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Quarterly Benchmarking for the Current Employment Survey

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Executive Summary

- This paper proposes a quarterly benchmarking procedure for the Current Employment Survey (CES) that explicitly corrects for differences in seasonality between the CES and the Quarterly Census of Employment and Wages (QCEW).
- Abstracting from seasonal adjustment issues, we show analytically that the proposed procedure yields improved estimates of March employment. This is in spite of the fact that revisions in various quarters are likely to be opposite signed.
- More frequent benchmarking is especially advantageous when CES errors are correlated over time, as tends to happen at turning points in the business cycle.
- The March revision is generally not a good measure of monthly errors in the CES. A small March revision does not in and of itself imply small monthly errors.
- The performance of the proposed quarterly benchmarking procedure depends on the variance of the CES estimator, potential errors in the QCEW, and on how well the seasonal factors in the CES and QCEW are estimated.
- Simulations show that the variance of the proposed estimator is smaller than that of the CES under the plausible assumption that errors in the QCEW are relatively small compared to errors in the CES. The larger the errors in the CES, the better is the relative performance of the proposed quarterly benchmark estimator even accounting for the fact that seasonal factors will be estimated less precisely.

Introduction

The CES is quick response business survey that provides information on employment, hours, and earnings each month.[2]The CES program benchmarks its employee series in order to re-anchor sample-based employment estimates to full population counts. This process is designed to improve the accuracy of the CES all employee series by replacing estimates with full population counts which are not subject to the sampling or modeling errors inherent in the CES monthly estimates. These population counts are derived from administrative records, and are much less timely than the sample-based estimates, but provide a near census of establishment employment. The CES program is investigating possible improvements in its benchmarking procedures.

[1] We thank Steve Miller and Ken Robertson for helpful comments on an earlier draft.

[2] For more background on the CES, see the Ken Robertson's forthcoming article in the Monthly Labor Review..

The major source of benchmark data for the CES survey is the Quarterly Census of Employment and Wages (QCEW) program, which collects employment and wage data from States' unemployment insurance (UI) tax records. All businesses subject to UI laws are required to report employment and wage information to the appropriate State Workforce Agency (SWA) quarterly; these UI records cover about 97 percent of nonfarm wage and salary jobs on civilian payrolls. Benchmarks for the remaining 3 percent of CES employment are constructed from alternate sources, primarily information from the County Business Patterns and the Annual Survey of Public Employment and Payroll publications from the US Census Bureau. Benchmark employment, also called population employment, is the sum of the QCEW employment count and the non-covered employment estimate from these other sources. In the rest of this paper the term QCEW is used to denote QCEW plus non-covered employment.

The size of the benchmark or March revision is equal to the difference between the March QCEW employment estimate and the CES estimate of March employment and is widely regarded as a measure of the accuracy of the CES estimates. For the National total nonfarm series, annual benchmark revisions have an absolute average of about three-tenths of one percent (0.3%) over the past decade. For National series, only March sample-based estimates are replaced with the population data. In contrast, for State and metropolitan area series, all available months of population data are used to replace sample-based estimates.

A team at BLS is investigating ways of improving the benchmarking procedures. The discussion in this paper is an outgrowth of the work of the CES Benchmarking Team.[3] Two improvements in the benchmarking procedures are being considered. In order to provide more timely revisions and to reduce the size of the March revisions, the CES program is looking into the possibility of benchmarking the CES quarterly instead of annually. Second, in order to achieve greater consistency among the National and the State and metropolitan area estimates, the program is exploring the possibility of adopting the same benchmarking procedure for State and metropolitan area estimates as is used for the National estimates. While the empirical work in this paper is confined to the National all employee series, our theoretical analysis has broader applicability. Our theoretical results and the results of our simulation exercise apply equally to any series, be it total or industry, or national or local.

Benchmarking the non-seasonally adjusted CES to the non-seasonally adjusted QCEW throughout the year is problematic because of the substantial difference in seasonal patterns between the QCEW and the CES series. The QCEW has always shown larger seasonal movements than the CES, both before and after the CES's conversion to a probability sample design in 2003. Consequently, we propose benchmarking *seasonally adjusted* CES estimates to the *seasonally adjusted* QCEW.

The next section of this paper describes the benchmarking procedure that is currently employed. We then turn to a discussion of the effect more frequent benchmarking can be expected to have on the March revision. With this information as background, we present our proposed benchmarking procedure and examine results when it is implemented for the total private CES employment estimates. We conclude with a simulation exercise that allows us to evaluate our proposed procedure when there are potential errors in both the CES and QCEW and when seasonal factors are measured with error.

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[3] In addition to the authors of this paper, the benchmarking team includes Ken Robertson, Greg Erkens, Larry Huff, Chris Manning, Kirk Mueller, and Dave Talan.

Current Benchmarking Procedure

For the CES National estimates, newly benchmarked data are released with the January Employment Situation in early February of each year. Not seasonally adjusted data are revised for 21 months and seasonally adjusted data are revised for 5 years. For example, with the March 2012 benchmark release, not seasonally adjusted data were revised from April 2011 through December 2012. Seasonally adjusted data were revised from January 2008 through December 2012.

Like all sample surveys, the CES is susceptible to two sources of error: sampling error and non-sampling error. Sampling error is present any time a sample is used to make inferences about a population. The magnitude of the sampling error, or variance, relates directly to sample size and the percentage of the universe covered by the sample. The CES survey captures slightly under one-third of the universe employment each month, exceptionally high by usual sampling standards. This coverage ensures a relatively small sampling error at the total nonfarm employment level for Statewide and the National series. Both the universe counts and the CES survey estimates are subject to non-sampling errors common to all surveys – coverage, response, and processing errors. The error structures for both the CES monthly survey and the UI universe are complex. Still, the two programs generally produce consistent total employment figures. Over the last decade, annual benchmark revisions at the National total nonfarm level have averaged 0.3 percent (in absolute terms), with an absolute range of 0.1 percent to 0.7 percent over the past decade.

While the benchmark revision often is regarded as a proxy for total survey error, this interpretation does not take into account error in the benchmark source data. The employment counts obtained from quarterly UI tax forms are administrative data that reflect employer record-keeping practices and differing State laws and procedures. The benchmark revision can be more precisely interpreted as the difference between two independently derived employment counts, each subject to its own error sources. Overall however, the universe employment counts are subject to smaller overall error than the CES sample-based estimates and therefore serve as a valuable input data to improve the accuracy of the CES through benchmarking.

At the time of annual benchmarking, the monthly sample-based estimates for the 11 months preceding and the 9 months following the March benchmark are also subject to revision. Each annual benchmark revision affects 21 months of data for not seasonally adjusted series.

Monthly estimates for the 11 months preceding the March benchmark are re-calculated using a "wedge back" procedure. The difference between the final benchmark level and the previously published March sample estimate is calculated and distributed back across the previous 11 months. The wedge is linear; eleven-twelfths of the March difference is added to the February estimate, ten-twelfths to the January estimate, and so on, back to the previous April estimate, which receives one-twelfth of the March difference. This method assumes that the total estimation error (in levels) since the last benchmark accumulated at a steady rate throughout the benchmark reference year.

Estimates for the 9 months following the March benchmark also are recalculated each year. These post-benchmark estimates reflect the application of sample-based monthly changes to new benchmark levels for March.[4]

A Closer Look at the Wedging Procedure

The current wedging procedure is one possible approach to adjusting monthly CES growth rate estimates. If one is only willing to rely on March information from the QCEW, this appears to be the most reasonable method of adjusting monthly CES employment estimates. However, it is important to realize that the wedging procedure implicitly makes questionable assumptions about the CES growth rate error process.

To see the implied error structure when wedged estimates are considered to be the truth, let E_m denote the true employment level in month m, let r_m denote the true monthly rate of change of employment from month $m-1$ to month m and let $\hat{r}_m$ denote the initial estimate of r_m. Then we may write

(1a) $\hat{r}_m = r_m \times exp(\varepsilon_m)$,

(1b) $\mathrm{E}(exp(\varepsilon_m)) = 1$

where exp(ε_m)-1 denotes the proportional error in the estimated rate of change and .

Note that the CES employment estimate in month *j* is given by

(2) $\hat{E}_j^{ces} = E_{March,t-1}^{qcew} \times \prod_{m=April,t-1}^{j} \hat{r}_m$,

while the true employment level is given by

(3) $E_j = E_{March,t-1}^{qcew} \prod_{m=April,t-1}^{j} r_m$.

Using (1a) and (3), we can rewrite ((2) as

(4) $\hat{E}_j^{ces} = E_j \times \prod_{m=April,t-1}^{j} exp(\varepsilon_m)$.

Letting

(5) $R_{March,t} = E_{March,t}^{qcew} - \hat{E}_{March,t}^{ces}$

denote the annual March revision in year t, the final wedged estimate of employment in month j (running from April of year $t-1$ to March of year t) is given by

(6) $\hat{E}_j^{ces-final} = E_{March,t-1}^{qcew} \times \prod_{m=April,t-1}^{j} \hat{r}_m + \frac{\#j}{12} \times R_{March,t}$

where $E_{March,t-1}^{qcew}$ is March employment count from the QCEW in year $t-1$, $\#j$ is the number of months beyond March of year $t-1$, so $\#April$ equals 1, $\#May$ equals 2, and so on. Equation (2) directly implies that

[4] New birth/death factors are also calculated using the more recent data. We will not go into this here, but a discussion of the birth-death model can be found on the CES webpage.

