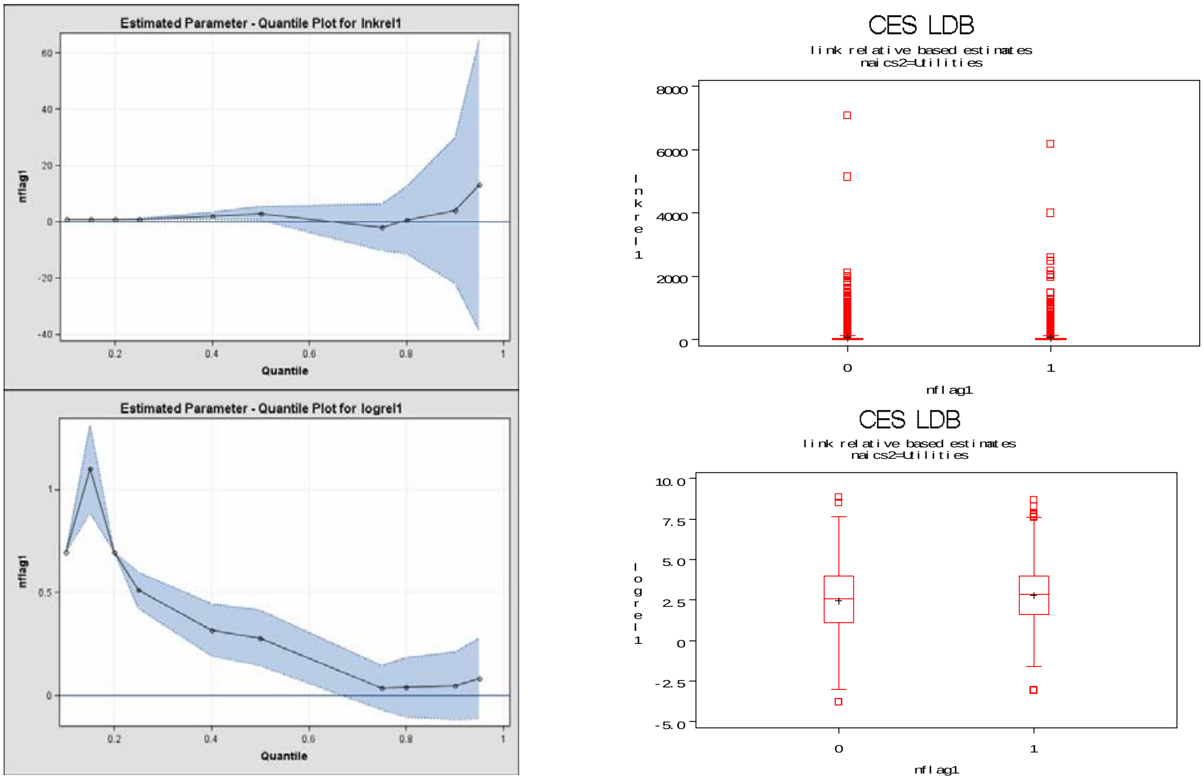
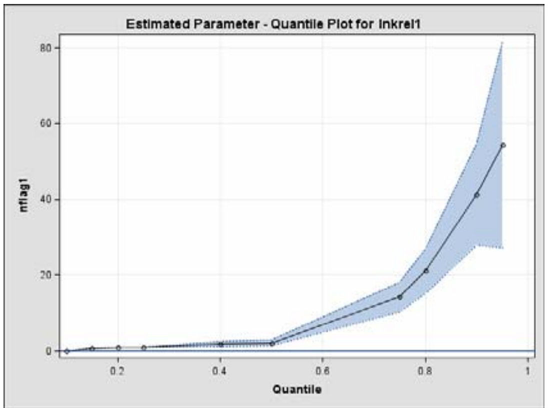


Figure 14: Information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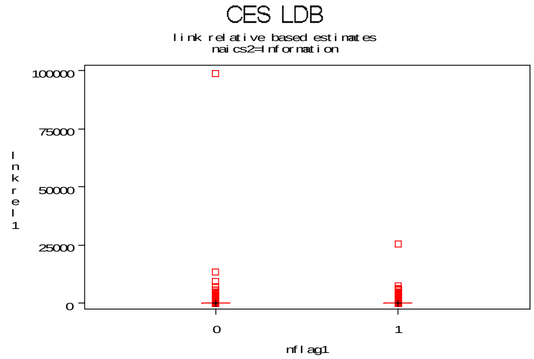
Quantile


CES LDB
link relative based estimates
naics2=Information
lnkrel1
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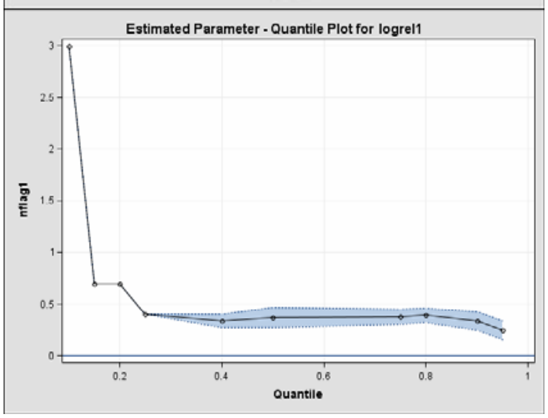
Estimated Parameter - Quantile Plot for logrel1
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Quantile

