Will the 'True' Productivity Series Please Stand Up? Identifying Inconsistencies across Productivity Series

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Abstract

We conduct a systematic empirical investigation into the consistency of competing industry-level total factor productivity (TFP) series in the United States. We apply an algorithm based on time-series methods to three widely-used databases frequently utilized by researchers to study productivity. Our analysis reveals a substantial proportion of inconsistent industry-level TFP series across these databases. We further delve into the potential causes of such discrepancies by examining the consistency of the individual output and input variables used in calculating the TFP series across databases. Our findings highlight the need for publishing agencies and researchers to explore opportunities for methodological standardization.

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"Productivity isn't everything, but in the long run it is almost everything."

Krugman (1994)

Economic growth can be achieved via increased use of inputs or via productivity growth, understood as improvements in the way inputs are combined to generate more goods and services. Methodologically, since productivity growth for a country is not directly observable, changes in total or multi factor productivity (TFP) are calculated as a residual, equivalent to the difference between changes in gross domestic product (GDP) and a weighted sum of changes in the levels of used inputs (e.g. labor, capital, intermediate inputs, etc.). The Organisation for Economic Cooperation and Development (OECD) periodically updates a compendium of productivity indicators, according to which TFP growth across developed countries slowed down in the 2010's compared to the previous decade (OECD 2021), suffered a striking deterioration during the Global Financial Crisis (2007-2010) and the first year of the COVID-19 pandemic (2020), and played an important role in the 2021 recovery of GDP growth in most countries (OECD 2023).

Industry-level TFP series have been widely used to investigate many important economic issues, including whether productivity gains have been concentrated in a few industries and whether such gains were linked to the use of information technology (Stiroh 2002), whether automation is labor-displacing (Autor and Salomons 2018), whether the recent rise in the capital share can be attributed to increased automation (Aghion, Jones, and Jones 2019), how GDP growth has been impacted by sectoral trends in TFP and labor growth (Foerster et al. 2022), the contributions of individual industries to U.S. aggregate TFP growth (Jorgenson, Ho, and Samuels 2019), and the reasons for the productivity gap between Europe and the United States in the late

1990s and early 2000s (van Ark, O'Mahony and Timmer 2008). Recently, growing concerns about environmental degradation and climate change have spurred interest in "environmentally-adjusted" TFP indicators, which consider the production of undesirable by-products and externalities, as well as how intensely natural resources are used (OECD 2020b).

For the agricultural sector, TFP series were used to analyze public sectoral investments (Fuglie, Wang, and Ball 2012; Fuglie 2018; Ortiz-Bobea et al. 2021), international trade (Garcia-Verdu et al. 2019; Yuan et al. 2021), and the design of policies aimed at decoupling productivity growth from environmental pressure (OECD 2020a), among other issues. In the United States, agricultural TFP measures have been extensively used to evaluate returns to public investments (Fuglie and Heisey 2007; Alston et al. 2011; Jin and Huffman 2016), identify the drivers of productivity growth (Capalbo 1988; Schimmelpfennig and Thirtle 1999; Huffman and Evenson 2006; Alston et al. 2010; Andersen, Alston and Pardey 2012; O'Donnell 2012, 2014; Plastina and Lence 2018), evaluate convergence in productivity across states (McCunn and Huffman 2000; Ball, Hallahan, and Nehring 2004; Poudel, Paudel, and Zilberman 2011), assess spillovers between agriculture and other sectors of the economy (Lence and Plastina 2020), and gauge the impact of weather and climate on aggregate productivity (Njuki, Bravo-Ureta, and O'Donnell 2018; Sabasi and Shumway 2018; Chambers and Pieralli 2020; Ortiz-Bobea, Knippenberg, and Chambers 2018; Plastina, Lence, and Ortiz-Bobea 2021; Ortiz-Bobea et al. 2021).

While the literature on the proper measures for the individual components of TFP (OECD 2001; Fuglie, Wang, and Ball 2012; Fuglie 2015; Shumway et al. 2017; USDA-ERS 2021) and the evaluation of the relative merits of alternative aggregation methods (Szulc 1964; Eltetö and Köves 1964; Jorgenson and Griliches 1967; Caves, Christensen, and Diewert 1982a, 1982b; Bjurek 1996; Balk and Althin 1996; O'Donnell 2012, 2016; Färe and Zelenyuk 2021) is vast,

there has been a dearth of studies evaluating the consistency of productivity series from competing sources. Productivity analyses usually rely on a single source of TFP data, even in cases where multiple TFP series are available for the same sector or country from alternative sources. Typically, no robustness analyses are conducted to assess the extent to which inferences hold using TFP series from alternative sources. Implicitly, studies assume that the TFP series being used is of sufficiently high quality to yield valid inferences. However, Alston (2018) and Andersen, Alston, and Pardey (2011) –among the few studies analyzing competing sources of TFP data– provide evidence that calls this assumption into question.[1]

The contributions of the present study to the economics literature are to present a time-series routine to systematically evaluate the consistency of competing productivity series, and to empirically examine the consistency of U.S. industry-level TFP series across three databases: (1) Jorgenson, Ho, and Samuels (2019), (2) the U.S. Bureau of Labor Statistics (2022), and (3) the U.S. Bureau of Economic Analysis (2021). These three sources are of special interest because they are highly regarded and their series have been used extensively by researchers to analyze productivity matters (e.g., Stiroh 2002; van Ark, O'Mahony and Timmer 2008; Autor and Salomons 2018; Aghion, Jones, and Jones 2019; Foerster et al. 2022; Jorgenson, Ho, and Samuels 2019). Succinctly, we find a high percentage of inconsistent industry-level TFP series across databases and further explore the potential drivers of such inconsistencies by evaluating the consistency across databases of the individual output and input variables used in the calculation of the TFP series. Our findings should spur interest among publishing agencies and

[1] Alston (2018) showed that two alternative sources of TFP data for the U.S. agricultural sector led to sharply different estimates for the rates of factor-neutral technical change and the elasticities of factor demand. Using the same data sources, Andersen, Alston, and Pardey (2011) had previously found substantial differences in the capital productivity estimates.

researchers in the exploration of opportunities for methodological standardization. The rest of the paper is organized into a methodological section and a data section, followed by a description of our results and concluding comments.

Methods

Consider the situation where there are two time series $\{x_t, y_t\}$ providing alternative measures of the true but unobservable TFP of a specific sector or entity over the same period. It should be clear from the outset that, with the true TFP being unobservable, any empirical analysis of x_t and y_t will be unable to determine whether either or both series are high-quality measures of the true TFP series. Thus, the goal of the method proposed here is to determine whether the x_t and y_t series are consistent with each other and, if they are, to investigate whether one of them is preferable to the other depending on their relative speeds of convergence to their long-run equilibrium levels. If the two series are found to be inconsistent with each other, it can clearly be concluded that at least one of them is a poor approximation to the true TFP, and thus of dubious use for empirical work. If this is the case, a careful study of the way in which each series is constructed is warranted, to determine the extent to which each of their individual components contribute to the inconsistency of the TFP series.

We introduce our proposed approach to assess whether the time series x_t and y_t are consistent with each other in the next subsection. That discussion is followed by another subsection focusing on ways to infer whether one of the series is preferable to the other.

Assessing the Consistency of Pairs of Time Series

Succinctly, since TFP series typically exhibit unit roots, the first step of the proposed approach is to find the order of integration of each series. If the order of integration of the two series is different (e.g., x_t is integrated of order one, $I(1)$, and y_t is integrated of order zero, I(0)) it can be immediately concluded that they are inconsistent. If the two series are found to be non-stationary but with the same order of integration, the next step is to determine whether they maintain at least one stable long-term relation between them, i.e., whether they are cointegrated.

Our proposed strategy to determine whether TFP time series x_t and y_t are consistent with each other is summarized schematically in Figure 1.[2] Since productivity time series are typically found to be $I(1)$, we start from a more conservative scenario by allowing for x_t and y_t to be $I(2)$ to avoid underestimating the number of roots.[3] To this end, we test the null hypothesis H_0: series is $I(2)$ versus the alternative H_1: series is $I(1)$ via Augmented Dickey-Fuller (ADF) tests on x_t and y_t. The ADF regressions at this stage are specified with no constant or trend, because we subtract the respective sample mean from each series to conduct the analysis (see "Data" section). We run the test by means of the urca package's ur.df function in the R programming language, which automatically selects the number of lags in the ADF regression (up to a maximum of three) based on the Akaike Information Criterion.

If the null of $I(2)$ cannot be rejected for x_t and y_t (see arrow "N" in Figure 1), we take it as evidence that both x_t and y_t are $I(2)$, and we test the null that $z_t \equiv y_t - x_t$ is $I(1)$ versus the alternative that z_t is $I(0)$. The rationale for this test is that if x_t and y_t are both $I(2)$, a long-run

[2] The abbreviation within parentheses by some of the arrows are used to facilitate the identification of the decisions described in Table 2.