(7) $\hat{E}_j^{ces-final} - \hat{E}_{j-1}^{ces-final} = \hat{E}_j^{ces} - \hat{E}_{j-1}^{ces} + \frac{1}{12} \times R_{March,t}$

or that the difference between the final, wedged OTM change estimate and the initial OTM change estimate is equal to a constant that is determined by the size of the revision.

If we assume that the wedged estimates are truth, that is, that $\hat{E}_j^{ces-final} = E_j$, then combining equations (2) and (3) and applying some algebra yields a condition on the original CES estimate prior to wedging:

(8) $\sum_{m=April,t-1}^{j} \varepsilon_m = ln\left(1 - \frac{\#j}{12} \times \frac{R_{March,t}}{E_j}\right).$

It follows directly that

(9) $\varepsilon_j = ln\left(1 - \frac{\#j}{12} \times \frac{R_{March,t}}{E_j}\right) - ln\left(1 - \frac{\#j-1}{12} \times \frac{R_{March,t}}{E_{j-1}}\right).$

Figure 1 shows the implied monthly errors prior to wedging for the national, total private CES estimates for the period from March 2004 to March 2013. The implied CES errors are roughly constant throughout the year except for January whose monthly growth rate is invariably measured with substantially greater error than the other months of the year.[5] This error structure seems implausible. We are not aware of any reason why the error in January should be so much greater (in absolute value) than the errors in the other months. And in general, the error in estimated employment should not be constant across the other 11 months.

Recall that we have no knowledge about the individual monthly errors, but we do have information about the total error from the size of the March revision. The natural choice of an error correction model would be to assume that the original rates are all mismeasured by different amounts, but that the implied errors in monthly employment sum to the March discrepancy. In a typical year, one would expect monthly errors to be roughly independent of each other and to have roughly constant variance. In years with a large March revision (typically at turning points in the cycle), the errors are likely to be correlated, possibly resulting from errors in the estimate of the birth-death residual. Of course, it is not possible to implement a more sophisticated error model without observing alternative employment estimates more frequently than once a year. If one only uses the March QCEW, there really is no alternative to wedging back for an entire year. However, if one benchmarks more frequently using the QCEW at other times, then one will need to wedge back for a shorter period of time, so the issue should be less serious.

More on the March Revision

When one benchmarks the CES to the March QCEW, one is implicitly treating the March QCEW employment figure as the "truth." Using (2), we can rewrite equation (5) as

[5] There is a ready explanation as to why the implied error is so large in January. Employment is generally lower in January than in other months throughout the year. As can be seen from equation (9), for any given March employment revision, a lower employment level implies a larger error in the estimated rate of employment change.

$$R_{March,t} = E^{qcew}_{March,t} - E^{qcew}_{March,t-1} \times \prod_{m=April,t-1}^{March,t} \hat{r}_m,$$

which can in turn be rewritten as

(10) $$R_{March,t} = E^{qcew}_{March,t-1} \times \left(\frac{E^{qcew}_{March,t}}{E^{qcew}_{March,t-1}} - \prod_{m=April,t-1}^{March,t} \hat{r}_m \right).$$

Equation (10) more clearly expresses what the March revision represents, namely the difference between the annual (March-to-March) growth rate implied by the QCEW level estimates and the annual growth rate implied by the CES monthly estimates.

Assuming that the annual growth rate from QCEW equals the "truth", we have

(11) $$\frac{E^{qcew}_{March,t}}{E^{qcew}_{March,t-1}} = \prod_{m=April,t-1}^{March,t} r_m.$$

With equations (1a) and (11), we can rewrite the March revision in equation (10) as

(12) $$R_{March,t} = E^{qcew}_{March,t} \times \left(1 - exp\left(\sum_{m=April,t-1}^{March,t} \varepsilon_m\right)\right).$$

Equation (12) makes explicit the relationship between the monthly errors and our interpretation of the March revision. Namely, the March revision depends on the *cumulative* (over the year) monthly errors in the CES rates and the closer the cumulative error is to zero, the smaller the March revision is. The March revision tells us very little about the individual monthly errors in the CES rates. Indeed, one would hope that monthly errors largely average out, leaving us with a relatively small revision. A large March revision likely means that monthly errors in a given year are highly correlated. An example of this was the start of the Great Recession, where CES underestimated the sizes of the early employment losses.

The Effect of Quarterly Benchmarking on March estimates and March Revisions

Although the March employment revision does not provide information about individual monthly errors, the March estimate does provide a natural diagnostic tool for evaluating the effect of more frequent updating. Throughout this paper, we will be focusing on quarterly updating.[6] It is therefore convenient to work with quarterly rather than monthly errors. Let $exp(\varepsilon_m) - 1$ denote the accumulated error in the CES estimate in quarter q of year t, where $\varepsilon_{q,t} = \sum_{m=m_1(q),t}^{m_3(q),t} \varepsilon_m$ and $m_j(q)$ represents month j in quarter q.

There is currently a 10 month lag between the QCEW reference period and the time that the QCEW employment figures are available for benchmarking. Consequently, CES estimates are currently revised every January (10 months after the preceding year's March QCEW estimates are available). With

[6] Not only does QCEW information become available on a quarterly basis, but as discussed below, QCEW employment information in the last month of a quarter is more reliable than QCEW employment information during the first two months of a quarter.

quarterly benchmarking, CES estimates would also be revised about 10 months after each quarter utilizing the June, September, and December QCEW numbers.[7]

Recall the initial estimate of March employment in year t as shown in equation (2). The estimate is comprised of two parts, the QCEW March employment level in year $t-1$ and the product of CES monthly growth rate estimates from April of year $t-1$ to March of year t. Using equation (1a) and our definition of quarterly errors, we can rewrite the initial March employment estimate as

$$(13) \quad \hat{E}^{ces}_{March,t} = E^{qcew}_{March,t} \times exp(\varepsilon_{2,t-1} + \varepsilon_{3,t-1} + \varepsilon_{4,t-1} + \varepsilon_{1,t}).$$

The estimate is again comprised of two parts, the QCEW March employment level in year t and the product of the quarterly errors in the CES rates from second quarter of year $t-1$ to the first quarter of year t.

Let us assume for the moment that the June of year $t-1$ QCEW employment level is the true population value such that[8]

$$(14) \quad E^{qcew}_{June,t-1} = E^{qcew}_{March,t-1} \times \prod_{m=April,t-1}^{June,t-1} r_m.$$

Incorporating the second quarter (June) of year $t-1$ QCEW information into the CES estimate when it first becomes available will result in a revised March estimate that can be written as

$$\begin{aligned}(15a) \quad \hat{E}^{ces(2)}_{March,t} &= E^{qcew}_{June,t-1} x \prod_{July,t-1}^{Sept,t-1} \hat{r}_m \, x \prod_{Oct,t-1}^{Dec,t-1} \hat{r}_m \;\, x \prod_{Jan,t}^{March,t} \hat{r}_m \\ &= E^{qcew}_{June,t-1} \times \prod_{July,t-1}^{march,t} r_m \, exp(\varepsilon_{3,t-1} + \varepsilon_{4,t-1} + \varepsilon_{1,t}). \\ &= E^{qcew}_{March,t} \times exp(\varepsilon_{3,t-1} + \varepsilon_{4,t-1} + \varepsilon_{1,t}).\end{aligned}$$

Essentially including the June QCEW information into the March estimate will eliminate the errors in the CES monthly rates from April to June of year $t-1$. Under reasonable assumptions about the error process, the variance of the revised estimate, $\hat{E}^{ces(2)}_{March,t}$, is lower than the variance of the initial estimate, $\hat{E}^{ces}_{March,t}$. Specifically, from equations (13) and (15a), it follows that

$$\begin{aligned}(16) \quad var(\ln(\hat{E}^{ces}_{March,t}/E^{qcew}_{March,t})) - var(\ln(\hat{E}^{ces(2)}_{March,t}/E^{qcew}_{March,t})) &= var(\varepsilon_{2,t-1}) + 2cov(\varepsilon_{2,t-1}, \varepsilon_{3,t-1}) \\ &+ 2cov(\varepsilon_{2,t-1}, \varepsilon_{4,t-1}) + 2cov(\varepsilon_{2,t-1}, \varepsilon_{1,t}).\end{aligned}$$

If the quarterly errors in the CES are uncorrelated, then the right hand side of (16) reduces to $var(\varepsilon_{2,t-1})$, which is unambiguously positive: eliminating the error in estimated employment growth from April to June of year $t-1$ improves the accuracy of the subsequent March estimate. With

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[7] A preliminary QCEW employment estimate is available 3 months earlier. It is quite possible that little accuracy is lost in using the preliminary QCEW estimates rather than waiting for the final QCEW estimates. We plan to explore this possibility in future work.

[8] The assumption that we can observe true employment levels quarterly helps simplify the exposition in this section, allowing us to focus on essentials. We will return to this point later on when we discuss our recommended benchmarking methodology,

sufficiently strong negative correlation, the right hand side of (16) could actually be negative, but this seems very unlikely. In contrast, there have been times during which the quarterly CES errors have in fact been positively correlated, a prime example being the onset of the Great Recession during which period CES understated employment losses.

In summary, provided that the CES yields an unbiased estimate of employment, the initial CES March year t employment estimate and the revised March year t employment estimate in April year t should on average equal the March QCEW estimate. However, the revised estimate in April will generally be closer to the March QCEW estimate.

We can also define subsequent March year t estimates made using the preceding September and December QCEW estimates) as

(15b) $\hat{E}^{ces(3)}_{March,t} = E^{qcew}_{March,t} \times exp(\varepsilon_{4,t-1} + \varepsilon_{1,t})$

(15c) $\hat{E}^{ces(4)}_{March,t} = E^{qcew}_{March,t} \times exp(\varepsilon_{1,t})$.

