# Using Quantile Regression to Model Revisions Due To Late Reporting in the Current Employment Statistics Survey 

John Dixon ${ }^{1}$, Clyde Tucker ${ }^{2}$


#### Abstract

This paper considers the possible effects that late responders and nonresponders to the Current Employment Statistics Survey (CES) have on bias in the employment estimates from the CES using data from the Quarterly Census of Employment and Wages (QCEW), which is a nominal census of US establishments based on unemployment insurance. Besides reporting on the level of bias produced by nonresponse and late reporting over time for all firms, the analysis also focuses on the relationship between size of firm and both nonresponse and late responding given that previous research found a relationship between firm size and nonresponse. In this latter case, quantile regression is used to estimate the relationship between size of firm and nonresponse and late reporting. Results are presented overall and by industry.


Key Words: Late reporting, nonresponse bias, quantile regression, payroll survey

## 1. Introduction

The Current Employment Statistics Survey (CES) collects employment, hours, and earnings monthly from a current sample based on approximately 146,000 businesses and government agencies representing approximately 623,000 worksites throughout the United States. The survey tracks the net gains and losses in jobs in various sectors of the economy. Late reporting in the CES occurs when an establishment doesn't provide data for the survey in time for the publication of the initial estimates. This can lead to bias if the estimates including the late reporters would differ from the estimates without them. Although the first estimates do not contain the late reports, they are included in subsequent estimates. The difference between the first estimates and the later estimates are called revisions. Large revisions are of concern to economists when they change the interpretation of labor trends in the economy. Nonresponse occurs when an establishment fails to respond to the survey at all. Nonresponse can also lead to bias in the estimates if the nonresponders are different from the responders, but nonresponse does not affect revisions since the data are never reported. CES estimates are adjusted for the missing reports prior to publication.

This paper considers the possible effects that late responders and nonresponders to the CES have on bias in the employment estimates from the CES using data from the Quarterly Census of Employment and Wages (QCEW), which is a nominal census of US establishments based on unemployment insurance. The QCEW provides the employment data for all firms on an ongoing basis and is available 6-9 months after the CES reference date. The bias in the initial CES estimates resulting from late responders leads to revisions

[^0]in CES estimates in later months. Late responding also may be related to eventual attrition. Besides reporting on the level of bias produced by nonresponse and late reporting over time for all firms, the analysis also focuses on the relationship between size of firm and both nonresponse and late responding given that previous research found a relationship between firm size and nonresponse. In this latter case, quantile regression is used to estimate the relationship between size of firm and nonresponse and late reporting. Results are presented overall and by industry. These results, in the case of the late responders, could be helpful in imputation and reducing the size of revisions.

## 2. Data

The data used in this paper are from the 2010-2014 CES and Quarterly Census of Employment and Wages (QCEW) (over 400,000 respondents). The QCEW serves as both the sampling frame and as the source of benchmark employment for the CES. Differences in definitions of establishment and employee, as well as differences in reporting may produce differences in estimates between the CES and the QCEW (Huff \& Gershunskaya 2009, and Fairman, Applebaum, Manning, \& Phipps 2009). However, the QCEW does have employment figures for CES responders, nonresponders, and late reporters that are ostensibly for the same time period covered by the CES. Many of the CES estimates involve the change in employment (the link-relative estimates). This analysis will only use the estimates of employment and not change in employment, because the QCEW estimates of change show a different pattern of changes than the CES.

## 3. Previous Research

Groen and colleagues (2013) found little difference in nonresponse rates over size of firm except for the largest size groups, which had higher nonresponse. Huff and Gershunskaya found nonresponse bias varied by year and industry, but the nonresponse bias was small. Other studies found that the largest firms had a higher late reporting rate (Copeland, $2003 \& 2007$; Robertson 2013). Copeland also found a higher rate of late reporting for months with a shorter reporting period (fewer days available to report or holidays in the reporting period).