[3] We follow Enders (2009, pp. 221-223) by starting with a test of the null that a series is $I(2)$ versus the alternative that the series is $I(1)$ because we suspect that each series has, at most, two unit roots. If, instead, we had started by testing the null that a series is $I(1)$, and failing to reject it then proceeded to test the null that a series is $I(2)$, in repeated samples we would have underestimated the number of roots (Enders 2009, p. 219). It is reassuring that the null hypothesis H_0: series is $I(3)$ was rejected in favor of the alternative H_1: series is $I(2)$ for all x_t and y_t.

relationship must exist between them for both of them to consistently measure the unobserved productivity, which implies that z_t must be $I(0)$. We also conduct this test using the ur.df function based on ADF regressions with no lags or trends, and with the optimal number of lags (up to a maximum of three) based on the Akaike Information Criterion. We infer that x_t and y_t are consistent if the null that z_t is $I(1)$ is rejected (see arrow "N.Y"); otherwise, we conclude that the series are inconsistent (see arrow "N.N").

If the null hypothesis that a series is $I(2)$ is rejected in favor of the alternative that the series is $I(1)$ for only one of the variables (see arrow "N"), one might infer that x_t and y_t are integrated of different orders and therefore a stable long-run relationship does not exist. However, a potential pitfall of testing for unit roots on the individual series is the possibility of concluding that x_t and y_t are integrated of different orders simply because the computed test statistics are very similar in magnitude but on opposite sides of the critical value. To avoid this problem, when the null of $I(2)$ is rejected for only one of the series, we test the null that z_t is $I(1)$ versus the alternative that z_t is $I(0)$. The series are considered to be consistent if the null is rejected in favor of the alternative that z_t is $I(0)$ (see arrow "N.Y"), because this result indicates that x_t and y_t have a long-run relationship. Otherwise, the series are categorized as inconsistent (see arrow "N.N").

The bottom half of Figure 1 shows that if the null of $I(2)$ is rejected in favor of the alternative of $I(1)$ for both x_t and y_t (see arrow "Y"), the proposed testing strategy to classify the series as $I(1)$ or $I(0)$ is almost analogous to the one depicted in the top half of the figure, which was just described. There is one major difference, however, in that a constant is incorporated into the original ADF regressions used to test the null that the series is $I(1)$ versus the alternative that the series is $I(0)$. This constant allows for the possibility of non-zero

stochastic trends in x_t and y_t, which are conceivable even if the series are demeaned. Since the constant term reduces the power of the ADF test when it actually does not belong in the regression (i.e., the series has no stochastic trend), we proceed as follows. If the Dickey-Fuller's τ_μ test statistic based on the ADF regression that includes a constant leads to rejection of the $I(1)$ null, we take it as evidence that the series is $I(0)$. If such τ_μ test statistic is not significant but the Dickey-Fuller ϕ_1 test statistic is significant, we conclude that the constant is different from zero but the series is $I(1)$. Finally, if neither the τ_μ test statistic nor the ϕ_1 test statistic are significant, we conclude that the constant doesn't belong in the ADF regression. Thus, in this latter case we re-estimate the ADF regression without a constant (so as to improve the power of the ADF test), and use it to test the null hypothesis of $I(1)$ against the alternative hypothesis of $I(0)$ in the underlying series.

If both x_t and y_t are inferred to be stationary, we conclude that x_t and y_t are consistent (see arrow "Y.Y").

Choosing the Better Series Among Consistent Pairs

Importantly, when x_t and y_t are found to be consistent, it is possible that one of the series is a preferable measure of the underlying productivity than the other one, in the time-series sense that after a permanent shock to the underlying productivity, the path of convergence of the preferable series to its new level consistent with the long-run relationship z_t is less noisy and faster than that of the other (less preferable) series.

As discussed earlier, z_t is $I(0)$ if the series are consistent. However, the order of integration of x_t and y_t may vary, as it can be the case that both x_t and y_t are classified by our algorithm as $I(0)$, $I(1)$, or $I(2)$. Crucially, the order of integration of x_t and y_t determines

whether these series need to be differenced if their lags are to be used as regressors, because standard inference requires the latter to be stationary. Thus, the specification of the proposed econometric model to assess the relative quality of the series depends on the order of integration of x_t and y_t.

If the series are consistent, for the most common scenario in which both x_t and y_t are $I(1)$, we propose to estimate the following vector error correction model (VECM)

$$(1) \qquad \Delta x_t = \phi_z z_{t-1} + \sum_{k=1}^{K} \phi_{x,k} \Delta x_{t-k} + \sum_{k=1}^{K} \phi_{y,k} \Delta y_{t-k} + \phi_0 + u_{x,t},$$

$$\Delta y_t = \theta_z z_{t-1} + \sum_{k=1}^{K} \theta_{x,k} \Delta x_{t-k} + \sum_{k=1}^{K} \theta_{y,k} \Delta y_{t-k} + \theta_0 + u_{y,t},$$

where ϕ's and θ's are coefficients, and $u_{x,t}$ and $u_{y,t}$ are residuals. Of particular interest for the advocated strategy are coefficients ϕ_z and θ_z, because they quantify the speed of convergence of each variable towards their new long-term equilibrium level after a permanent shock to the underlying productivity. More specifically, given that $z_t \equiv y_t - x_t$, restoring the long-term relationship between x_t and y_t when $z_t > 0$ requires a ceteris paribus positive change in x_t and/or a negative change in y_t, which implies $\phi_z \geq 0$ and $\theta_z \leq 0$. Further, the smaller the absolute magnitude of the speed of convergence coefficient of one of the series compared to that of the other, the more preferable the former series is compared to the other. In the limit, a speed of convergence to the long-run equilibrium relationship tending to zero for one of the series means that such series is weakly exogenous, so that the other series does most of the adjustment to maintain the long-run relationship $x_t = y_t$ after the permanent shock. Thus, the series that does most of the adjustment is noisier and therefore less preferable than the weakly exogenous one, as it moves in response to changes in the latter to maintain their long-run relationship.

We also propose to estimate a VECM for the most unusual scenario in which series are consistent but $I(2)$. In this instance, VECM (2) involves twice-differenced x_t and y_t series,

$$(2) \qquad \Delta^2 x_t = \phi_z z_{t-1} + \sum_{k=1}^{K} \phi_{x,k} \Delta^2 x_{t-k} + \sum_{k=1}^{K} \phi_{y,k} \Delta^2 y_{t-k} + \phi_0 + u_{x,t},$$

$$\Delta^2 y_t = \theta_z z_{t-1} + \sum_{k=1}^{K} \theta_{x,k} \Delta^2 x_{t-k} + \sum_{k=1}^{K} \theta_{y,k} \Delta^2 y_{t-k} + \theta_0 + u_{y,t}.$$

As for VECM (1), the series with the greatest speed of convergence in absolute terms in VECM (2) may be considered to be the least preferable one.

Finally, for the case where both x_t and y_t are stationary (i.e., $I(0)$), the proposed regression is the following VAR

$$(3) \qquad \Delta x_t = \sum_{k=1}^{K} \phi_{x,k} \Delta x_{t-k} + \sum_{k=1}^{K} \phi_{y,k} \Delta y_{t-k} + u_{x,t},$$

$$\Delta y_t = \sum_{k=1}^{K} \theta_{x,k} \Delta x_{t-k} + \sum_{k=1}^{K} \theta_{y,k} \Delta y_{t-k} + u_{y,t}.$$

In this instance, one may conclude that one series is preferable over the other if (a) past values of the former help predict the latter even after accounting for the information contained in the latter's past values, and (b) the reverse is not true.[4] That is, x_t (y_t) is preferable to y_t (x_t) if x_t (y_t) Granger-causes y_t (x_t) whereas y_t (x_t) does not Granger-cause x_t (y_t). In terms of the coefficients in VAR (3), x_t (y_t) Granger-causes y_t (x_t) if $\sum_{k=1}^{K} \left|\theta_{x,k}\right| > 0$ ($\sum_{k=1}^{K} \left|\theta_{y,k}\right| > 0$), and

[4] VAR (3) has no intercepts because, as discussed later in the "Data" section, the x_t and y_t series are demeaned to conduct the analysis. VECM (1) has intercepts to allow for trends in the series (i.e., the first differences may be different from zero even if the levels have zero means). VECM (2) has intercepts for similar reasons.

y_t (x_t) does not Granger-cause x_t (y_t) otherwise. The proposed use of Granger causality to select the most preferable stationary series is in line with the criteria used for the case of nonstationary series. This is true because if, e.g., series x_t Granger-causes series y_t whereas y_t does not Granger-cause x_t, one could reasonably interpret it as evidence that x_t reflects a more fundamental value to which y_t adjusts over time.