The revision utilizing QCEW information through the third quarter (September) of year $t-1$ will result in an additional improvement over the first revision using only the June QCEW. Specifically, it is straightforward to show that

(17) $var(\ln(\hat{E}^{ces(2)}_{March,t}/E^{qcew}_{March,t})) - var(\ln(\hat{E}^{ces(3)}_{March,t}/E^{qcew}_{March,t})) = var(\varepsilon_{3,t-1}) + 2cov(\varepsilon_{3,t-1}, \varepsilon_{4,t-1})$

$+ 2cov(\varepsilon_{3,t-1}, \varepsilon_{1,t})$.

Similarly, the revision using the December t – 1 QCEW will yield a still tighter estimate of the March year t employment estimate.

The discussion above indicates that more frequent updating yields improved employment estimate, using the March estimate as a convenient benchmark. What can we say about the revisions themselves?

The March revision using the preceding second quarter estimate of the QCEW is given by

(18a) $R^{(2)}_{March,t} = \hat{E}^{ces(2)}_{March,t} - \hat{E}^{ces}_{March,t}$,

$=E^{qcew}_{March,t} exp(\varepsilon_{3,t-1} + \varepsilon_{4,t-1} + \varepsilon_{1,t}) \times [1 - exp(\varepsilon_{2,t-1})]$

Similarly, the March revisions using the preceding third and fourth quarter QCEW year t -1 estimates are respectively given by

(18b) $R^{(3)}_{March,t} = \hat{E}^{ces(3)}_{March,t} - \hat{E}^{ces(2)}_{March,t}$

$=E^{qcew}_{March,t} exp(\varepsilon_{4,t-1} + \varepsilon_{1,t}) \times [1 - exp(\varepsilon_{3,t-1})]$

(18c) $R^{(4)}_{March,t} = \hat{E}^{ces(4)}_{March,t} - \hat{E}^{ces(3)}_{March,t}$

$$=E^{qcew}_{March,t} exp(\varepsilon_{1,t}) \times [1 - exp(\varepsilon_{4,t-1})] .$$

The final revision using the actual March QCEW is given by

(18d) $R^{(F)}_{March,t} = E^{qcew}_{March,t} - \hat{E}^{ces(4)}_{March,t}$

$$=E^{qcew}_{March,t}[1 - exp(\varepsilon_{4,t-1})]$$

Note that $R^{(q)}_{March,t} > (<)\ 0$ as $\varepsilon_{q,t-1} < (>)0$. Also, note that

$R^{(2)}_{March,t} + R^{(3)}_{March,t} + R^{(4)}_{March,t} + R^{(F)}_{March,t} = R_{March,t}$. That is, the four quarterly benchmark revisions sum to the benchmark revision when we only benchmark annually. In addition, note that

(19) $|^{(2)}_{March,t}| + |R^{(3)}_{March,t}| + |R^{(4)}_{March,t}| + |R^{(F)}_{March,t}| \geq |R_{March,t}|$,

with equality holding if and only if the quarterly benchmark revisions are all positive or all negative. When CES errors are opposite signed in different quarters, the revision in one quarter will at least partly offset that in another quarter. This leads to a seeming puzzle: earlier we saw that each revision yielded a better estimate of March employment than the previous one. If this is so, why should the revisions be offsetting, with a positive revision in one quarter being followed by a negative revision in a subsequent quarter or vice versa?

A positive initial revision using the QCEW in the second quarter of year t – 1 means that the CES initially underestimated employment growth from April to June in year $t - 1$ and a negative second revision using the QCEW in the third quarter of year t – 1 means that the CES initially overestimated employment growth from July to September in year $t - 1$. Occurrences like this should be quite common if errors in the CES are uncorrelated over time. When the initial errors in different quarters are in different directions, the revisions (which will be opposite signed from the errors) will also be. Actually, it should be reassuring when the quarterly revisions are not all of the same sign because this means that the CES is not making systematic errors. When the CES errors are all in the same direction, so will be the revisions. Quarterly benchmarking is especially valuable in such a case because it allows us to begin correcting the systematic errors more quickly than annual benchmarking would.[9]

To summarize, offsetting quarterly revisions should not be disturbing because they are an indication that the CES is not making systematic errors. In those hopefully rare occasions when errors are correlated (which tend to occur at turning points in the business cycle), quarterly benchmarking provides an important safeguard against systematic errors being baked into the estimates for an unnecessarily long period of time.

A Benchmarking Methodology Using Seasonally Adjusted CES and QCEW Data

As is well documented, the QCEW and the CES have different seasonal patterns – see, for example, Berger and Phillips (1993), Berger and Phillips (1994), and Groen (2011). These seasonal patterns are, of

[9] The discussion has abstracted from the possibility that errors in the CES are negatively correlated. In such a case, there would be an even greater tendency for the sum of the absolute values of the quarterly March revisions to exceed the absolute value of the annual March revision. This situation is unlikely to occur in practice. But again, it would not mean that the quarterly revisions do not improve the employment estimates throughout the year.

course, not an issue when one benchmarks annually. However, they must be accounted for if one benchmarks more frequently. A team at BLS has examined several methods of dealing with the different seasonal patterns in the QCEW and has determined that it is best to explicitly model and estimate the seasonal patterns in the CES and QCEW, as methods that implicitly adjust for seasonality have been found lacking.

Our proposed procedure is quite simple conceptually. The intuition behind the method follows directly from the relationship between the estimated monthly growth rate and the true growth rate in equation (1a). We can rewrite the quarterly growth rate estimate as

(20) $$\prod_{m=m_1(q)}^{m_3(q)} \hat{r}_m = \prod_{m=m_1(q)}^{m_3(q)} r_m \times exp\left(\sum_{m=m_1(q)}^{m_3(q)} \varepsilon_m\right) \Rightarrow \hat{r}_q = r_q \times exp(\varepsilon_q)$$

so the observed quarterly growth rate equals the true quarterly growth rate times the over-the-quarter error term.

The proposed method assumes that the ratio of the seasonally adjusted quarterly growth rate from the QCEW to the seasonally adjusted quarterly growth rate from the CES is a noisy signal of the over-the-quarter error term such that

(21) $$\frac{\hat{r}_q^{SA-QCEW}}{\hat{r}_q^{SA-CES}} = \exp(\eta_q),$$

The error term η_q is in turn given by

(21b) $$\eta_q = \gamma_q - \varepsilon_q$$

where γ_q is the residual error term reflecting an error in the estimation of the seasonal factors or in QCEW itself. In particular, when a new quarter of QCEW data becomes available, our proposed method adjusts monthly rates in that quarter by a constant determined by the ratio of seasonally adjusted quarterly growth rates. The adjusted monthly rates can be written as

(22) $$\tilde{r}_{m(q)} = \hat{r}_{m(q)} \times exp\left(\frac{1}{3} ln\left(\frac{\hat{r}_q^{SA-QCEW}}{\hat{r}_q^{SA-CES}}\right)\right)$$

Multiplying the monthly rates over the quarter, equation (22) implies that

(23) $$\tilde{r}_q = \hat{r}_q \times exp(\eta_q) \Rightarrow \tilde{r}_q = r_q \times exp(\varepsilon_q + \eta_q) = r_q \times exp(\gamma_q)$$

so the adjusted quarterly rate equals the true quarterly growth rate times the residual error term.

Having calculated the adjusted rates for the months in quarter q, one can readily obtain revised employment growth estimates for quarter q that in turn yield a revised estimate for employment at the end of the quarter. The revised estimate for the end of quarter employment level in turn leads to a revised employment level in subsequent months. For example, in April 2015, we would obtain corrected values for April 2014 – March 2015 employment growth. The corrected values from April 2014 to June 2014 are obtained by applying the adjusted rates for the period April 2014 – June 2014. The corrected values from July 2014 to March 2015 are obtained by applying the new June 2014 employment base, but using the initial CES growth rates.[10] Similarly, revised estimates could be published when QCEW estimates in September and December become available.[11]

As is the case with the three preceding revisions, in the January revision, adjusted growth rates for the months January, February and March are calculated according to equations (22) and (23); these adjusted growth rates in turn yield revised estimates for employment growth for the January – March period. However, the published revision in January also includes a second component arising from the fact that the adjusted quarterly growth rates will have some error. Multiplying the adjusted quarterly growth rates over the year yields an estimate of the over-the-year growth rate that is equal to

$$(24)\quad \prod_{q=2,t-1}^{1,t} \tilde{r}_q = \prod_{q=2,t-1}^{1,t} r_q \times exp\left(\sum_{q=2,t-1}^{1,t} \gamma_q\right) = \frac{E_{March,t}^{qcew}}{E_{March,t-1}^{qcew}} \times exp\left(\sum_{q=2,t-1}^{1,t} \gamma_q\right)$$

The second component of the March revision is given by the difference between the March employment level and the employment level predicted from the adjusted quarterly growth rates:

$$(25)\quad R_{March,t}^{final} = E_{March,t}^{qcew} - E_{March,t-1}^{qcew} \times \prod_{q=2,t-1}^{1,t} \tilde{r}_q = E_{March,t}^{qcew} \times \left(1 - exp\left(\sum_{q=2,t-1}^{1,t} \gamma_q\right)\right)$$

The error term $R_{March,t}^{final}$ reflects errors in the estimation of the seasonal factors. If the seasonal factors were estimated perfectly, $R_{March,t}^{final}$ should be 0.[12]

In order to guarantee that the estimated over-the-year growth rate equals the over-the-year growth rate from the QCEW (which is assumed to be the true over-the-year growth rate) we make a final rate adjustment. This could be viewed as similar in spirit to the current wedging procedure with a different functional form. Since we have no additional information we will assume that $\gamma_q = \gamma$ for all quarters and that the adjustment is equal across all months in the quarter. This results in a final monthly rate estimate equal to

$$(26)\quad \tilde{r}_m^{final} = \tilde{r}_m \times exp\left(\frac{\hat{\gamma}}{3}\right)$$

[10] The proposed revision procedure only utilizes QCEW employment estimates for the final month of any quarter because the QCEW employment estimate for the final month of a quarter is much more reliable than the estimates for the first two months of any quarter. Evidence for this is provided by the existence of “seam effects” across quarters - monthly employment changes between the last month of a quarter are typically larger in absolute value and less likely to be zero than the employment changes between the months within a quarter, suggesting that employers filling out the UI reports underlying the QCEW have a tendency to copy backward from the third month of the quarter to the first and second months.