## 4. Methods

Relative bias is used to compare measures of bias when different scales or subgroups are involved.

$$
\text { Relative bias }=100 *(\bar{y} \mathrm{r}-\bar{y} \mathrm{n}) / \bar{y} \mathrm{t}
$$

The $y$ is reported payroll employment. The difference between response: $\bar{y}$ r, and nonresponse: $\bar{y} \mathrm{n}$, relative to the complete measure: $\bar{y} \mathrm{t}$ is converted to a percent. $\bar{y} \mathrm{t}$ is the average reported employment. The same formula can be used to measure bias from late reporters relative to responders.
${ }^{1}$ Bureau of Labor Statistics, $2 \underset{{ }^{2} \text { Independent consultant }}{\text { Massachusets Ave, NE, DC, } 20212 \text { dixon.john@bls.gov }}$

Quantile regression is used to model the relationship between a predictor and the conditional quantiles of a response variable. This estimates of the relationship between the predictor and the response variable can change over the conditional distribution of the response variable. The predictor in this case is whether or not the firm responded. Because size of firm is known to be related to the propensity to respond, size of firm serves as the dependent variable. The coefficient from a quantile regression can describe the relationship between the independent variable (whether or not a firm responded) over the distribution of the dependent variable, in this case firm size. 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).

The quantile curves show how the relationship between late reporting or 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 not only overall but also by industry.

The results are based on a test of the difference in employment between CES responders and late responders or nonresponders at various points on the distribution of size of firm. $Y=a+B x+e$ is estimated for different size quantiles, where $x$ is an indicator of late responding or nonresponse (essentially a t-test). If size of firm is associated with late reporting or 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 late reporting or 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.

[^1]
## 4. Results



Figure 1: Relative bias for nonresponse and late reporting.
Looking at the entire sample of firms, Figure 1 shows the absolute relative bias produced by nonresponders and late responders. The red line shows the differences in the QCEW total employment estimates for those who responded to the CES and those who did not respond (labeled as missing here). Note that the trend over time is very stable. The blue line shows the difference in QCEW employment estimates between the late responders and the timely responders. These estimates are somewhat more variable than for the nonresponders, but are also stable over time. At this point, the relative biases from nonresponse is quite a bit larger than that for late reporting.
${ }^{1}$ Bureau of Labor Statistics, 2 Massachusetts Ave, NE, DC, 20212 dixon.john@bls.gov
${ }^{2}$ Independent consultant


Figure 2: Relative bias adjusted for nonresponse using the benchmark data
Using the QCEW benchmark of industry groups to adjust the estimates for nonresponse eliminates much of the bias due to nonresponse (Figure 2). The benchmarking used by the CES in production is more fine-tuned (smaller benchmark groups), and achieves greater efficiency. The adjusted relative bias in this model was about $10 \%$, but in the CES it averages less than $0.4 \%$ in absolute value. Thus, benchmarking by industry and size has a desirable effect. Since the CES production estimator was not utilized in this study, the resulting bias measures are not directly applicable to survey results. Rather, the bias measures serve only to provide a relative measure of which sources of bias are likely to be more important--late reporters or nonresponders.
${ }^{1}$ Bureau of Labor Statistics, 2 Massachusetts Ave, NE, DC, 20212 dixon.john@bls.gov
${ }^{2}$ Independent consultant


Figure 3: Relative bias adjusting for both nonresponse and late reporting
Attempting to adjust the late reporters with the same benchmarking technique was unsuccessful (Figure 3). The bias estimates, unlike in the case of the nonresponders, did not change. The variability of late reporting may have little to do with the size characteristics. While late reporting may be related to size, within size categories it doesn't appear to be related, unlike nonresponse.
${ }^{1}$ Bureau of Labor Statistics, 2 Massachusetts Ave, NE, DC, 20212 dixon.john@bls.gov
${ }^{2}$ Independent consultant


Figure 4: Quantile regression for nonresponse " $M$ " and late reporting " $L$ "
Turning now to quantile regression for examining the influence of size of firm on bias in the entire sample (shown in Figure 4), the intercept (top graph) shows the distribution of the sizes of reported employment (possibly a logistic or Poisson distribution). It was similar for all the regressions. The "L" group is for the late reporting group relative to the timely reporting group, here showing the coefficients begin to deviate from zero at an accelerating pace as the size of firm grows larger. Among the larger firms, the later reporting ones are smaller than timely reporters as size of firm increases. The " M ", "missing", or nonresponse group, shows a similar effect. Note that, with all firms included, the confidence intervals for bias are quite narrow. Recalling the equation used in quantile regression, $Y=a+B x+e$, the fact that in both cases the smaller of the larger firms in the large firm classes are missing implies that the initial estimate of firm size at that point on the size distribution would be too high and that the estimate $(Y)$ has to be adjusted downward by the amount indicated at different points on the curve. If the largest of the firms were missing, the curve would have an upward trajectory indicating the initial estimates of firm size were too small, so the adjustment to the estimate would be positive. This will become clear when looking at how the patterns of bias differ by industry as defined by the North American Industrial Classification System (NAICS). Some examples of these different patterns are described below. When considering the biases shown in Figure 4, keep in mind that, since both are in the same direction, the effects on overall estimates could be compounded.