Further Investigation of Inconsistent Series

If the procedure proposed to assess the consistency of x_t and y_t indicates that they are inconsistent, it is recommended that both series be thoroughly examined to find the possible causes of the inconsistency and to determine whether there is evidence that one of the series is more reliable than the other as a measure of the true but unobservable productivity. If it can be clearly demonstrated that one series is superior, it would be advisable to refrain from using the other series for analyzing productivity in the underlying industry.

The analysis of the inconsistent series should aim at finding out the possible causes of the discrepancies found, and should most likely involve investigating the data sources and the methods used to construct the series. Although such analysis is beyond the scope of the present study, here we propose an econometric approach to supplement it. More specifically, we advocate conducting the pairwise analyses discussed in the preceding subsections on the series used as inputs for the computation of the TFP series. For example, suppose that $\{q_{xt}, k_{xt}, l_{xt}, m_{xt}\}$ are, respectively, the series of real output, capital, labor, and materials quantity indexes used to compute the x_t TFP series, and that $\{q_{yt}, k_{yt}, l_{yt}, m_{yt}\}$ are their counterparts for the y_t TFP series. Then, the procedure outlined in the previous subsections could be used at a second stage on each pair $\{q_{xt}, q_{yt}\}$, $\{k_{xt}, k_{yt}\}$, $\{l_{xt}, l_{yt}\}$, $\{m_{xt}, m_{yt}\}$ to shed

light on the consistency of such pair of series across databases. Furthermore, this analysis could also be applied to the original nominal-value series and to the price index series used to construct each quantity index series.

Data

We conduct pairwise analyses of TFP time series data from three highly-regarded sources, namely, (1) Jorgenson, Ho, and Samuels (2019), (2) the U.S. Bureau of Labor Statistics (2022), and (3) the U.S. Bureau of Economic Analysis (2021). Henceforth, these databases will be labeled as JHS, BLS, and BEA, respectively.

The JHS database consists of analytical KLEMS-type data.[5] It contains the annual sectoral-level amounts of output, capital, labor, and materials in both nominal and real terms for 65 industries in the U.S. National Income and Product Accounts from 1947 through 2014. Because JHS is of KLEMS-type, its series are computed using harmonized definitions and aggregation procedures across industries—that is, individual series are comparable across industries because they are based on the same or similar definitions. The JHS database does not report TFP; however, from the published series we are able to construct the chained (Törnqvist) TFP index for each industry as the ratio of real output to real input, where real input is the Törnqvist input index obtained from the capital, labor, and intermediate input series in the database.

[5] The acronym KLEMS stands for capital (K), labor (L), energy (E), materials (M), and services (S). Analytical KLEMS-type data are constructed by researchers in the WORLD KLEMS consortium; they have harmonized definitions and aggregation procedures so as to obtain industry-level productivity measures that are comparable across countries. The data are available online at http://www.worldklems.net/data.htm.

The BLS data are industry-level annual TFP series reported by the U.S. Bureau of Labor Statistics covering the period 1987 through 2020. The BLS data are the "official" TFP series for the United States; they are chained indexes, whose construction is described at https://www.bls.gov/opub/hom/msp/calculation.htm#output. Finally, the BEA database contains industry-level integrated annual TFP series estimated by the U.S. Bureau of Economic Analysis for the period 1987 through 2020. These data, as well as the BEA/BLS integrated industry-level production accounts used to calculate them, are available at https://apps.bea.gov/scb/2021/10-october/1021-industry-annual-update.htm. The industry-level output series used by BEA to construct their TFP indexes are consistent with the measures of gross domestic product for the United States, but are different from the TFP series constructed by the BLS in concepts and coverage (Garner et al. 2021).

Each of the original TFP series consists of an index with a value of 100 for an arbitrarily chosen base year. To apply the proposed method, we first take the logarithms of such series and then subtract their respective sample means, effectively rendering the sample mean of each of the (log) series employed for the econometric analysis equal to zero.[6] Also, we restrict attention to the 61 industries listed in the first column of Table 1, which are the industries that the databases have in common (e.g., the four government sectors included in JHS are not analyzed because data for them is not reported by either BLS or BEA).

Results

[6] The demeaning is performed for each pairwise analysis because the periods covered by the BLS and BAE series are identical, but they are different from the period covered by the JHS series. Thus, for example, the BLS industry series used for the comparison with the corresponding JHS (BAE) is equal to the logarithm of the original series minus the average of the log-series over 1987-2014 (1987-2020).

Our main results are summarized at the bottom of Table 2. This table shows that between 21 (for BEA vs. JHS) and 27 (for BLS vs. BEA) out of the 61 industries being compared have consistent series across sources. Alternatively, between 56% to 66% of the industries have TFP data that are inconsistent between series pairs. These results strongly suggest that empirical analyses based on a single data source may not be sufficiently robust to draw strong inferences and implications. The results also demonstrate the need to devote greater attention to harmonizing TFP series.

Importantly, between 30% and 40% of the inconsistent pairs (13 out of 34 for BLS vs. BEA, 14 out of 35 for BLS vs. JHS, and 12 out of 40 for BLS vs. BEA) are classified as such because the series have different orders of integration. This finding means that around one-fourth of the pairs being tested (19.7% for BLS vs. BEA, 23% for BLS vs. JHS, and 29.5% for BLS vs. BEA) are rendered inconsistent due to fundamental differences in behavior over time. Furthermore, this result cannot be attributed to test statistics for the individual series being similar but on opposite sides of the critical value. This is true because, to avoid this pitfall, our methodology also tests for the null that the difference between the series (z_t) is $I(1)$ versus the alternative that it is $I(0)$.

The top part of Table 2 shows the number of pairs corresponding to each branch of the decision tree depicted in Figure 1. Clearly, most series are found to be $I(1)$, so that they need to be first-differenced to render them stationary. Relatively few series are $I(0)$, and fewer still are $I(2)$.

The outcomes specific to each industry are shown in Table 1. Bold font is used to highlight the eight industries where the TFP series are pairwise-consistent for all three possible pairs: one of them is $I(1)$ (industry {15}), five are $I(0)$ (industries {16, 17, 22, 46, 55}), one is

simultaneously classified as $I(1)$ for one pair of TFP series and $I(0)$ for the other two pairs (industry {50}), and one is simultaneously classified as $I(1)$ for two pairs of TFP series and $I(0)$ for the other pair (industry {40}). For illustrative purposes, Figures A1-A3 in the Appendix depict examples of the behaviors of the series for the three outcomes associated with consistent pairs (i.e., "N.Y", "Y.N.Y", and "Y.Y").

The shaded cells in Table 1 show the pairs of series found to be inconsistent. In total, there are 16 industries (industries {2, 3, 6, 12, 14, 19, 20, 23, 28, 36, 39, 43, 47, 49, 52, 53}) with inconsistent series regardless of the pairs being assessed. Figures A4 and A5 in the Appendix illustrate the behavior of series found to be inconsistent based on outcomes "Y.N" and "Y.N.N", respectively.

Further Results for Consistent Series

The coefficients measuring the speed of convergence to the long-run relationship from the VECM (1) are reported in Table 3. Cells are left empty if the outcome of the consistency tests shown in Table 1 does not warrant estimating VECM (1). For example, for the BLS-BEA pairs, cells for industries {24, 29, 30, 34, 35, 41, 57, 58} are empty because their series are inconsistent, and cells for industry {40} ({50}) are empty because they are consistent but the series are $I(0)$ ($I(1)$) (see Table 1). To save space, speed-of-convergence coefficients for the VECM (2) are shown in Table A1 in the Appendix. Strikingly, most of the coefficients measuring convergence speed are not significantly different from zero. Furthermore, the coefficients that are significantly different from zero often have the opposite sign of what would be expected. Overall, the VECM estimates reported in Table 3 and Appendix Table A1 are uninformative regarding the relative quality of the series under analysis.

An explanation for the lack of significance of most of the coefficients shown in Table 3 and Appendix Table A1 is that, even though stationarity of the difference series (z_t) implies a VECM, the ADF test on z_t is a more powerful test of cointegration than testing for the significance of the coefficient for the speed of convergence to the long-run relationship in the VECMs. Thus, it is quite possible to reject the null of a unit root in the difference series (z_t), while at the same time finding that the speed of convergence coefficients in the VECMs are not significant.