[11] We should note that even though more current CES data is available, the ratio of seasonally adjusted QCEW to CES rates used in (22) is based on data from quarter q and backward for both series (that is, seasonal factors are estimated over the same period of time for both the CES and QCEW). Further, the CES rate in equation (22) is only adjusted once. We do not propose adjusting the rate in subsequent quarters even though revised estimates of the seasonal factors may lead to a change in the ratio of the seasonally adjusted QCEW to the seasonally adjusted CES. For example, we adjust the June 2014 quarterly rate in April 2015 when the June 2014 QCEW becomes available. In July 2015 when the September 2014 QCEW becomes available we could estimate a new ratio for June 2014 but choose not to. In this sense, the not seasonally adjusted series is fixed when the next year’s March value becomes available and the final revision is made.

[12] We may note that possible monthly errors in the QCEW are not reflected in $R_{March,t}^{final}$, as these will average out to zero over the year.

where

$$(27) \quad \hat{\gamma} = \frac{1}{4} ln\left(\frac{E^{qcew}_{March,t}}{E^{qcew}_{March,t-1}} \Big/ \prod_{q=2,t-1}^{1,t} \tilde{r}_q \right)$$

It follows directly that

$$(28) \quad \prod_{m=April,t-1}^{March,t} \tilde{r}_m^{final} = \frac{E^{qcew}_{March,t}}{E^{qcew}_{March,t-1}}$$

so the estimated (March-to-March) annual growth rate equals the annual growth rate implied by QCEW employment levels.

Table 1 shows the revisions that result when one applies the method outlined to revise estimates of total private employment during the period from 2007 – 2013.[13] Although the March revision does not tell us much about the accuracy of the individual monthly errors, it is nevertheless an informative statistic. Recall from our earlier discussion a large revision when benchmarking is only done annually suggests that the monthly estimates are correlated over the past year and therefore do not average out to zero.

Looking at the estimates in the second table, we see that as a rule, the estimated March employment generally improves as it is revised throughout the year. In some years, the improvement is quite noticeable, especially in years where the initial CES estimate differs substantially from the QCEW value.

The estimates in the last column are simply the error term $R^{final}_{March,t}$. These estimates indicate how well the adjustment model is estimating March employment. In every year the absolute value of the March revision is smaller under our proposed method than under the current method. At the very least this suggests that the ratio of the seasonally adjusted QCEW quarterly growth rate to the seasonally adjusted CES quarterly growth rate contains some useful information regarding the nature of monthly errors in CES growth rates. This information seems particularly useful when the monthly errors tend be correlated as they seem to be from April 2008 to March 2009 and from April 2009 to March 2010. In these years, it seems that the CES is systematically overestimating the growth rate which results in a large negative revision. In these years our quarterly rate adjustments are always negative which indicates that capitalizing on the information contained in non-March QCEW data may give an earlier (than the next March) indication that the CES is systematically over or under estimating the growth rates.

While we do not know how well we are estimating employment in the intermediate months, the results in the table are suggestive. Note from equation (23), that the accuracy of the benchmark revision depends on the size of γ_q which reflects the error in the estimated seasonal QCEW and CES seasonal factor. The real question, however, is not whether there is error in the seasonal factors, but how large this error is relative to the error ε_q in the CES estimate. The larger is the error in the CES estimate relative to the error in the estimated seasonal factors, the larger is the gain from benchmarking.

[13] Unlike the current practice, we have estimated the seasonal factors concurrently. This distinction is not central to our analysis.

A Simulation Exercise

The results above provide a strong indication that the proposed benchmark procedure results in an improved March estimate. One suspects that the revised quarterly estimates are improvements over the initial CES estimates, but there is insufficient information to show this definitively (after all, if we knew the true quarterly estimates, we would not need the benchmarking procedure). In order to get a better handle on this, we now perform a simulation exercise.

The simulation exercise is helpful in answering another important question. The success of the proposed benchmarking procedure depends crucially on how accurately we estimate the seasonal factors. As one drills down by industry and/or area, the finer CES estimates will have a larger error component. This in and of itself makes the proposed benchmarking procedure more advantageous. But there is an offsetting effect. The greater the error in the CES estimate, the greater will be the errors in the resulting estimates of the seasonal factors. At some point, will the errors in the estimates of the seasonal factors be sufficiently great that the quarterly benchmarking procedure actually results in errors that exceed those in the unadjusted CES estimates?

In laying out our simulation model, it is convenient to slightly modify the notation from that used above.

Let the "true" employment growth that we would like to measure with the CES be given by $r_{q,t}^{true-ces} = r_{q,t} \times exp(\delta_q^{ces})$, where $exp(\delta_q^{ces})$ represents a seasonal factor. The CES estimate of employment growth in quarter *q* of year *t* is then given by

(29) $\hat{r}_{q,t}^{ces} = r_{q,t} \times exp(\delta_q^{ces}) \times exp(\varepsilon_{q,t}^{ces})$,

where $exp(\varepsilon_{q,t}^{ces})$ is the error in the CES estimate of the growth rate.

We are seemingly implicitly assuming that the seasonal variation in the CES represents true seasonal variation in the underlying employment. In reality, the seasonal factors could also reflect systematic seasonal errors in the CES. However, without additional information, one cannot distinguish empirically between true seasonal variation in the underlying employment series and seasonal variation that reflects systematically seasonal measurement error.

Similarly, let the QCEW estimate of employment be given by

(30) $\hat{r}_{q,t}^{qcew} = r_{q,t} \times exp(\delta_q^{qcew}) \times exp(\varepsilon_{q,t}^{qcew})$.

Note that we are no longer assuming that the QCEW is measured without error. Rather, like the CES, the QCEW error has a random component $\varepsilon_{q,t}^{qcew}$. In addition, there is a QCEW seasonal factor that may partly reflect QCEW measurement error that has a systematic seasonal component. (As one example, employers may tend to clean out their employee lists in January).

Letting $\hat{\delta}_q^{ces}$ denote the estimated value of δ_q^{ces}, the seasonally adjusted estimated CES quarterly growth rate is given by

(31) $\hat{r}_{q,t}^{ces-sa} = r_{q,t} \times exp(\delta_q^{ces}) \times exp(\varepsilon_{q,t}^{ces}) \times exp(-\hat{\delta}_q^{ces})$.

Similarly, the seasonally adjusted QCEW quarterly growth rate is given by

(32) $\hat{r}_{q,t}^{qcew-sa} = r_{q,t} \times exp(\delta_q^{qcew}) \times exp(\varepsilon_{q,t}^{qcew}) \times exp(-\hat{\delta}_q^{qcew})$.

Finally, the benchmarked CES growth rate is given by

(33) $\tilde{r}_{q,t}^{ces} = \hat{r}_{q,t}^{ces} \times \left(\frac{\hat{r}_{q,t}^{qcew-sa}}{\hat{r}_{q,t}^{ces-sa}}\right) = r_{q,t} \times exp(\hat{\delta}_q^{ces}) \times exp(\delta_q^{qcew} - \hat{\delta}_q^{qcew} + \varepsilon_{q,t}^{qcew})$.

The log difference between the CES estimator and true employment growth is simply

(34) $ln(\hat{r}_{q,t}^{ces}) - ln(r_{q,t}^{true-ces}) = ln(r_{q,t}) + \delta_q^{ces} + \varepsilon_{q,t}^{ces} - (ln(r_{q,t}) + \delta_q^{ces}) = \varepsilon_{q,t}^{ces}$

while the difference between the benchmark estimate and true employment growth is

(35) $ln(\tilde{r}_{q,t}^{ces}) - ln(r_{q,t}^{true-ces}) = (\hat{\delta}_q^{ces} - \delta_q^{ces}) + (\delta_q^{qcew} - \hat{\delta}_q^{qcew}) + \varepsilon_{q,t}^{qcew}$.

Provided that both the CES and QCEW errors are mean zero and the seasonal factor estimators from both the CES and QCEW series are unbiased, it follows that the estimators in (29) and (33) are also unbiased. The point of the simulation exercise is to compare the variances of the two estimators. Of course, since the estimators are unbiased, the variance of each is equal to its mean squared error (MSE).

In our simulations, we normalize $r_{q,t}$ to 1 (i.e., no employment change) for all four quarters *q* and all years *t* (t runs from 1 to 5). We set the seasonal factors to be the following:

(36) $exp(\delta_1^{ces}) = 0.995$, $exp(\delta_2^{ces}) = 1.003$, $exp(\delta_3^{ces}) = 0.998$, $exp(\delta_4^{ces}) = 1.004$

(37) $exp(\delta_1^{qcew}) = 0.990$, $exp(\delta_2^{qcew}) = 1.004$, $exp(\delta_3^{qcew}) = 0.997$, $exp(\delta_4^{qcew}) = 1.009$

Note from (36) and (37) that we have set the QCEW to be more seasonal than the CES.