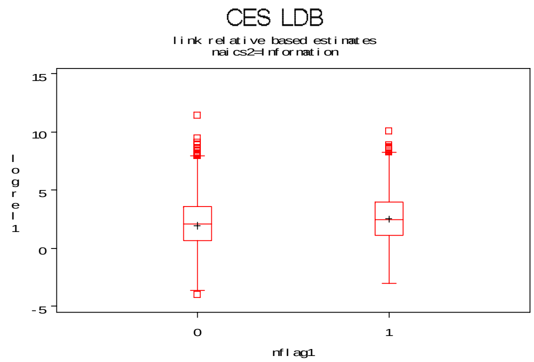
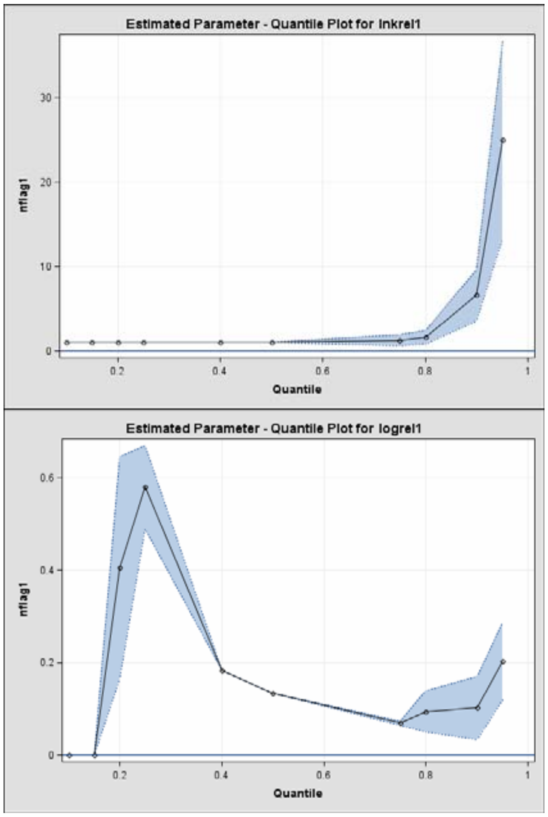
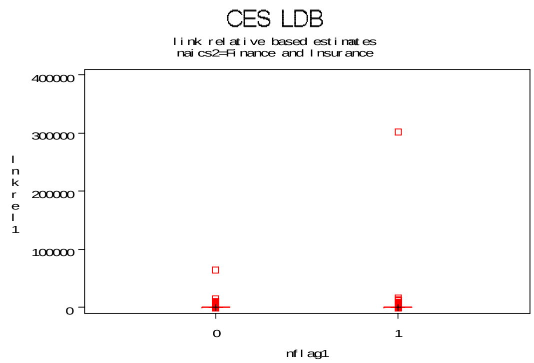