[^2]

Figure 5: Positive late bias, negative nonresponse bias: Utilities, Education
For both utilities (shown in Figure 5) and education establishments, again the biases increase as the size of firm increases. It is the largest establishments that are most likely to be late responders leading to a growing positive bias. However, in the case of nonresponders, the smallest firms among the large establishments are less likely to respond, leading to a downward-sloping curve for the largest size classes or quantiles. The standard errors are also much wider for the larger size classes, reflecting fewer establishments and more relative size variability within the quantile. So we cannot exclude the possibility that, in fact, there may be no bias and the curve biases are actually close to zero. If, however, the direction of the bias is truly different for late reporters compared to nonresponders, there may be some counterbalancing of the bias.
${ }^{1}$ Bureau of Labor Statistics, 2 Massachusetts Ave, NE, DC, 20212 dixon.john@bls.gov
${ }^{2}$ Independent consultant


Figure 6: Both negative bias: Retail, Finance, and Health
Retail is one of the largest categories of establishments. Its pattern is of smaller establishments in the largest size quantiles for late responders as well as nonresponders (Figure 6). This pattern was also typical of the Finance and Health industries. Since the bias is in the same direction, there may be, again, some concern the variability or bias may be additive, producing larger revisions.
${ }^{1}$ Bureau of Labor Statistics, 2 Massachusetts Ave, NE, DC, 20212 dixon.john@bls.gov
${ }^{2}$ Independent consultant


Figure 7: Both positive bias: Wholesale trade
Wholesale trade showed increasing relative size in the largest quantiles for both late reporters and nonresponders (Figure 7). Again, the wide confidence intervals makes it difficult to distinguish the bias from zero at some points. To the extent both biases are in the positive direction, the bias could be magnified.

${ }^{1}$ Bureau of Labor Statistics, 2 Massachusetts Ave, NE, DC, 20212 dixon.john@bls.gov
${ }^{2}$ Independent consultant

Figure 8: Both flat: Management, Food
In the food industry (Figure 8), the bias from late reporting looks positive, and the bias from nonresponse is negative. However, given the wide confidence intervals for the curve for late responders, the bias may be flat. The nonresponse effect is only for the largest quantile. These patterns of bias also were the same for the Management establishments.


Figure 9: Increasing late bias, decreasing nonresponse bias: Manufacturing (Metal and Wood)

The curves for both Wood and Metal manufacturing (Figure 9) indicate late reporting for the larger firms in the largest quantiles and a greater level of missingness for the smaller firms in the largest quantiles, although the bias may be zero at certain points on the curves for nonresponse. These effects may counterbalance each other. The opposite pattern; decreasing size effect for late responders and increasing size effect of nonresponders was rare over all the industries for all the months examined.
${ }^{1}$ Bureau of Labor Statistics, 2 Massachusetts Ave, NE, DC, 20212 dixon.john@bls.gov
${ }^{2}$ Independent consultant


Figure 10: Mixed patterns of bias between months: Real estate
Some industries showed mixed effects over time. In the left graph, in some months Real Estate showed smaller relative establishment sizes for the larger quantiles for both late responders and nonresponders. In other months, however, (the right graph) the late responders showed the opposite effect. This switching of effects over months may contribute to the unpredictability of the revisions.

## 5. Summary and Limitations

Although the size of the bias from nonresponse initially is large, adjusting using benchmarking seems to work well in reducing its size. The bias from late respondents can be fairly small, but benchmarking does not reduce it further. Based on the quantile regressions, it is clear that there was considerable variability in patterns of nonresponse and late reporting across industries, and sometimes within industries over time. The model used here was very simple due to the difficulty of fitting quantile regressions with additional covariates.