Table 4 reports the *p*-values for the Granger causality tests corresponding to VAR (3). As in Table 3, cells are left empty if the respective outcome of the consistency test does not warrant the estimation of VAR (3) (i.e., cells contain *p*-values only for pairs deemed consistent according to outcome "Y.Y" in Table 1). It can be observed that there is no evidence of Granger causality for the vast majority of the pairs examined. There are two instances where the series are found to Granger-cause each other (industry {16} for BLS-JHS and BEA-JHS pairs, and industry {22} for BLS-BEA and BEA-JHS pairs). Interestingly, there are only four occasions where Granger causality is found to run in only one direction: (a) for industries {13} and {22} the JHS series Granger-causes the BLS series, whereas the latter does not Granger-cause the former; (b) for industry {51} the JHS series Granger-causes the BEA series but the BEA series does not Granger-cause the JHS series; and (c) for industry {56} the BEA series Granger-causes the BLS series, while the opposite does not hold. Thus, only for these few VARs it can be concluded that one series (JHS for cases (a) and (b), and BEA for case (c)) is preferable to the other (BLS for cases (a) and (c), and BEA for case (b)).

Additional Results for Inconsistent Series

The analysis of the individual components of the 34 BLS-BEA pairs found to be inconsistent is summarized in Table 5. This table reveals that for the BLS-BEA pairs, the inconsistency in the nominal value output series is the most prevalent source of the TFP inconsistencies across industries. In fact, nominal output series are consistent for only four industries ({3, 6, 7, 9}) out of the 34 industries reported in the table. On the other hand, the price series for capital are consistent for half of the industries. Industries {33, 41}, for which only two of the series comprised in the TFP indexes are inconsistent, are the ones with the largest number of consistent series underlying TFP. At the opposite extreme, there are five industries ({2, 14, 35, 39, 58}) for which all of the pairs of individual components underlying the TFP indexes are inconsistent. Overall, it is clear that all of the individual components of the TFP series contribute to inconsistencies found for the BLS-BEA TFP pairs (see Tables 1 and 2).

In the case of the individual components for the BLS-JHS pairs, Table A2 in the Appendix shows that for the majority of the industries the inconsistency in the nominal value output series is also the most common source of the TFP inconsistencies, as there is only one industry ({10}) out of the 35 industries examined for which nominal output is consistent across sources. On the other hand, the series of nominal value of capital and price indexes for output and capital are the ones with the largest number of consistencies (for 16 out of 35 industries). Both results conform to the aforementioned findings for the BLS-BEA pairs in Table 4. At the industry level, there are nine industries ({4, 10, 11, 14, 21, 25, 28, 36, 54}) for which seven out of the eight series underlying the TFP pairs for BLS-JHS are inconsistent; contrastingly, in the best case for consistency, there are only two industries ({27, 44}) for which five out of the eight underlying series are consistent.

The results of the analysis of individual TFP components for the BEA-JHS pairs, which are shown in Appendix Table A3, are somewhat different than the ones discussed above for the BLS-BEA and BLS-JHS pairs. In particular, the series pairs with the largest number of inconsistencies across industries for BEA-JHS is the one for output prices, and the series pairs with the fewest inconsistencies are those for labor (both its nominal value and its price). All of the series pairs underlying the TFP index for industries {7, 10, 21} are inconsistent, whereas all but one of the eight series pairs for industry {12} are consistent.

Overall, the results of the consistency analysis summarized in Tables 5, A2, and A3 indicate that the consistency of the pairs of the series for the individual components underlying the construction of the TFP indexes exhibits clear patterns. For BLS-BEA and BLS-JHS (BEA-JHS), a source of the TFP inconsistencies for the majority of the industries is the inconsistency in the nominal value output series (output price series). In contrast, the series with the fewest inconsistencies across all industries consist of the capital price for BLS-BEA and BLS-JHS, and the nominal value and price of labor for BEA-JHS.

Conclusions

Productivity analyses usually rely on a single source of TFP data, even in cases where multiple TFP series are available for the same sector or country from alternative sources. Typically, no robustness analyses are conducted to assess the extent to which inferences hold using TFP series from alternative sources. Implicitly, studies assume that the TFP series being used is of sufficiently high quality to yield valid inferences. We argue that a systematic examination of the consistency of TFP series from alternative sources provides valuable insights on the robustness of research results to the source of TFP data, and develop a time-series routine to implement the

examination. Our proposed methodology can be applied to TFP series constructed using different types of index numbers (i.e., different index formulas).

We apply the proposed methodology to U.S. industry-level TFP series from Jorgenson, Ho, and Samuels (2019), the U.S. Bureau of Labor Statistics (2022), and the U.S. Bureau of Economic Analysis (2021) to find a high percentage of inconsistent industry-level TFP series across databases. The potential drivers of such inconsistencies are evaluated by applying our proposed method to pairs of individual TFP components across databases.

Our findings should spur interest among government agencies and researchers in the exploration of opportunities for methodological standardization. A natural extension of the present study is the application of our methodology to labor productivity series (i.e., units of aggregate output per unit of labor), which are widely used to track the labor market situation and inflationary pressure on producers (BLS 2023) as well as progress towards the achievement of the Millennium Development Goals and the Sustainable Development Goals (International Labour Organization 2024).

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Table 1. TFP series pairs corresponding to each outcome

Industry	BLS vs. BEA	BLS vs. JHS	BEA vs. JHS
1. Accommodation	Y.N.N	Y.N.N	Y.Y
2. Administrative and support services	Y.N.N	Y.N.N	Y.N.N
3. Air transportation	N.N	N.N	Y.N.N
4. Ambulatory health care services	Y.Y	Y.N.N	Y.N.N
5. Amusements gambling and recreation industries	Y.N.Y	Y.N.Y	Y.N.N
6. Apparel and leather and allied products	Y.N.N	Y.N.N	Y.N.N
7. Broadcasting and telecommunications	Y.N.N	N.Y	N.N
8. Chemical products	Y.N.Y	N.Y	N.Y
9. Computer and electronic products	N.N	N.Y	N.N
10. Computer systems design and related services	Y.N.Y	N.N	N.N
11. Construction	N.N	N.N	N.Y
12. Crop and animal production (farms)	Y.N.N	Y.N.N	Y.N.N
13. Data processing internet publishing and other inf. services	Y.N.Y	Y.Y	Y.N.N
14. Educational services	Y.N.N	N.N	N.N
15. Electrical equipment appliances and components	**Y.N.Y**	**Y.N.Y**	**Y.N.Y**
16. Fabricated metal products	**Y.Y**	**Y.Y**	**Y.Y**
17. Federal Reserve banks credit interm. and rel. activities	**Y.Y**	**Y.Y**	**Y.Y**
18. Food and beverage and tobacco products	Y.N.N	Y.Y	Y.N.N
19. Food services and drinking places	Y.N.N	Y.N.N	Y.N.N
20. Forestry fishing and related activities	N.N	Y.N.N	N.N
21. Funds trusts and other financial vehicles	Y.Y	N.N	N.N
22. Furniture and related products	**Y.Y**	**Y.Y**	**Y.Y**
23. Hospitals and nursing and residential care facilities	N.N	Y.N.N	Y.N.N
24. Insurance carriers and related activities	Y.N.N	Y.N.Y	Y.N.N
25. Legal services	Y.N.N	N.N	N.Y
26. Machinery	Y.Y	Y.N.N	Y.N.N
27. Management of companies and enterprises	Y.Y	N.N	N.N
28. Mining except oil and gas	Y.N.N	Y.N.N	Y.N.N
29. Miscellaneous manufacturing	Y.N.N	Y.N.Y	Y.N.N
30. Miscellaneous professional scientific and tech. services	Y.N.N	Y.N.Y	Y.N.Y
31. Motion picture and sound recording industries	Y.N.Y	Y.N.N	Y.N.N
32. Motor vehicles bodies and trailers and parts	Y.N.Y	Y.N.Y	Y.N.N
33. Nonmetallic mineral products	Y.N.N	Y.Y	Y.Y
34. Oil and gas extraction	Y.N.N	Y.N.Y	Y.N.Y
35. Other services except government	Y.N.N	Y.N.Y	N.N
36. Other transportation and support activities	Y.N.N	Y.N.N	Y.N.N
37. Other transportation equipment	Y.N.Y	Y.N.N	Y.N.N
38. Paper products	Y.Y	Y.N.N	Y.Y
39. Performing arts spect. sports museums and rel. activities	Y.N.N	Y.N.N	N.N