CES LDB
link relative based estimates
naics2=Information
logrel1
nflag1

Figure 15: Finance and Insurance





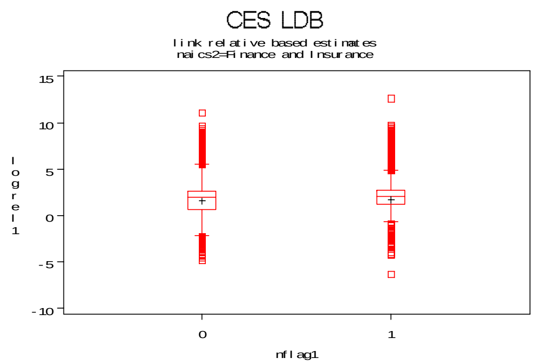


Figure 16: Real Estate and Rental and Leasing

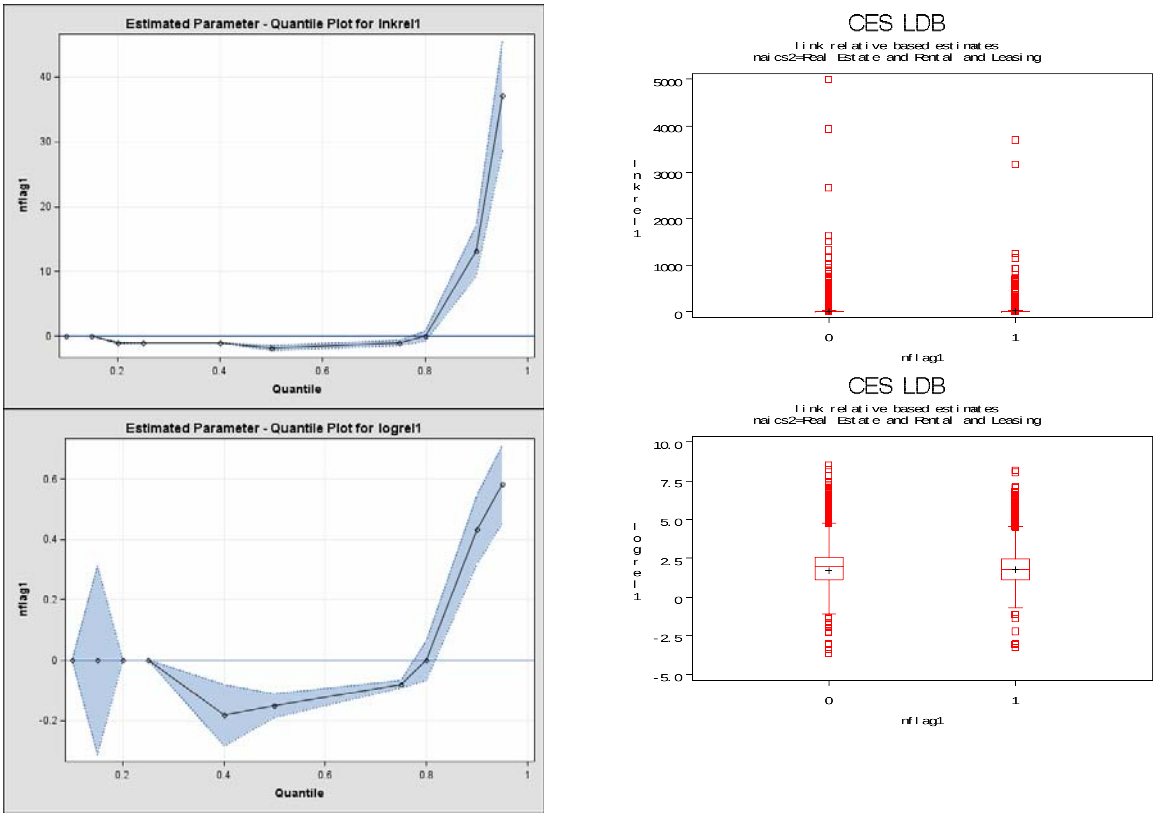