Finally, we assume that the random errors in the CES and the QCEW are normally distributed with respective variance σ_{ces}^2 and σ_{qcew}^2:[14]

(38) $\varepsilon_{q,t}^{ces} \sim N(0, \sigma_{ces}^2)$, $\varepsilon_{q,t}^{qcew} \sim N(0, \sigma_{qcew}^2)$.

Let

(39) $p \equiv \sigma_{qcew}^2 / \sigma_{ces}^2$

In the simulations to follow, we allow both p and σ_{ces}^2 to vary. For a given value of σ_{ces}^2, a lower p is equivalent to an decrease in σ_{qcew}^2. Thus, the lower is p, the more precise is the QCEW relative to the CES. We should expect this in turn to lead to improved performance of the benchmark estimator relative to the initial CES estimator. For a given p, a higher value of σ_{ces}^2 also means an increase in σ_{qcew}^2. This in turn means that both the initial CES estimate and the benchmarked estimate will be less precise. There is another likely effect of an increase in σ_{ces}^2 and σ_{qcew}^2. The greater are these variances, the less precise are the estimates of the seasonal factors likely to be, which in turn lowers the precision of the benchmarked estimate. The net effect on the performance of the benchmark estimator relative to the initial CES estimator is an open question. It is not obvious a priori whether for a given value of p

[14] This is a minor modification from our assumption earlier in the paper that we make because in calculating mean squared errors below, we will be dealing logs instead of levels

a greater σ^2_{ces} is associated with improved or worsened performance of the benchmark estimator relative to the initial CES estimator.

For any given combination of p and σ^2_{ces}, we run 1000 simulations of both $\varepsilon^{ces}_{q,t}$ and $\varepsilon^{qcew}_{q,t}$. This yields 1000 estimates of the original CES estimate, $\hat{r}^{ces}_{q,t}$, and the proposed CES estimate, $\tilde{r}^{ces}_{q,t}$ for all quarters for five years. Seasonal factors are estimated using PROC x12 in SAS. Since we are estimating 20 targets, the mean squared error of the unadjusted CES estimate and the benchmarked estimate are given by

$$MSE\left(\hat{r}^{ces}_{q,t}\right) = \frac{1}{1000 \times 4 \times 5} \sum_{t=1}^{5} \sum_{q=1}^{4} \sum_{s=1}^{1000} \left[ln\left(\hat{r}^{ces,(s)}_{q,t}\right) - ln\left(r^{true-ces}_{q,t}\right)\right]^2$$

(40)

$$MSE\left(\tilde{r}^{ces}_{q,t}\right) = \frac{1}{1000 \times 4 \times 5} \sum_{t=1}^{5} \sum_{q=1}^{4} \sum_{s=1}^{1000} \left[ln\left(\tilde{r}^{ces,(s)}_{q,t}\right) - ln\left(r^{true-ces}_{q,t}\right)\right]^2$$

where (s) indicates the simulation number.

Our simulation results are summarized in Figures 2, 3, and 4. First consider curve labelled "RMSE of the original estimate." Noting that the root mean squared error (RMSE) is graphed on the vertical axis and σ^2_{ces} on the horizontal, we see that as expected, the RMSE of the CES estimate increases with σ^2_{ces}.

The remaining curves in Figure 2 illustrate the performance of the proposed benchmark estimator. Each of these curves is associated with a different value of p. Rightward movement along any of these curves is associated with a higher RMSE. This is, of course, expected since for a given p, a higher σ^2_{ces} also means a higher σ^2_{qcew}. Now consider the effect of variations in p, recalling that for a given σ^2_{ces}, a lower *p* is associated with a lower value of σ^2_{qcew}. The lowest curve in the figure is that corresponding to a value of p equal to 0. This curve lies well below that corresponding to the original CES estimate: when p (and therefore σ^2_{qcew}) is 0, the RMSE of the proposed benchmark estimate is always less than that of the original CES estimate for any given value of σ^2_{ces}.

As p increases the associated RMSE curve moves up indicating a degradation in the performance of the proposed benchmark estimator. However, for plausible values of p, the proposed estimator still yields a substantial performance gain. This gain is eliminated entirely only when p is close to 1. As indicated by the uppermost curve in the figure, when $p = 1$ (so that $\sigma^2_{qcew} = \sigma^2_{ces}$), the RMSE of the benchmark estimate exceeds that of the original CES estimate. This is what we would expect because of the error in the benchmark estimate induced by error in the estimation of the seasonal factors.

Figure 3 shows the effect of an increase in σ^2_{ces} on the MSE of the CES estimate and the MSE of the estimated seasonal factors. As we already knew to be the case, the MSE of the CES estimate increases one for one with the increase in σ^2_{ces}. The MSE of the seasonal factors also increases with the increase in σ^2_{ces}, but at a much slower rate (note that the slope of orange curve is well below 1). While not pictured, the same is true for the relationship between the MSE of the QCEW seasonal factors and σ^2_{qcew}. Recall from Figure 2 that for a plausible value of p, the RMSE of the proposed estimator is smaller than that of the simple CES estimator for any value of σ_{ces}^2, as indicated by the fact that the RMSE curve for the proposed estimator lies entirely below that for the CES estimator. This result makes sense in light of our finding in Figure 2 that increases in σ_{ces}^2 and σ_{qcew}^2 cause the mean squared errors in the estimated seasonal factors to increase, but at a slower rate.

We obtain an even stronger result in Figure 4, which shows the performance of the proposed estimator relative to that of the CES estimator. As in the Figures 2 and 3, we plot σ_{ces}^2 on the horizontal axis in Figure 4. On the vertical axis, we now plot $MSE\left(\tilde{r}_{q,t}^{ces}\right)/MSE\left(\hat{r}_{q,t}^{ces}\right)$, the ratio of the mean squared error of the proposed estimator to the mean squared error of the CES. Each curve in the figure corresponds to a different value of p. As expected, the lower is p, the lower is the corresponding curve in the figure, reflecting the fact that for a given value of σ_{ces}^2, the performance gain of the benchmark estimator increases as σ_{qcew}^2 falls. Less predictable is the fact that the curves in Figure 4 are all (nearly) straight lines with slope equal to 0. This tells us that the ratio of the mean squared error of the proposed estimator to the mean squared error of the CES depends only on p and not on σ_{ces}^2. An increase in σ_{ces}^2 accompanied by an increase in σ_{qcew}^2 so as to maintain a constant p causes the mean squared errors of the proposed estimator and the CES estimator to increase by the same proportion. Note that this means that the arithmetic difference between the two mean squared errors increases (as shown by the distance between the curves in Figure 2).

At the risk of belaboring the obvious, it may be worth explicitly tracing out the effect of increasing σ_{ces}^2 holding σ_{qcew}^2 constant. When σ_{qcew}^2 is held constant, an increase in σ_{ces}^2 implies a fall in p. In both Figures 2 and 4, this would be represented by both a drop to a lower curve and a movement to the right. We therefore have the unambiguous result that for a given precision of the QCEW, other things the same, the less precise is the CES estimator, the greater is both the relative and absolute gain offered by the proposed benchmark estimator.

Seasonally adjusted estimates are often of greater analytical interest than non-seasonally adjusted one. Figures 5 summarizes the performance of the proposed estimator after when it is seasonally adjusted. The curves in Figure 5 have the same general shape as those in Figure 2 and those in Figure 6 have the same shape as those in Figure 2.

One last point. Our simulation analysis has assumed that the seasonal patterns of the CES and the QCEW are constant over time. If seasonal patterns change over time, the seasonal factors will be more difficult to estimate. Greater errors in the seasonal factors will reduce the performance of the benchmarked non-seasonally adjusted CES estimate relative to that of the non-benchmarked non-seasonally adjusted CES estimate. However, it is not clear what happens to the performance of the benchmarked seasonally adjusted CES estimate relative to that of the non-benchmarked seasonally adjusted CES estimate since both of these estimates will be less precise. We plan to analyze this in future work.

Conclusion

Rather than the annual benchmarking procedure that is currently in place for national estimates, we propose benchmarking seasonally adjusted CES estimates to the seasonally adjusted QCEW every quarter. The proposed estimator performs well when applied to the National all employee series. The gain to more frequent updating is especially large when monthly CES error are positively correlated, as was the case at the beginning of the Great Recession.

The results of our simulation exercise apply equally to *any series*, be it total or industry, or national or local. We used the simulation exercise to compare the performance of the proposed quarterly benchmarking estimate with the initial CES estimate. The results demonstrate that even controlling for a loss of precision in the estimation of seasonal factors, *the greater the variance of the CES estimate, the greater is both the relative and absolute gain provided by the proposed quarterly benchmarking procedure*. The CES industry and area estimates have a greater variance than the National all employee series. One can therefore reasonably argue that there is an even stronger case for applying the proposed quarterly benchmarking procedure to the industry and area estimates.

As noted above, our simulation analysis has made the simplifying assumption that the seasonal patterns of the CES and the QCEW are constant over time. We plan to relax this assumption in future work.

Finally, the discussion in this paper has focused more on the national CES estimates than the state and area estimates. However, the methodology can be applied to state and area estimates in addition to national estimates. As noted in the introduction, state and metropolitan area estimates are currently benchmarked annually by replacing sample-based estimates with all available months of population data. An undesirable feature of the resulting hybrid series is the confounding of QCEW and CES seasonality. Difficulties remain when seasonally adjusting the hybrid series.