Industry	BLS vs. BEA	BLS vs. JHS	BEA vs. JHS
40. Petroleum and coal products	**Y.Y**	**Y.N.Y**	**Y.N.Y**
41. Pipeline transportation	Y.N.N	Y.N.N	Y.N.Y
42. Plastics and rubber products	Y.N.Y	Y.N.N	Y.N.N
43. Primary metals	Y.N.N	Y.N.N	Y.N.N
44. Printing and related support activities	Y.N.Y	Y.N.N	Y.N.N
45. Publishing industries except internet (incl. software)	Y.N.Y	Y.N.N	Y.N.N
46. Rail transportation	**Y.Y**	**Y.Y**	**Y.Y**
47. Real estate	Y.N.N	N.N	N.N
48. Rental and leasing services and lessors of intang. assets	N.N	N.Y	N.Y
49. Retail trade	Y.N.N	N.N	N.N
50. Securities commodity contracts and investments	**Y.N.Y**	**Y.Y**	**Y.Y**
51. Social assistance	Y.N.N	Y.Y	Y.Y
52. Support activities for mining	Y.N.N	Y.N.N	Y.N.N
53. Textile mills and textile product mills	Y.N.N	Y.N.N	Y.N.N
54. Transit and ground passenger transportation	Y.Y	Y.N.N	Y.N.N
55. Truck transportation	**Y.Y**	**Y.Y**	**Y.Y**
56. Utilities	Y.Y	Y.N.N	Y.N.N
57. Warehousing and storage	Y.N.N	Y.N.Y	Y.N.Y
58. Waste management and remediation services	Y.N.N	Y.N.Y	Y.N.N
59. Water transportation	Y.N.Y	Y.N.N	Y.N.N
60. Wholesale trade	Y.Y	Y.N.N	Y.N.N
61. Wood products	N.N	Y.Y	Y.Y

Note: Shaded cells denote inconsistent pairs of TFP series. Industries in bold font represent industries with consistent outcomes across all pairs of TFP series.

Table 2. Number of TFP series pairs corresponding to each decision and outcome

Decisions and Outcomes	BLS vs. BEA	BLS vs. JHS	BEA vs. JHS
Test $H_{0x}: x_t$ is $I(2)$ vs. $H_{1x}: x_t$ is $I(1)$ and $H_{0y}: y_t$ is $I(2)$ vs. $H_{1y}: y_t$ is $I(1)$			
• "N". Neither H_{0x} nor H_{0y} is rejected, or only one of H_{0x} and H_{0y} is rejected	7	13	15
Test $H_{0z}: z_t$ is $I(1)$ vs. $H_{1z}: z_t$ is $I(0)$			
• "N.N". H_{0z} is not rejected (⇒ Inconsistent)	7	9	11
• "N.Y". H_{0z} is rejected (⇒ Consistent)	0	4	4
• "Y". Both H_{0x} and H_{0y} are rejected	54	48	46
Test $H_{0x}: x_t$ is $I(1)$ vs. $H_{1x}: x_t$ is $I(0)$ and $H_{0y}: y_t$ is $I(1)$ vs. $H_{1y}: y_t$ is $I(0)$			
• "Y.N". Neither H_{0x} nor H_{0y} is rejected, or only one of H_{0x} and H_{0y} is rejected	40	37	35
Test $H_{0z}: z_t$ is $I(1)$ vs. $H_{1z}: z_t$ is $I(0)$			
• "Y.N.N". H_{0z} is not rejected (⇒ Inconsistent)	27	26	29
• "Y.N.Y." H_{0z} is rejected (⇒ Consistent)	13	11	6
• "Y.Y". Both H_{0x} and H_{0y} are rejected (⇒ Consistent)	14	11	11
Summary of Outcomes			
A. Consistent	27	26	21
A.1. x_t and y_t are $I(2)$	0	4	4
A.2. x_t and y_t are $I(1)$	13	11	6
A.3. x_t and y_t are $I(0)$	14	11	11
B. Inconsistent	34	35	40
B.1. x_t and y_t have different order of integration	13	14	12
B.2. x_t and y_t are nonstationary and have same order of integration, but z_t is not $I(0)$	21	21	28

Table 3. Estimated speeds of convergence to long-run relationship from vector error correction models (VECMs) using first-differenced series.

Industry	Speed of Convergence					
	BLS-BEA VECM		BLS-JHS VECM		BEA-JHS VECM	
	BLS[a]	BEA[b]	BLS[a]	JHS[c]	BEA[c]	JHS[c]
5	0.330	0.412	0.111	-0.007		
8	0.775**	0.296				
10	-0.070	-0.258				
13	0.633*	0.310				
15	**0.236**	**0.238**	**0.333**	**-0.007**	**0.546**	**-0.535**
24			1.490***	0.767***		
29			0.302	-0.376		
30			0.612*	0.451*	-0.005	0.009
31	-0.308	-0.370				
32	1.928***	0.986***	0.464**	0.280		
34			1.137**	0.603	0.348	0.295
35			-0.126	-0.211*		
37	-0.003	-0.381				
40			**0.928*** **	**0.337***	**-0.925**	**-1.205**
41					0.694	0.157
42	-0.332	-0.308				
44	-0.336*	-0.393**				
45	0.670**	0.515*				
50	**0.814**	**0.594**				
57			0.066	0.126	0.128	0.154
58			-0.164	-0.094		
59	-0.705	-0.611				

Note: Shaded cells denote inconsistent pairs of TFP series. Industries in bold font represent industries with consistent outcomes across all pairs of TFP series. Empty (non-shaded) cells denote different orders of integration for the pairs of TFP series.

*** (**, *) Significantly different from zero at the 1% (5%, 10%) level.

[a] Speed of convergence of BLS.

[b] Speed of convergence of BEA.

[c] Speed of convergence of JHS.

Table 4. Results of Granger causality tests from vector autoregressions (VARs) estimated using series in levels.

Industry	*p*-value					
	BLS-BEA VAR		BLS-JHS VAR		BEA-JHS VAR	
	BLS[a]	BEA[b]	BLS[c]	JHS[d]	BEA[e]	JHS[f]
1					0.703	0.177
4	0.327	0.093				
13			0.534	0.016**		
16	**0.153**	**0.396**	**0.004*** **	**0.001*** **	**0.002*** **	**0.001*** **
17	**0.341**	**0.374**	**0.483**	**0.612**	**0.437**	**0.502**
18			0.260	0.120		
21	0.404	0.408				
22	**0.063***	**0.001*** **	**0.178**	**0.007*** **	**0.038** **	**0.010*** **
26	0.594	0.649				
27	0.330	0.761				
33			0.412	0.911	0.363	0.613
38	0.746	0.151			0.194	0.306
40	**0.323**	**0.986**				
46	**0.148**	**0.333**	**0.069**	**0.212**	**0.115**	**0.245**
50			**0.288**	**0.139**	**0.437**	**0.250**
51			0.117	0.187	0.186	0.022**
54	0.982	0.973				
55	**0.102**	**0.138**	**0.254**	**0.368**	**0.376**	**0.480**
56	0.502	0.006***				
60	0.439	0.732				
61			0.361	0.224	0.386	0.343

Note: Shaded cells denote inconsistent pairs of TFP series. Industries in bold font represent industries with consistent outcomes across all pairs of TFP series. Empty (non-shaded) cells denote non-stationarity of at least one of the TFP series.

*** (**, *) Significantly different from zero at the 1% (5%, 10%) level.

[a] *p*-value for the test of the null hypothesis that BLS does not Granger cause BEA.

[b] *p*-value for the test of the null hypothesis that BEA does not Granger cause BLS.

[c] *p*-value for the test of the null hypothesis that BLS does not Granger cause JHS.

[d] *p*-value for the test of the null hypothesis that JHS does not Granger cause BLS.

[c] *p*-value for the test of the null hypothesis that BEA does not Granger cause JHS.