Figure 17: Professional, Scientific, and Technical Services

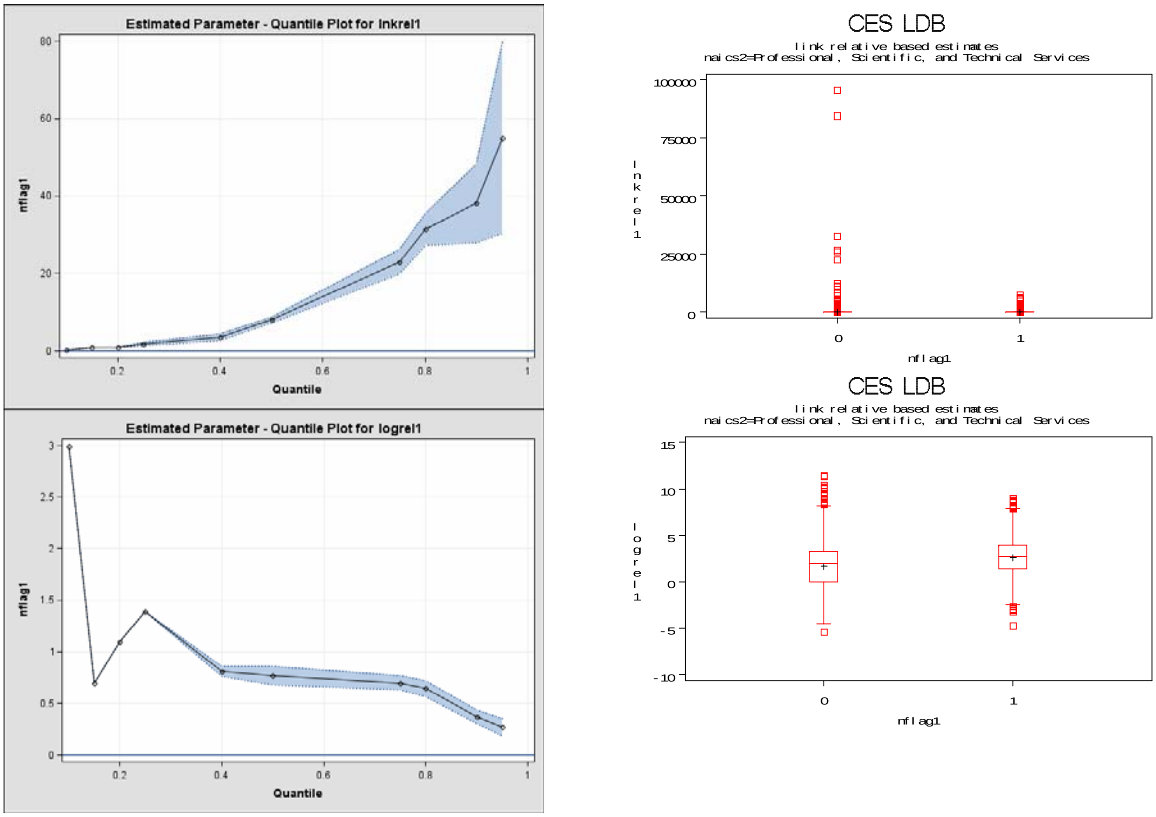


Figure 18: Management of Companies and Enterprises

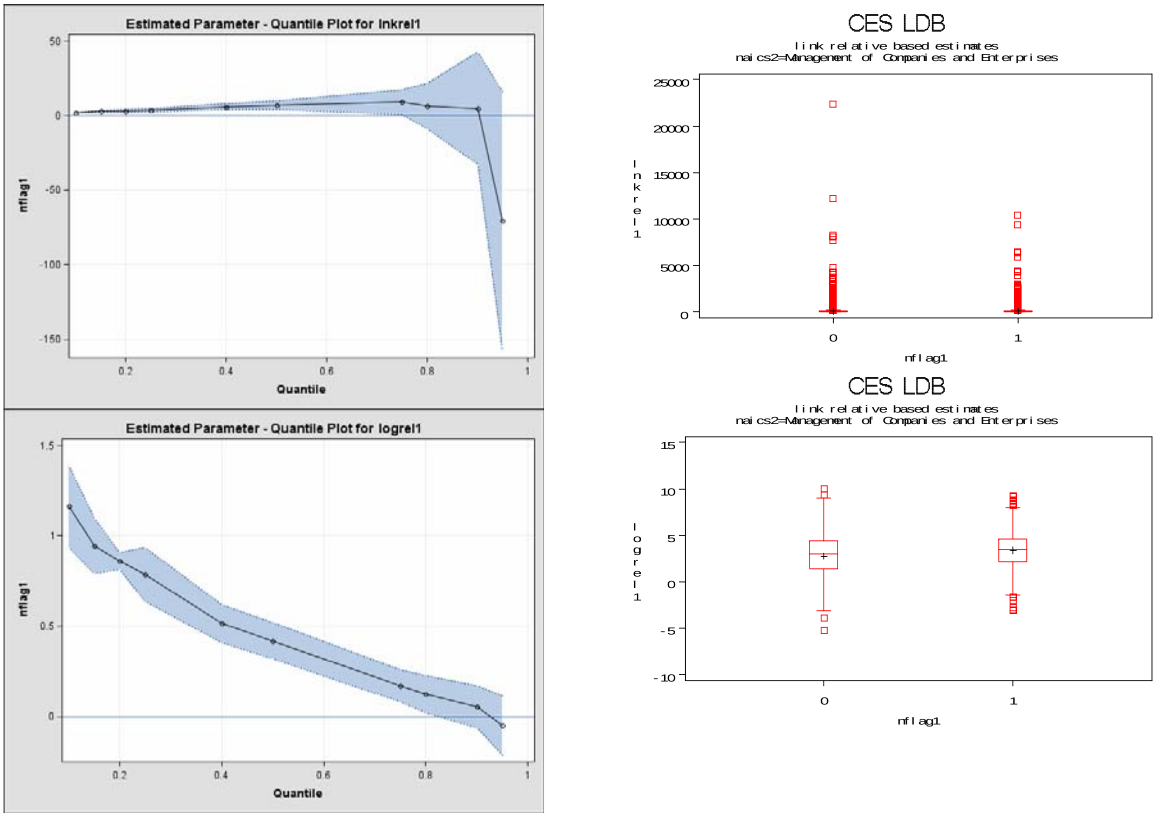


Figure 19: Administrative and Support Services and Waste Management and Remediation Services