As originally noted by Berger and Phillips (1993), it is best to seasonally adjust the QCEW and CES components of the hybrid series separately. However, as discussed by Scott, Stamas, Sullivan and Chester (1994) and Phillips and Wang (2015), a problem arises at the seam where the QCEW data end and the CES data begin because differences in the seasonal factors at the seam will affect the growth rate of the hybrid series at the seam point. However, our proposed methodology produces a series that has CES seasonality throughout.[15] Seasonally adjusting this series is therefore straightforward.[16]

[15] In fact, the benchmarked quarterly growth rates are essentially the QCEW growth rates with the CES seasonality.

[16] Of course, a second advantage of our proposed methodology is that QCEW estimates are incorporated sooner. As outlined on their webpage, the Federal Reserve Bank of Dallas incorporates the QCEW information as soon as the QCEW data are available, but like the current BLS procedure, does so by producing a hybrid series. In a recent paper, Walstrum (2015) examines the effect of applying this early benchmarking procedure to update the CES employment estimates for the five states in the Seventh Federal Reserve District.

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Table 1. Analysis of proposed employment estimates and revisions

Employment estimates

Date	QCEW value	Original CES estimate	Revised estimate as of April	Revised estimate as of July	Revised estimate as of October	Revised estimate as of January (never published)
Mar-09	108,250,800	109,124,676	109,179,508	108,977,936	108,893,811	108,365,917
Mar-10	105,535,500	106,097,960	105,951,628	105,626,170	105,679,140	105,570,462
Mar-11	107,565,200	107,194,505	107,355,770	107,415,776	107,415,776	107,467,022
Mar-12	110,009,400	109,777,090	109,604,541	110,096,767	109,795,585	110,155,060
Mar-13	112,699,400	112,152,430	112,265,409	112,076,221	111,923,700	112,427,355
Mar-14	114,907,500	114,940,754	115,001,394	114,969,354	114,991,067	114,855,962
Mar-15	117,717,000	117,925,267	118,033,062	117,982,639	118,048,168	117,688,749

Absolute difference between QCEW and estimate

Date	Original CES estimate	Revised estimate as of April	Revised estimate as of July	Revised estimate as of October	Revised estimate as of January (never published)
Mar-09	873,876	928,708	727,136	643,011	115,117
Mar-10	562,460	416,128	90,670	143,640	34,962
Mar-11	370,695	209,430	149,424	149,424	98,178
Mar-12	232,310	404,859	87,367	213,815	145,660
Mar-13	546,970	433,991	623,179	775,700	272,045
Mar-14	33,254	93,894	61,854	83,567	51,538
Mar-15	208,267	316,062	265,639	331,168	28,251

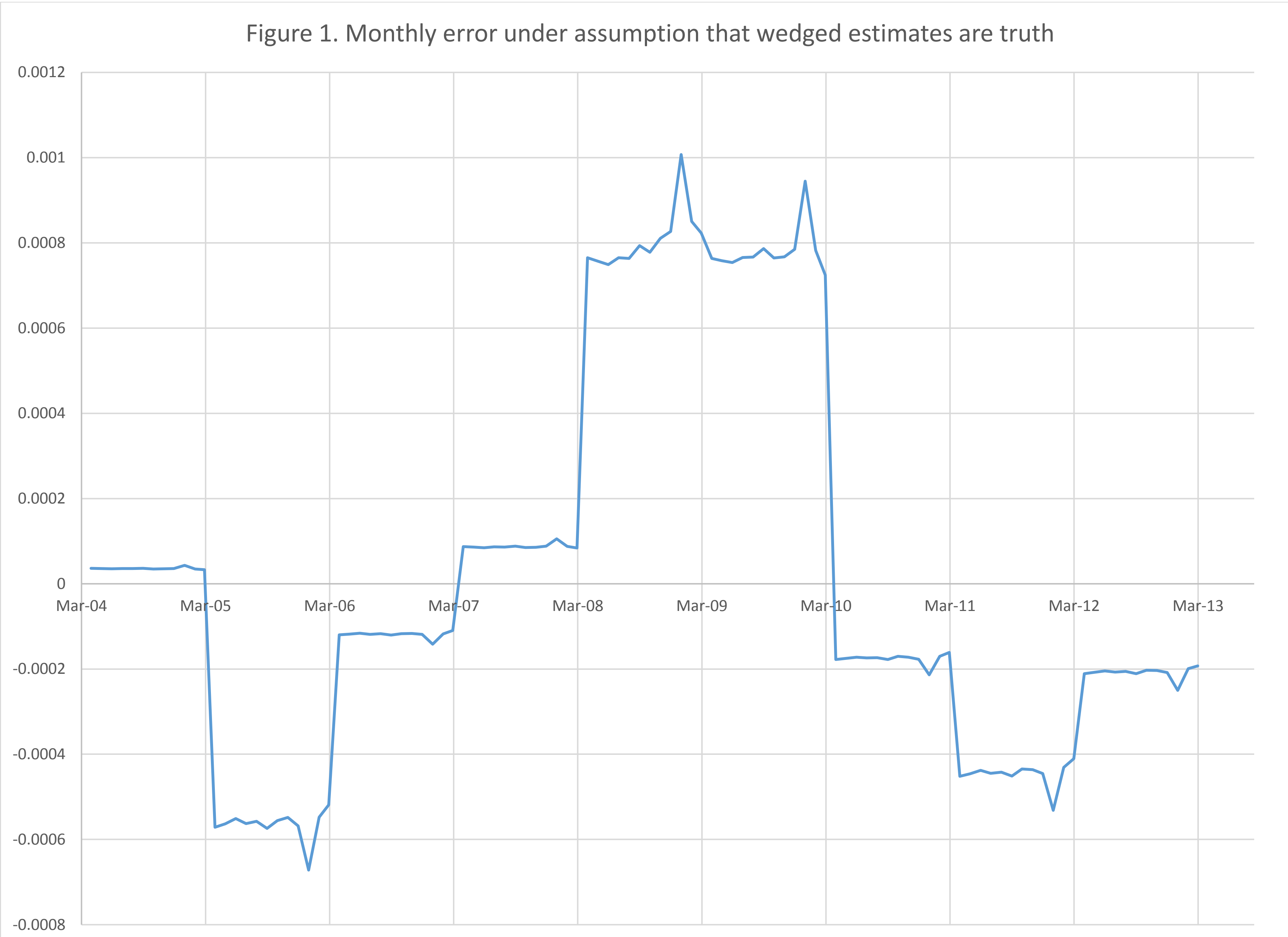

Figure 1. Monthly error under assumption that wedged estimates are truth
0.0012
0.001
0.0008
0.0006
0.0004
0.0002
0
-0.0002
-0.0004
-0.0006
-0.0008
Mar-04
Mar-05
Mar-06
Mar-07
Mar-08
Mar-09
Mar-10
Mar-11
Mar-12
Mar-13

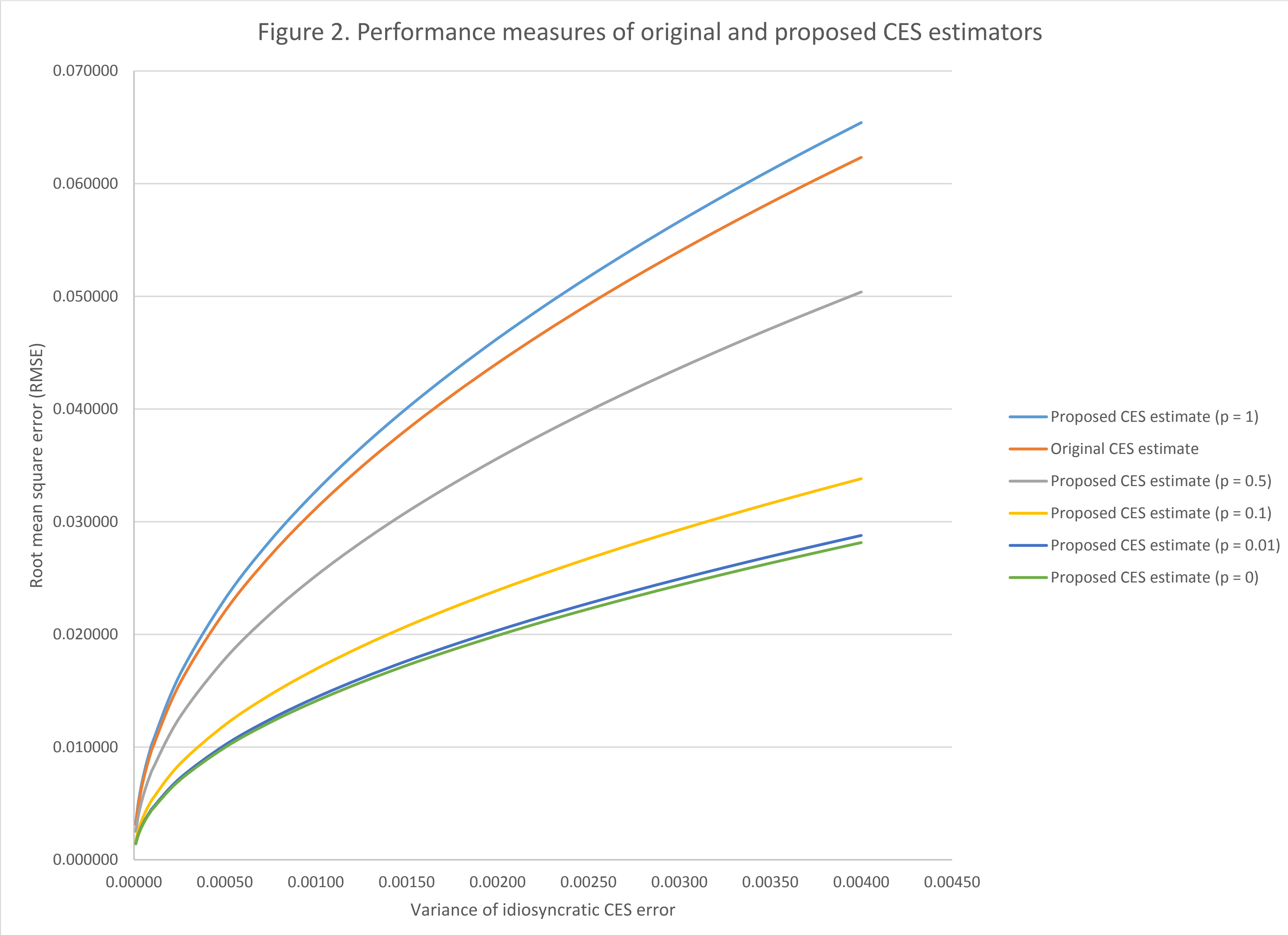
Figure 2. Performance measures of original and proposed CES estimators
Root mean square error (RMSE)
0.070000
0.060000
0.050000
0.040000
0.030000
0.020000
0.010000
0.000000
0.00000
0.00050
0.00100
0.00150
0.00200
0.00250
0.00300
0.00350
0.00400
0.00450
Variance of idiosyncratic CES error
Proposed CES estimate (p = 1)
Original CES estimate
Proposed CES estimate (p = 0.5)
Proposed CES estimate (p = 0.1)
Proposed CES estimate (p = 0.01)
Proposed CES estimate (p = 0)