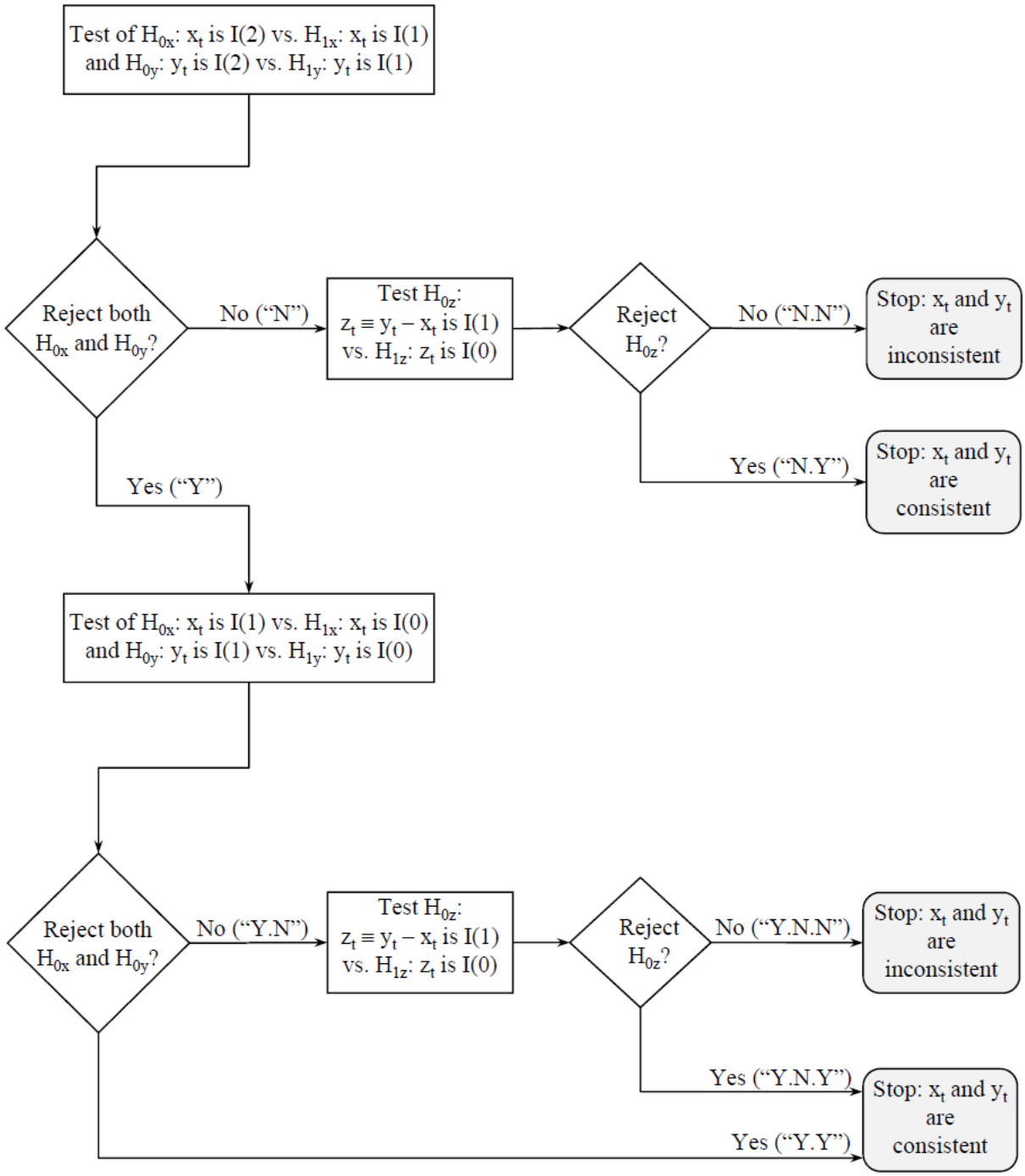
[d] *p*-value for the test of the null hypothesis that JHS does not Granger cause BEA.

Table 5. Consistency test outcomes for BLS-BEA series pairs of indexes of nominal values and prices.

Industry	Nominal Value Indexes				Price Indexes			
	Output	Capital	Labor	Int. Inp.	Output	Capital	Labor	Int. Inp.
1	N.N	N.N	Y.N.Y	N.N	N.N	N.Y	N.Y	N.N
2	N.N	N.N	N.N	N.N	N.N	Y.N.N	N.N	N.N
3	Y.N.Y	N.N	Y.N.Y	Y.N.N	Y.N.N	N.N	N.Y	Y.N.N
6	N.Y	Y.N.Y	N.N	N.N	N.Y	Y.N.Y	N.N	N.N
7	N.Y	N.Y	N.N	N.N	Y.N.N	Y.N.Y	N.N	Y.N.N
9	Y.N.Y	Y.N.N	Y.N.N	N.N	N.N	Y.Y	N.N	N.N
11	N.N	N.Y	Y.N.N	N.N	N.N	Y.N.Y	N.N	N.N
12	Y.N.N	Y.N.Y	Y.N.N	Y.N.N	Y.N.Y	Y.N.Y	Y.N.Y	N.N
14	N.N	N.N	N.N	Y.N.N	N.N	N.N	N.N	N.N
18	N.N	Y.N.N	N.N	N.Y	N.N	Y.N.N	Y.N.Y	N.Y
19	N.N	N.N	N.N	N.N	N.N	N.N	N.Y	N.N
20	Y.N.N	Y.Y	Y.N.N	Y.Y	Y.N.N	Y.N.N	N.N	Y.N.Y
23	N.N	Y.N.N	N.N	N.Y	N.Y	Y.N.N	N.N	N.Y
24	N.N	Y.N.N	N.Y	Y.N.Y	N.Y	Y.N.N	N.Y	N.Y
25	N.N	N.N	N.N	Y.N.N	N.Y	Y.N.N	N.N	N.N
28	Y.N.N	N.N	Y.N.Y	Y.N.N	N.Y	Y.N.N	N.Y	Y.N.N
29	N.N	Y.N.Y	N.Y	N.N	N.N	Y.N.Y	N.Y	Y.N.N
30	N.N	N.N	N.Y	N.N	N.N	Y.Y	N.N	N.N
33	Y.N.N	Y.N.Y	Y.N.Y	Y.N.Y	N.Y	Y.N.Y	N.N	N.Y
34	Y.N.N	Y.N.N	Y.N.Y	Y.N.N	Y.N.N	Y.N.N	N.Y	Y.N.N
35	N.N	N.N	N.N	N.N	N.N	Y.N.N	N.N	N.N
36	N.N	Y.N.Y	N.Y	N.N	N.N	Y.N.Y	Y.N.N	Y.N.N
39	N.N	N.N	N.N	N.N	N.N	N.N	N.N	N.N
41	N.N	Y.N.Y	Y.N.Y	Y.Y	N.Y	Y.N.Y	Y.N.N	N.Y
43	Y.N.N	Y.N.N	Y.Y	Y.N.N	Y.N.N	Y.N.N	Y.N.Y	Y.N.N
47	N.N	N.Y	N.N	N.Y	N.Y	N.Y	N.N	N.Y
48	N.N	Y.N.N	N.N	Y.N.N	N.Y	N.N	N.N	N.N
49	N.N	N.Y	N.N	N.Y	N.N	Y.N.Y	N.N	N.Y
51	N.N	N.Y	N.N	N.Y	N.N	Y.N.Y	Y.N.N	N.Y
52	Y.N.N	Y.N.N	Y.N.N	Y.N.Y	Y.N.N	Y.N.N	Y.N.N	N.Y
53	Y.N.N	Y.Y	Y.N.Y	Y.N.N	N.N	Y.Y	N.N	N.N
57	N.N	Y.N.Y	N.N	Y.N.N	Y.N.N	Y.N.Y	N.N	N.N
58	N.N	Y.N.N	N.N	Y.N.N	N.N	Y.N.N	Y.N.N	N.N
61	Y.N.N	Y.N.Y	Y.Y	Y.Y	Y.N.N	Y.N.Y	N.N	Y.N.Y

Note: Shaded cells denote inconsistent pairs for the series shown in the column header.

Figure 1. Econometric strategy to classify pairs of time series.



Will the 'True' Productivity Series Please Stand Up? Identifying Inconsistencies across Productivity Series

Appendix

Table A1 in this appendix reports the coefficients measuring the speed of convergence to the long-run relationship from the VECM (2). Cells are left empty if the outcome of the consistency tests shown in Table 1 does not warrant estimating VECM (2). For example, for the BLS-BEA pairs in Table A1, cells for industries {7, 9, 11, 25, 48} are empty because their series are inconsistent, and cells for industry {7} are empty because they are consistent but the series are $I(1)$.

Tables A2 and A3 present the results of analyzing individual TFP components for the BLS-JHS and BEA-JHS pairs, respectively. These tables are similar to Table 3, which contains data for the BLS-BEA pairs.

Figures A1-A3 depict the behavior of the series for the three most typical outcomes associated with consistent pairs. In each figure, Panel A depicts the actual series, whereas Panel B represents the difference between the series (i.e., z_t). Figure A1 shows the behavior of the BLS-JHS series for industry {8}, which is an example of outcome "N.Y". In this instance, both of the individual series are $I(2)$. Figure A2 represents the BLS-BEA series for industry {59}, which illustrates outcome "Y.N.Y". This is the most typical case of consistent pairs, where the individual series are $I(1)$. Finally, Figure A3 depicts the BLS-BEA series for industry {16} to examplify outcome "Y.Y". In this scenario, the two series are stationary (i.e., $I(0)$).

Figures A4-A5 illustrate the behavior of series found to be inconsistent based on outcomes "N.N" and "Y.N.N". Figure A4 is drawn with BLS-BEA data for industry {20} to depict an example of outcome "N.N". Here, the series have different orders of integration, with

one being $I(2)$ and the other $I(< 2)$. Figure A5 shows the behavior of the BLS-BEA series for industry {51}, as a case of outcome "Y.N.N". As in Figure A4, the series have different orders of integration, but in the case of Figure A5 one of the series is $I(1)$ and the other is $I(0)$.