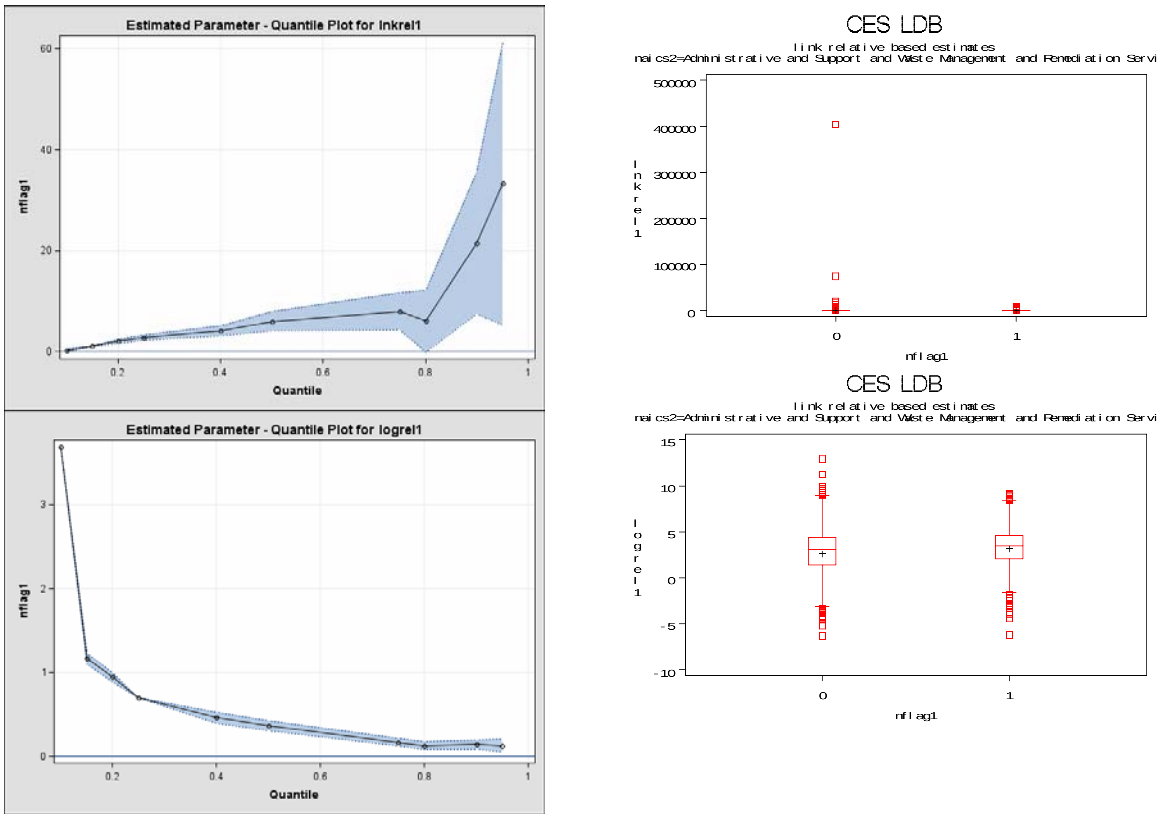


Figure 20: Education Services

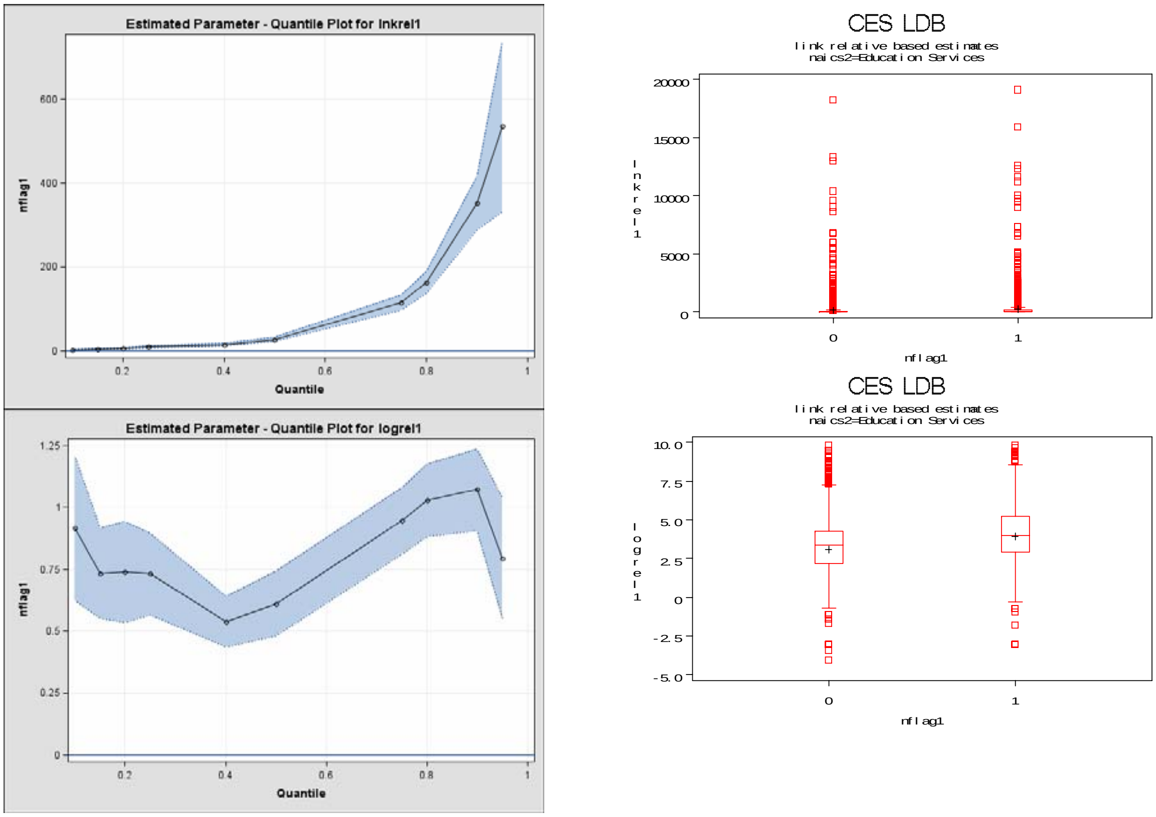
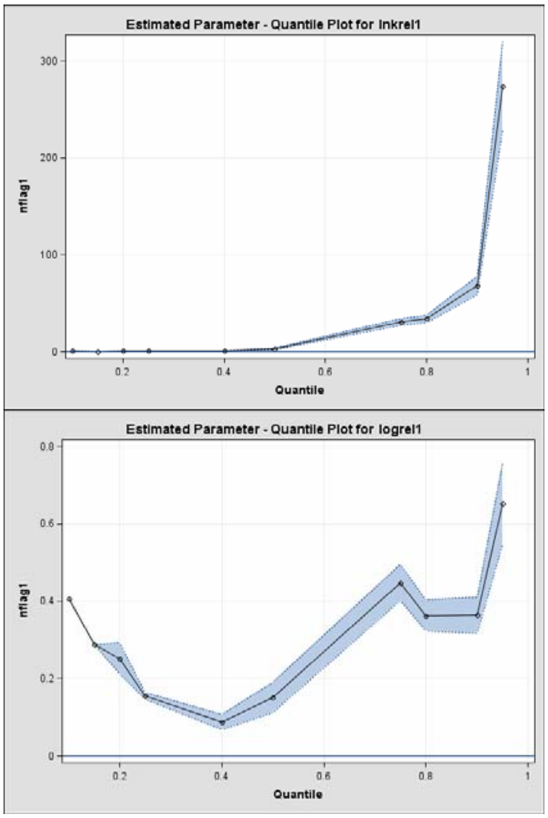