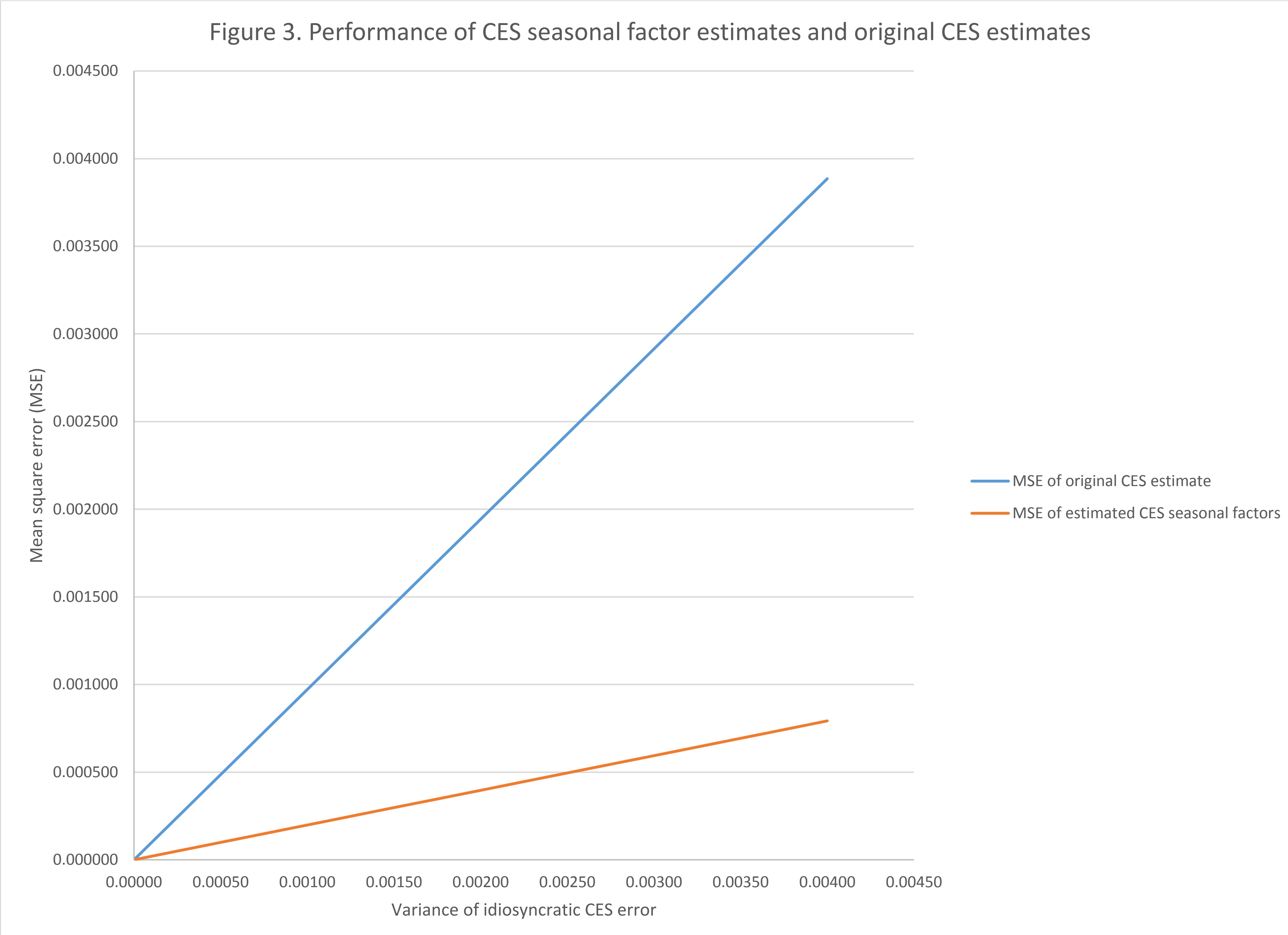
Figure 3. Performance of CES seasonal factor estimates and original CES estimates
0.004500
0.004000
0.003500
0.003000
0.002500
0.002000
0.001500
0.001000
0.000500
0.000000
Mean square error (MSE)
0.00000
0.00050
0.00100
0.00150
0.00200
0.00250
0.00300
0.00350
0.00400
0.00450
Variance of idiosyncratic CES error
MSE of original CES estimate
MSE of estimated CES seasonal factors

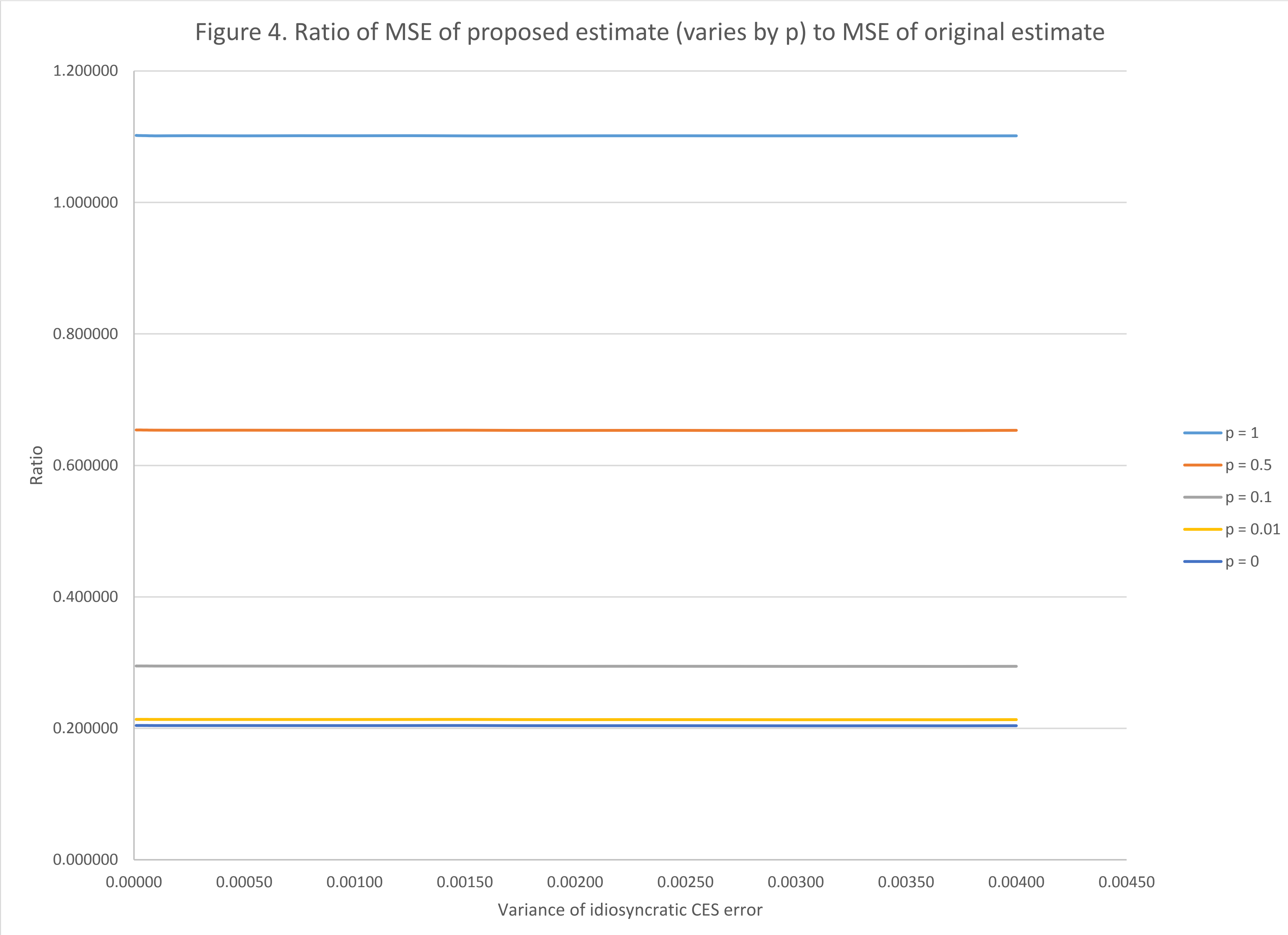
Figure 4. Ratio of MSE of proposed estimate (varies by p) to MSE of original estimate
1.200000
1.000000
0.800000
0.600000
0.400000
0.200000
0.000000
Ratio
0.00000
0.00050
0.00100
0.00150
0.00200
0.00250
0.00300
0.00350
0.00400
0.00450
Variance of idiosyncratic CES error
p = 1
p = 0.5
p = 0.1
p = 0.01
p = 0