Table A1. Estimated speeds of convergence to long-run relationship from vector error correction models (VECMs) using second-differenced series.

Industry	Speed of Convergence					
	BLS-BEA VECM		BLS-JHS VECM		BEA-JHS VECM	
	BLS[a]	BEA[b]	BLS[a]	JHS[c]	BEA[b]	JHS[c]
7. Broadcasting and telecommunications			-0.545	-0.437*		
8. Chemical products			0.268	-0.002	0.265	0.209
9. Computer and electronic products			-0.159	-0.076		
11. Construction					0.893*	0.807
25. Legal services					-0.286	-0.156
48. Rent. & leas. services and lessors of intang. assets			0.214	0.310*	0.194	0.288

Note: Shaded cells denote inconsistent pairs of TFP series. Empty (non-shaded) cells denote different orders of integration for the pairs of TFP series.
*** (**, *) Significantly different from zero at the 1% (5%, 10%) level.
[a] Speed of convergence of BLS.
[b] Speed of convergence of BEA.
[c] Speed of convergence of JHS.

Table A2. Consistency test outcomes for BLS-JHS series pairs of indexes of nominal values and prices.

Industry	Nominal Value Indexes				Price Indexes			
	Output	Capital	Labor	Int. Inp.	Output	Capital	Labor	Int. Inp.
1. Accommodation	N.N	N.Y	N.Y	N.N	N.N	N.Y	N.N	N.N
2. Administrative and support services	N.N	N.N	N.N	N.Y	N.N	Y.N.N	N.Y	N.Y
3. Air transportation	Y.N.N	Y.N.Y	Y.N.Y	Y.N.N	Y.N.N	Y.N.Y	N.N	Y.N.N
4. Ambulatory health care services	N.N	Y.N.N	N.N	N.N	Y.N.N	Y.N.Y	Y.N.N	N.N
6. Apparel and leather and allied products	N.N	Y.N.N	N.N	Y.N.Y	N.N	Y.N.N	Y.N.Y	N.Y
10. Computer systems design and related services	N.Y	N.N	N.N	N.N	Y.N.N	Y.N.N	N.N	N.N
11. Construction	N.N	N.N	N.N	N.N	N.Y	Y.N.N	N.N	N.N
12. Crop and animal production (farms)	N.N	Y.N.N	Y.N.Y	N.N	N.Y	Y.N.Y	Y.N.Y	N.N
14. Educational services	N.N	N.N	N.N	N.N	N.N	N.N	Y.N.Y	N.N
19. Food services and drinking places	N.N	N.Y	N.N	N.Y	N.Y	N.N	N.N	N.Y
20. Forestry fishing and related activities	Y.N.N	Y.N.N	Y.N.N	Y.N.Y	Y.N.Y	Y.N.N	N.N	N.Y
21. Funds trusts and other financial vehicles	Y.N.N	Y.N.N	Y.N.N	Y.N.N	N.N	Y.N.Y	Y.N.N	N.N
23. Hospitals & nursing & residential care facilities	N.N	N.Y	Y.N.N	N.N	N.N	Y.N.Y	Y.N.N	N.N
25. Legal services	N.N	N.N	N.N	Y.N.N	N.Y	Y.N.N	N.N	N.N
26. Machinery	Y.N.N	Y.N.N	Y.N.Y	Y.N.Y	N.N	Y.N.N	N.N	N.Y
27. Management of companies and enterprises	N.N	Y.N.Y	N.Y	N.Y	N.N	Y.N.Y	Y.N.N	N.Y
28. Mining except oil and gas	N.N	N.N	Y.N.N	Y.N.N	N.Y	Y.N.N	N.N	N.N
31. Motion picture and sound recording industries	N.N	Y.N.N	N.Y	Y.N.N	Y.N.N	Y.N.N	N.Y	N.N
36. Other transportation and support activities	N.N	Y.N.N	N.N	N.N	N.N	Y.N.N	Y.N.Y	N.N
37. Other transportation equipment	Y.N.N	Y.N.N	Y.N.Y	Y.N.N	N.Y	Y.N.Y	N.Y	N.N
38. Paper products	Y.N.N	Y.Y	N.Y	Y.N.N	Y.N.N	Y.Y	N.Y	Y.N.N
39. Perf. arts spect. sports museums & rel. activities	N.N	N.N	N.Y	N.N	N.Y	N.N	Y.N.Y	N.N
41. Pipeline transportation	N.N	N.N	Y.N.Y	Y.N.N	N.Y	Y.N.N	Y.N.Y	N.N
42. Plastics and rubber products	Y.N.N	Y.N.N	Y.N.Y	Y.N.N	N.Y	Y.Y	N.N	N.N
43. Primary metals	Y.N.N	Y.N.Y	Y.Y	Y.N.N	Y.N.Y	Y.N.Y	Y.N.N	Y.N.N
44. Printing and related support activities	Y.N.N	Y.N.Y	Y.N.Y	Y.N.N	N.Y	Y.N.Y	N.Y	Y.N.N
45. Publish. indust. except internet (incl. software)	N.N	Y.N.N	N.Y	N.N	Y.N.Y	Y.Y	N.N	N.N
47. Real estate	N.N	N.Y	N.N	N.N	N.N	N.Y	N.N	N.N

Industry	Nominal Value Indexes				Price Indexes			
	Output	Capital	Labor	Int. Inp.	Output	Capital	Labor	Int. Inp.
49. Retail trade	N.N	N.N	N.N	Y.N.Y	N.Y	Y.N.N	N.N	N.Y
52. Support activities for mining	N.N	Y.N.N	N.N	Y.N.Y	Y.N.N	Y.N.N	N.Y	N.Y
53. Textile mills and textile product mills	Y.N.N	Y.Y	Y.N.Y	Y.N.N	N.Y	Y.Y	N.N	N.N
54. Transit and ground passenger transportation	N.N	N.N	N.N	Y.N.N	N.Y	Y.N.N	N.N	N.N
56. Utilities	Y.N.N	Y.N.Y	N.N	Y.N.Y	N.N	Y.N.Y	N.N	Y.N.Y
58. Waste management and remediation services	N.N	Y.N.Y	N.Y	N.N	N.N	N.N	Y.N.N	N.N
59. Water transportation	N.N	Y.Y	N.N	Y.N.N	Y.N.N	Y.N.Y	N.N	N.N

Note: Shaded cells denote inconsistent pairs for the series shown in the column header.

Table A3. Consistency test outcomes for BEA-JHS series pairs of indexes of nominal values and prices.