## 6. Future research

The limitations of the quantile models in terms of the ability to converge with many estimates constrained the current study. Using Poisson or generalized models would allow a larger number of covariates. Models using CES estimates as well as QCEW estimates would help to better understand reporting differences as described in Fairman et al. (2009). In addition to modeling the employment estimates, modeling the change in estimates (the link relative estimator) would be especially important for understanding many of the published estimates. Adding area characteristics to the models (local unemployment, urbanicity, etc.) may help improve prediction of late reporting and nonresponse. Adding establishment characteristics (change in profits, sales) may help better characterize the economic influences on nonresponse and late reporting. Adding a birth/death model to the study would make for a more complete picture. Seasonality may be more important for some industries than others. The length of time available to respond influences late responding in some industries. Other studies haven't found an
${ }^{1}$ Bureau of Labor Statistics, 2 Massachusetts Ave, NE, DC, 20212 dixon.john@bls.gov
${ }^{2}$ Independent consultant
effect of mode of response on late reporting or nonresponse, but that could interact with other covariates.

## References

Buchinsky, M. (1998). Recent Advances in Quantile Regression Models: A Practical Guideline for Empirical Research, The Journal of Human Resources, 33.1, 88-126.
Kennon R. Copeland, "Reporting Patterns in the Current Employment Statistics Survey", JSM, 2003. https://www.amstat.org/sections/srms/proceedings/y2003/Files/JSM2003-000207.pdf
Kennon R. Copeland, Richard Valliant, "Imputing for Late Reporting in the U.S. Current Employment Statistics Survey", Journal of Official Statistics, Vol.23, No.1, 2007. pp. 69-90
Fairman, K., Applebaum, M., Manning, C., Phipps, P., "Response Analysis Survey: Examining reasons for employment differences between the QCEW and the CES survey", JSM, 2009. https://www.amstat.org/sections/srms/proceedings/y2009/Files/304445.pdf
Groen, J., "Sources of Error in Survey and Administrative Data: The Importance of Reporting Procedures," Journal of Official Statistics, 28(2), June 2012, pp. 173-198.
Groen, J., L. Kerrie, J. Gershunskaya, P. Hu, T. Kratzke, M. McCall, E. Park, and A. Polivka, 2013. An Investigation into Nonresponse Bias in CES Hours and Earnings .Final Report. Internal BLS report.
Huff, L., and Gershunskaya, J., "Components of Error Analysis in the Current Employment Statistics Survey", Proceedings of the Survey Research Methods Section, American Statistical Association, 1-6 August 2009. Washington, DC: American Statistical Association, 2009. http://www.bls.gov/osmr/abstract/st/st090050.htm
Koenker, R. and Machado, A. F. (1999). Goodness of Fit and Related Inference Processes for Quantile Regression. Journal of the American Statistical Association, 94, 12961310.

Lengermann, P. A. and Vilhuber, L. (2002). Abandoning the Sinking Ship; The Composition of Worker Flows Prior to Displacement. Technical Paper TP-2002-11. http://www.lehd-test.net/documents/pdf/tp-2002-11.pdf
Robertson, Kenneth W. (2013), A Working Paper Presenting a Profile of Revisions in the Current Employment Statistics Program, No 466, Working Papers, U.S. Bureau of Labor Statistics. http://www.bls.gov/ore/pdf/ec 130070.pdf

[^3]
[^0]:    ${ }^{1}$ Bureau of Labor Statistics, 2 Massachusetts Ave, NE, DC, 20212 dixon.john@bls.gov
    ${ }^{2}$ Independent consultant

[^1]:    ${ }^{1}$ Bureau of Labor Statistics, 2 Massachusetts Ave, NE, DC, 20212 dixon.john@bls.gov
    ${ }^{2}$ Independent consultant

[^2]:    ${ }^{1}$ Bureau of Labor Statistics, 2 Massachusetts Ave, NE, DC, 20212 dixon.john@bls.gov
    ${ }^{2}$ Independent consultant

[^3]:    ${ }^{1}$ Bureau of Labor Statistics, 2 Massachusetts Ave, NE, DC, 20212 dixon.john@bls.gov
    ${ }^{2}$ Independent consultant