Figure 21: Health Care and Social Assistance



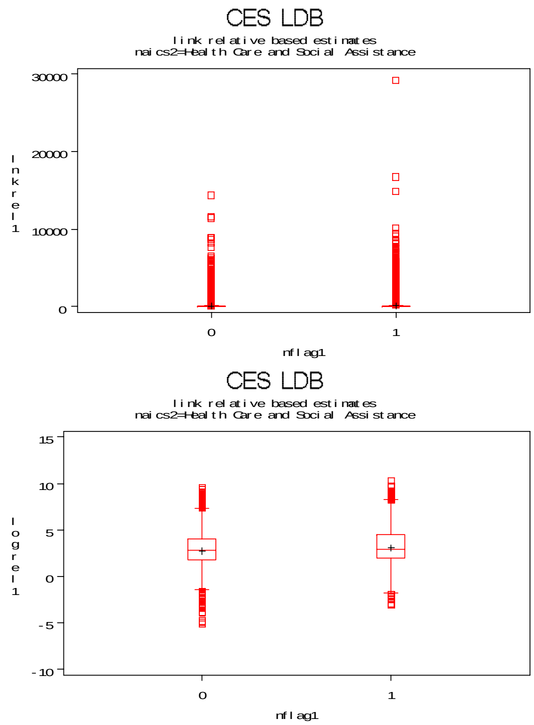


Figure 22: Arts, Entertainment, and Recreation

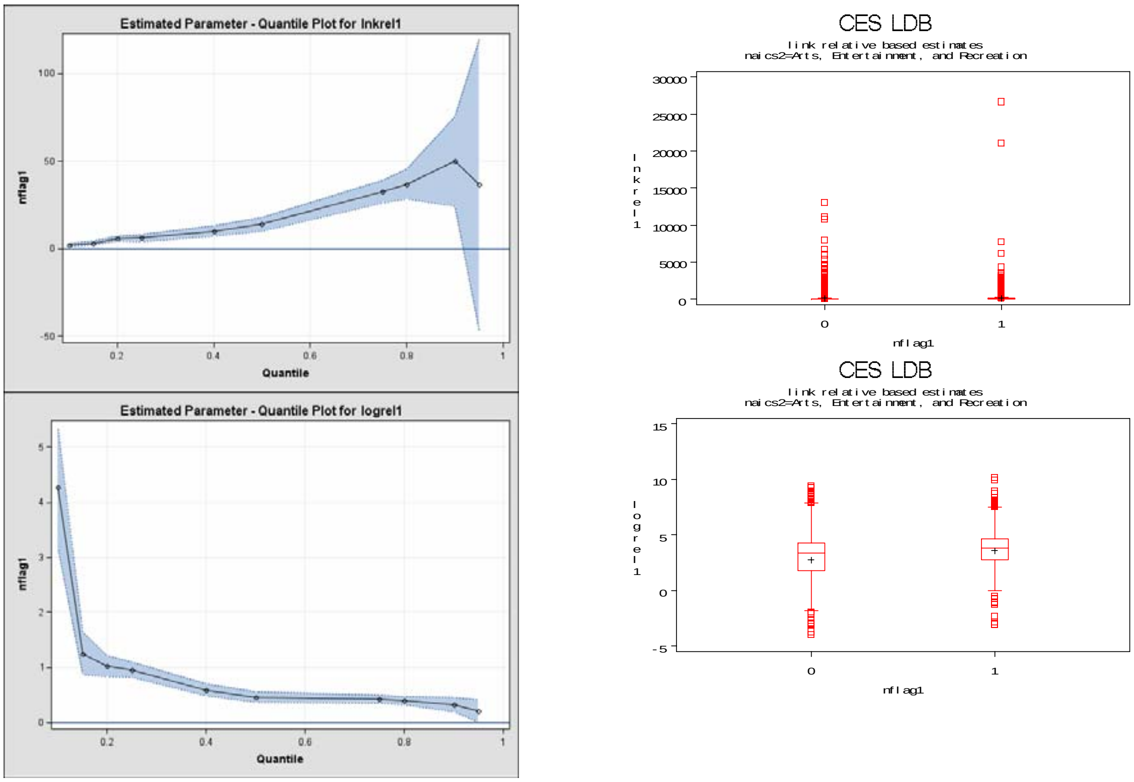


Figure 23: Accommodation and Food Services

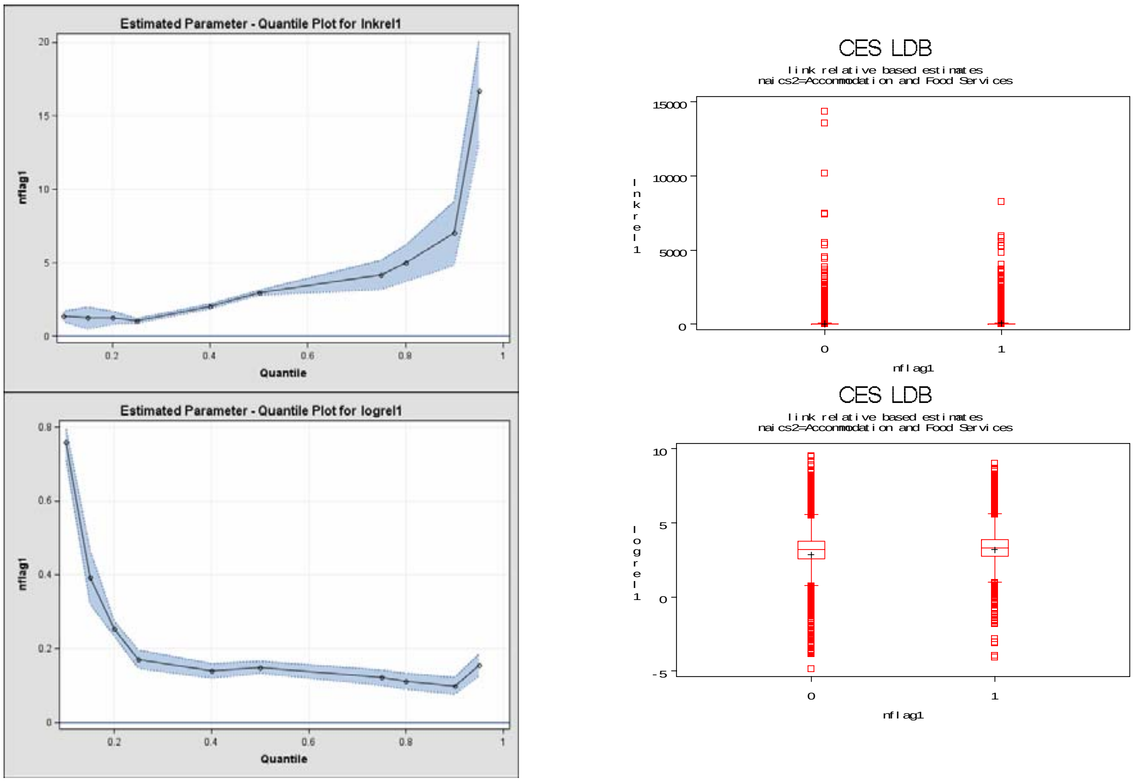
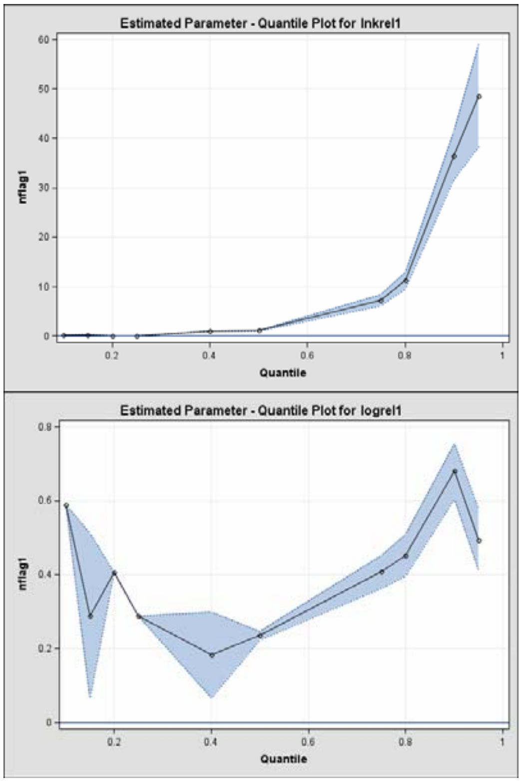
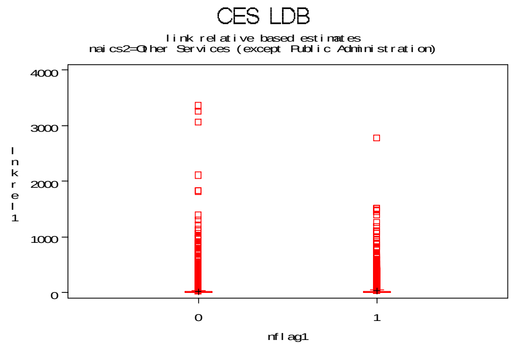


Figure 24: Other Services (except Public Administration)