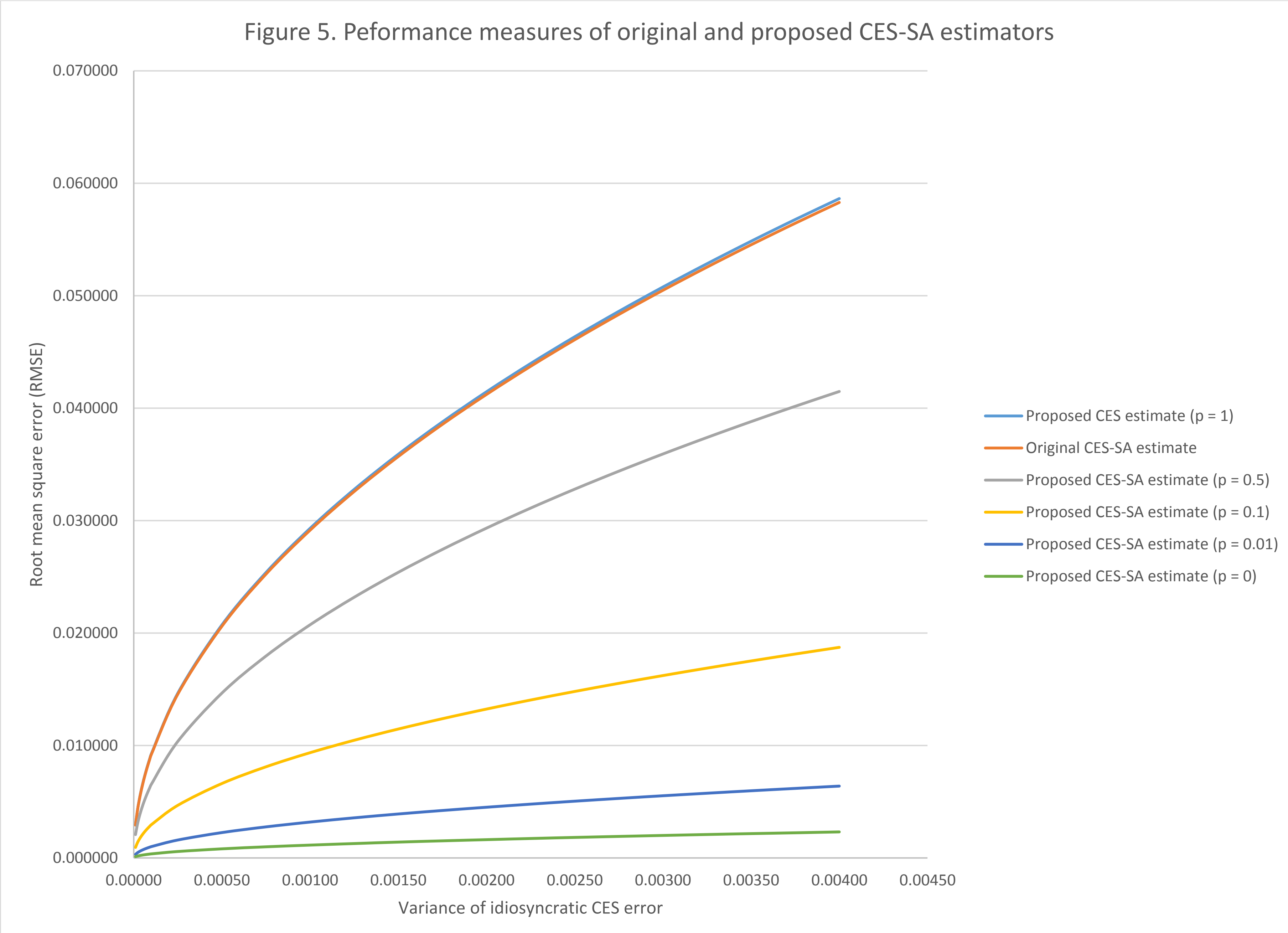

Figure 5. Peformance measures of original and proposed CES-SA estimators
Root mean square error (RMSE)
0.070000
0.060000
0.050000
0.040000
0.030000
0.020000
0.010000
0.000000
0.00000
0.00050
0.00100
0.00150
0.00200
0.00250
0.00300
0.00350
0.00400
0.00450
Variance of idiosyncratic CES error
Proposed CES estimate (p = 1)
Original CES-SA estimate
Proposed CES-SA estimate (p = 0.5)
Proposed CES-SA estimate (p = 0.1)
Proposed CES-SA estimate (p = 0.01)
Proposed CES-SA estimate (p = 0)

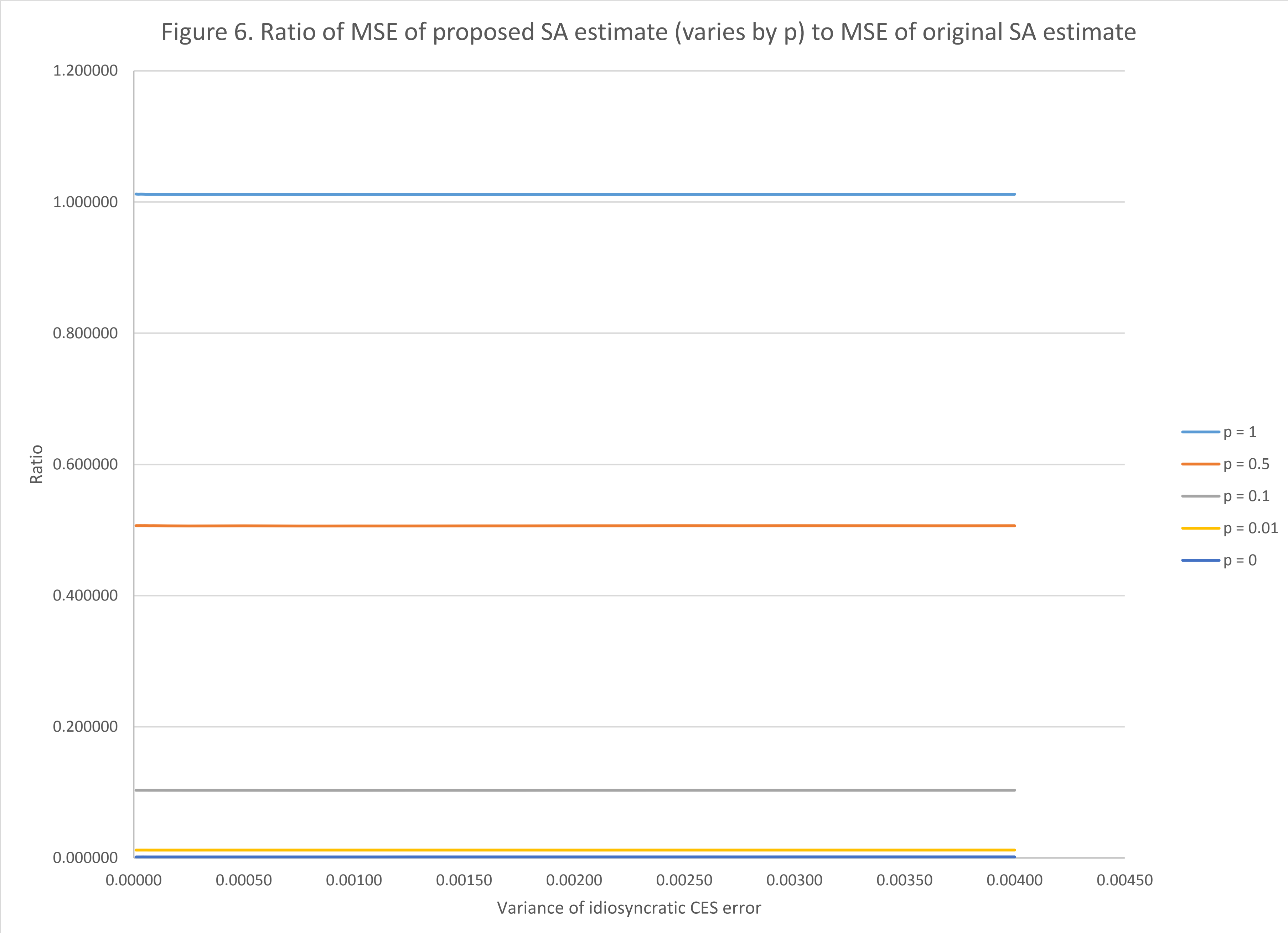
Figure 6. Ratio of MSE of proposed SA estimate (varies by p) to MSE of original SA estimate
1.200000
1.000000
0.800000
0.600000
0.400000
0.200000
0.000000
Ratio
0.00000
0.00050
0.00100
0.00150
0.00200
0.00250
0.00300
0.00350
0.00400
0.00450
Variance of idiosyncratic CES error
p = 1
p = 0.5
p = 0.1
p = 0.01
p = 0