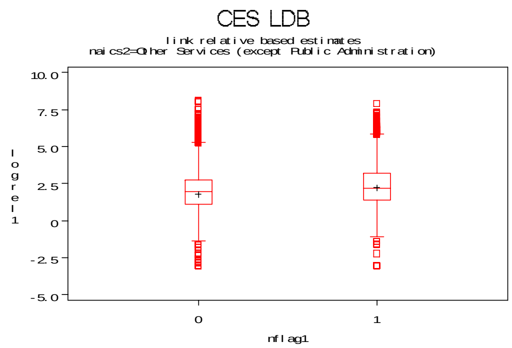


Figure 25: Agriculture, Forestry, Fishing and Hunting

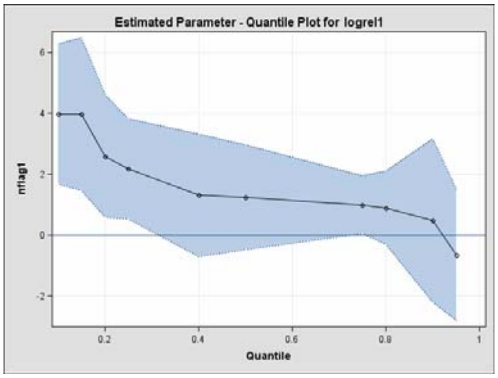


Figure 26: Mining

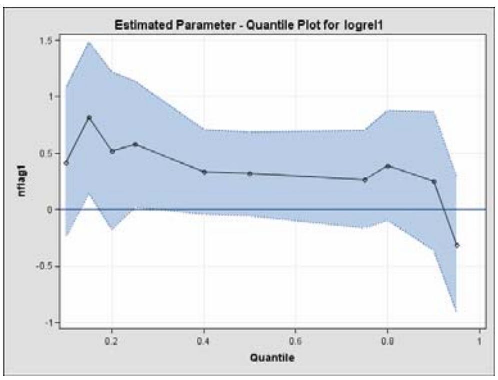


Figure 27: Utilities

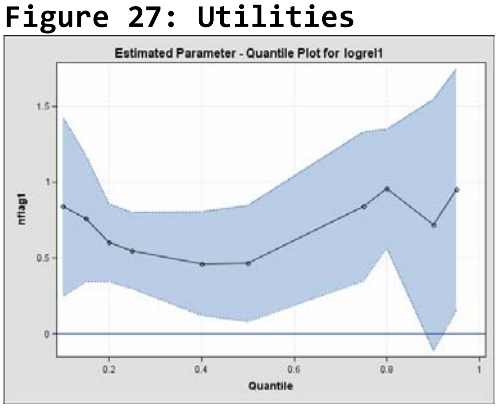


Figure 28: Construction

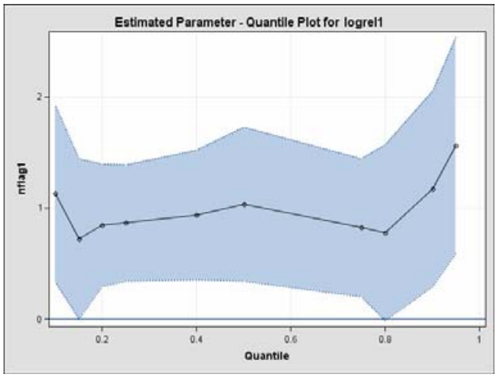


Figure 29: Food Manufacturing

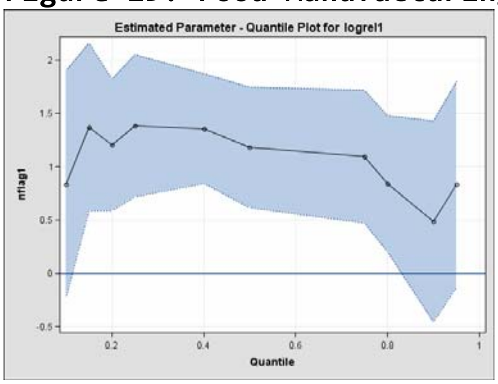


Figure 30: Wood and mineral Manufacturing

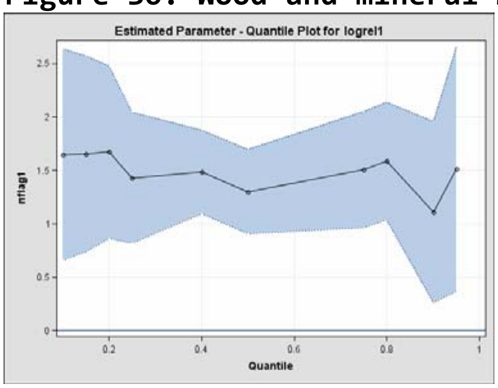


Figure 31: Metal Manufacturing

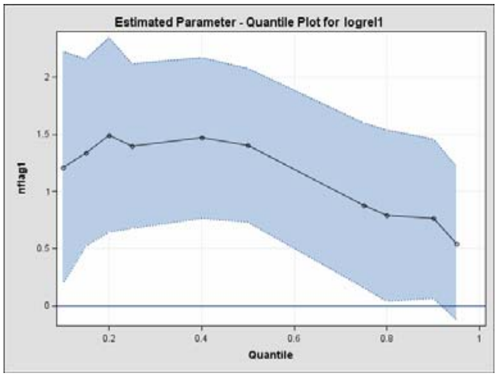


Figure 32: Wholesale Trade

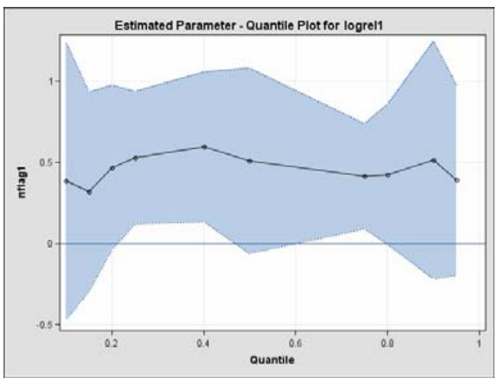


Figure 33: Retail Trade

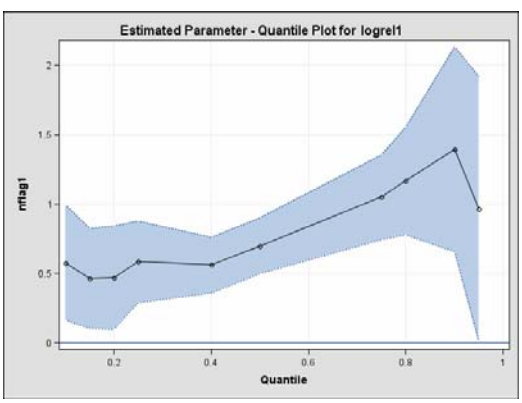


Figure 34: Transportation and Warehousing

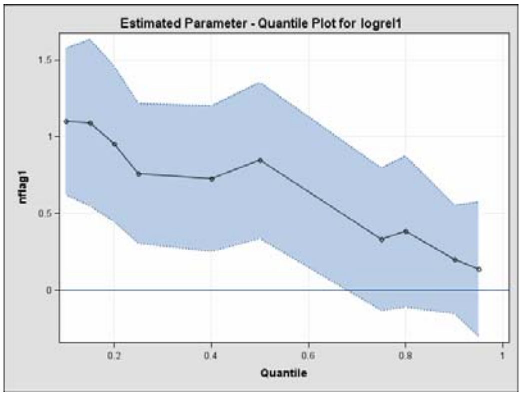


Figure 35: Information

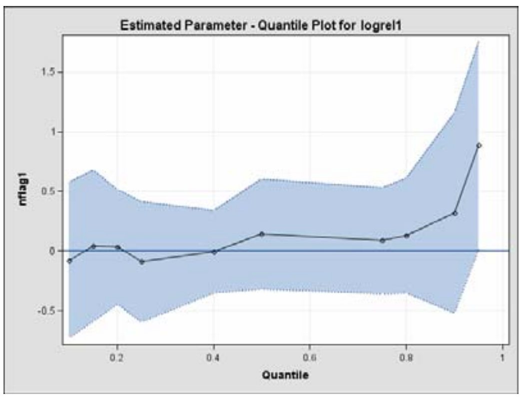


Figure 36: Finance and Insurance

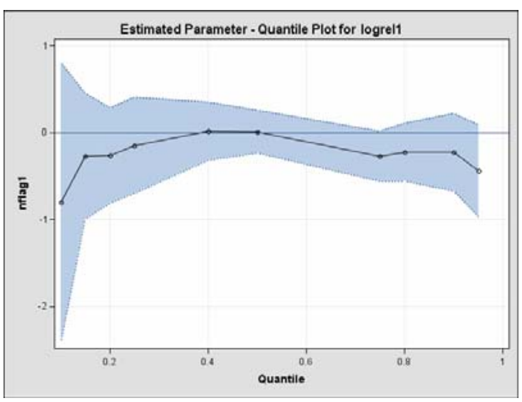


Figure 37: Real Estate, Rental/Leasing

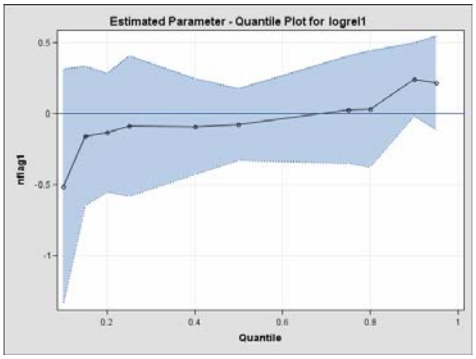


Figure 38: Professional, Scientific, and Technical Services

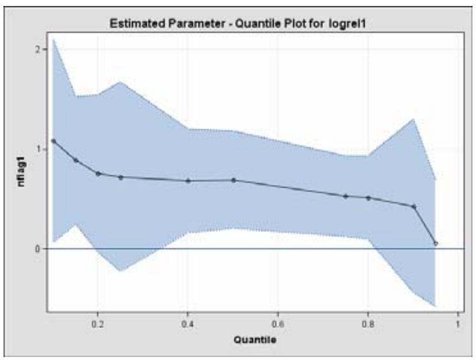


Figure 39: Management of Companies and Enterprises

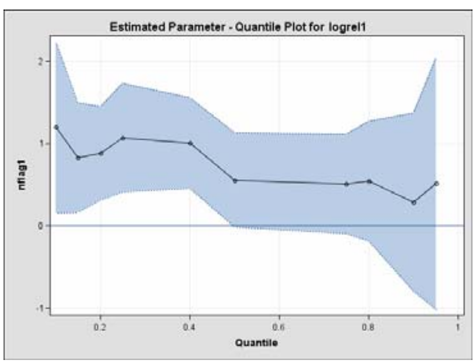


Figure 40: Administrative and Support Services and Waste Management and Remediation Services

Figure 41: Education Services

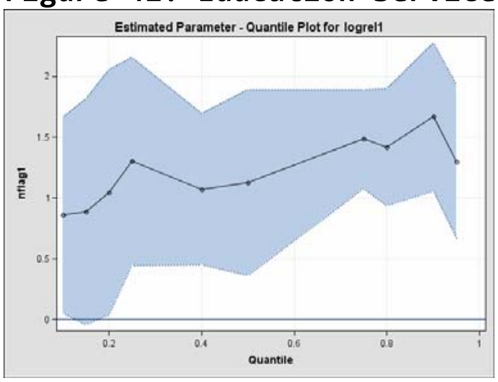


Figure 42: Health Care and Social Assistance

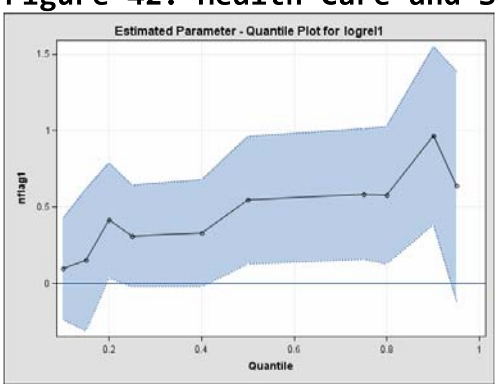


Figure 43: Arts, Entertainment, and Recreation

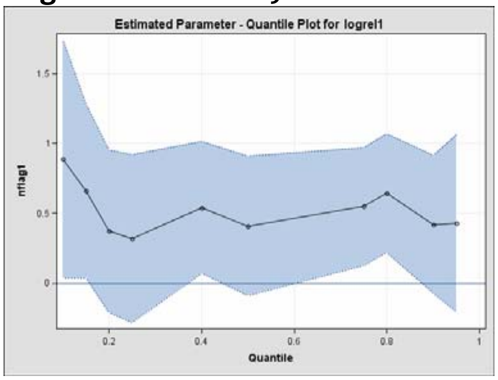


Figure 44: Accommodation and Food Services

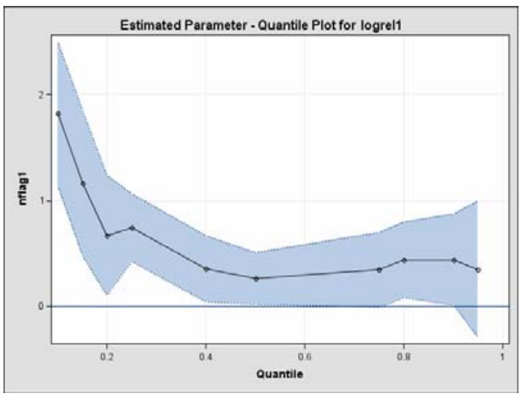


Figure 45: Other Services (except Public Administration)