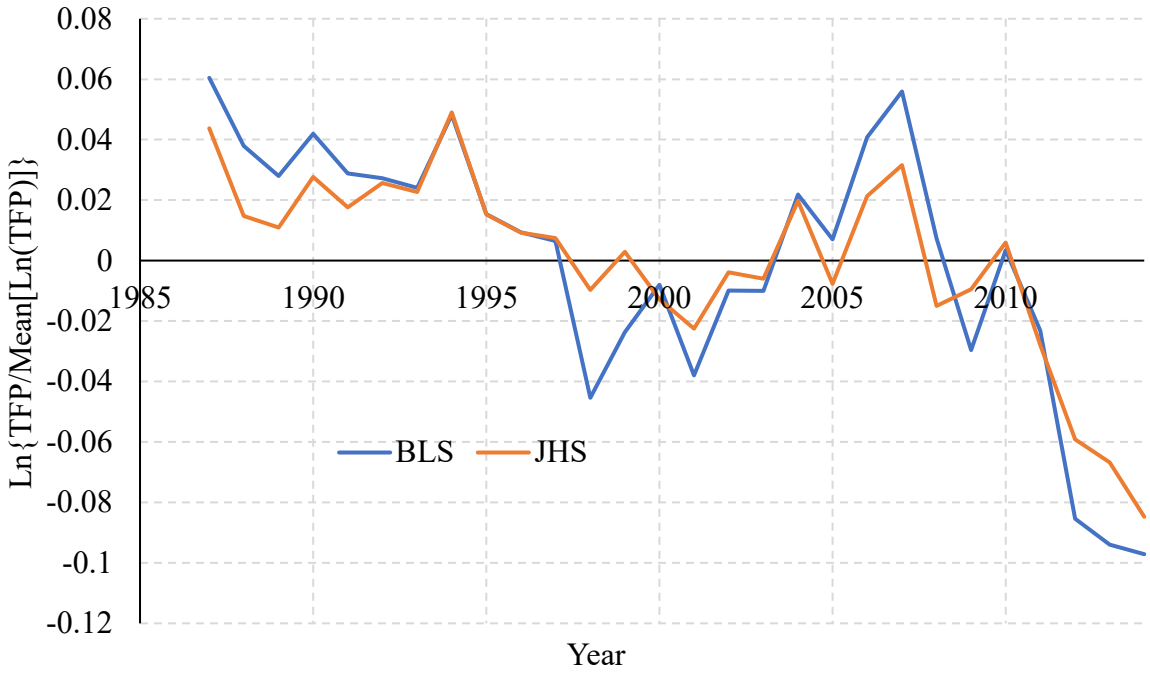
Industry	Nominal Value Indexes				Price Indexes			
	Output	Capital	Labor	Int. Inp.	Output	Capital	Labor	Int. Inp.
2. Administrative and support services	N.Y	N.N	N.N	N.Y	N.N	Y.N.N	N.N	N.Y
3. Air transportation	N.N	Y.N.N	Y.N.Y	Y.N.N	Y.N.N	Y.N.N	N.N	N.N
4. Ambulatory health care services	N.N	Y.N.N	N.N	N.N	Y.N.N	Y.N.N	N.Y	N.N
5. Amusements gambling and recreation industries	N.N	Y.N.Y	N.Y	N.N	N.N	Y.N.N	N.N	N.N
6. Apparel and leather and allied products	N.Y	Y.N.N	N.N	N.N	N.N	Y.N.N	N.N	N.N
7. Broadcasting and telecommunications	N.N	N.N	N.N	N.N	Y.N.N	Y.N.N	N.N	Y.N.N
9. Computer and electronic products	Y.Y	N.Y	Y.N.Y	Y.N.N	N.N	Y.Y	N.Y	N.N
10. Computer systems design and related services	N.N	Y.N.N	N.N	N.N	Y.N.N	Y.N.N	N.N	N.N
12. Crop and animal production (farms)	N.Y	Y.N.Y	Y.N.Y	N.Y	N.N	Y.N.Y	Y.N.Y	N.Y
13. Data proc. internet publish. & other inf. services	N.N	Y.N.N	N.Y	Y.N.Y	Y.Y	Y.N.N	Y.N.N	N.Y
14. Educational services	N.N	N.N	N.Y	N.N	N.N	Y.N.N	N.N	N.N
18. Food and beverage and tobacco products	N.Y	Y.N.N	N.N	N.Y	N.N	Y.N.Y	N.N	N.Y
19. Food services and drinking places	N.N	N.Y	N.N	N.N	N.N	N.N	N.N	N.N
20. Forestry fishing and related activities	Y.N.Y	Y.N.N	Y.N.Y	Y.Y	Y.N.N	Y.N.N	Y.N.Y	N.N
21. Funds trusts and other financial vehicles	Y.N.N	Y.N.N	Y.N.N	Y.N.N	N.N	Y.N.N	Y.N.N	N.N
23. Hospitals and nursing and resident. care facility.	N.N	N.Y	N.Y	N.N	Y.N.Y	Y.N.Y	N.N	N.N
24. Insurance carriers and related activities	N.N	Y.N.N	N.N	N.Y	N.Y	Y.N.N	N.N	N.Y
26. Machinery	Y.N.Y	Y.N.N	Y.N.Y	Y.N.N	N.N	Y.N.N	N.Y	N.N
27. Management of companies and enterprises	N.N	Y.N.Y	N.Y	N.Y	N.N	Y.N.Y	Y.N.Y	N.Y
28. Mining except oil and gas	Y.N.N	N.N	Y.N.N	Y.N.Y	N.N	Y.N.N	N.N	N.Y
29. Miscellaneous manufacturing	N.N	Y.N.Y	N.N	N.N	N.N	Y.N.N	N.N	N.N
31. Motion picture and sound recording industries	N.N	Y.N.N	N.Y	Y.N.N	Y.N.N	Y.N.N	N.Y	N.N
32. Motor vehicles bodies and trailers and parts	Y.N.N	Y.Y	Y.Y	Y.N.N	Y.N.Y	Y.Y	Y.N.Y	N.N
35. Other services except government	N.N	Y.N.Y	N.Y	N.Y	N.Y	Y.N.N	N.Y	N.Y
36. Other transportation and support activities	N.N	Y.N.N	N.N	N.N	N.N	Y.N.N	Y.N.Y	N.N
37. Other transportation equipment	Y.N.Y	Y.N.N	Y.N.Y	Y.N.Y	N.N	Y.N.Y	N.Y	N.Y
39. Perform. arts spect. sports museums & rel. act.	N.N	Y.N.N	N.N	N.N	N.N	Y.N.N	N.Y	N.N
42. Plastics and rubber products	Y.N.Y	Y.N.N	Y.N.Y	Y.N.N	N.N	Y.Y	N.N	N.N

43. Primary metals	Y.N.N	Y.N.Y	Y.Y	Y.N.N	Y.N.N	Y.N.Y	Y.N.Y	Y.N.N
44. Printing and related support activities	Y.N.Y	Y.N.N	Y.N.Y	Y.N.N	Y.N.N	Y.N.N	N.Y	Y.N.N
45. Publish. Indust. except internet (incl. software)	N.N	Y.N.N	N.Y	Y.N.Y	Y.N.N	Y.Y	N.N	N.Y
47. Real estate	N.Y	N.N	N.N	N.N	N.N	N.N	N.Y	N.N
49. Retail trade	N.Y	N.N	N.N	Y.N.Y	N.Y	Y.N.N	N.N	N.Y
52. Support activities for mining	Y.N.N	Y.N.N	Y.N.N	Y.N.N	Y.N.N	Y.N.N	Y.N.Y	N.N
53. Textile mills and textile product mills	Y.N.Y	Y.Y	Y.N.N	Y.N.N	N.N	Y.Y	N.N	N.N
54. Transit and ground passenger transportation	N.Y	N.N	N.N	Y.N.N	N.Y	Y.N.N	N.Y	N.N
56. Utilities	Y.N.N	Y.N.N	N.N	Y.N.N	N.Y	Y.N.N	N.N	N.N
58. Waste management and remediation services	N.N	N.N	N.Y	Y.N.N	N.N	Y.N.Y	N.N	N.N
59. Water transportation	N.N	Y.N.Y	N.Y	N.N	N.N	N.Y	Y.N.N	N.N
60. Wholesale trade	N.N	N.N	N.Y	Y.N.Y	Y.N.N	Y.N.N	N.Y	N.Y

Note: Shaded cells denote inconsistent pairs for the series shown in the column header.

Figure A1. Illustration of a consistent pair of TFP series (outcome "N.Y"): BLS and JHS series for industry {8} Chemical Products.

A. BLS and JHS series.



B. Difference between BLS and JHS series.

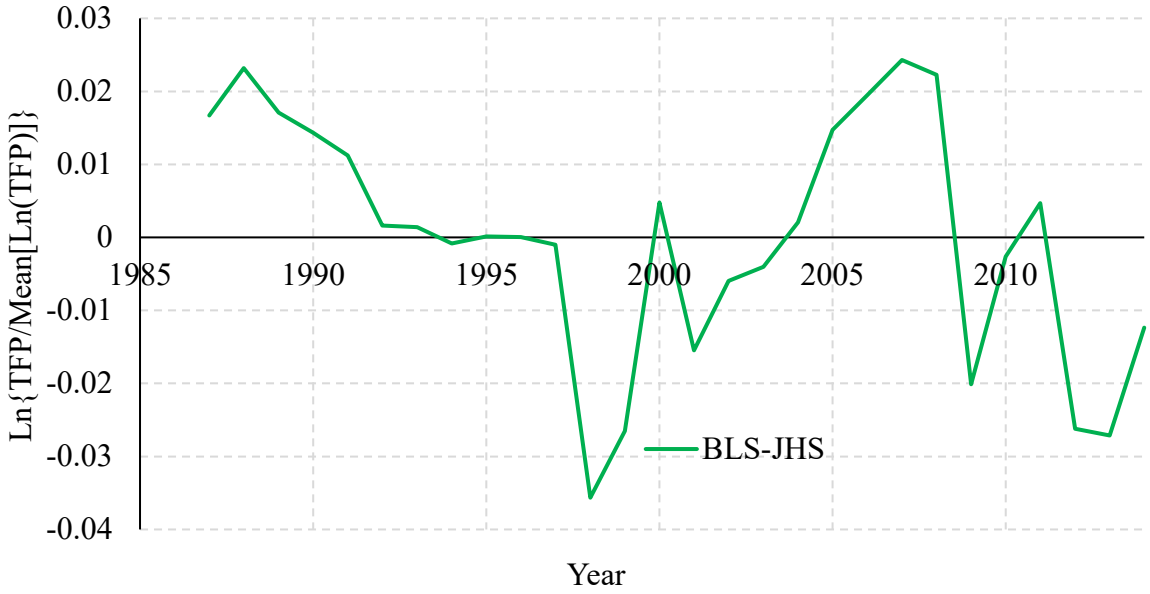
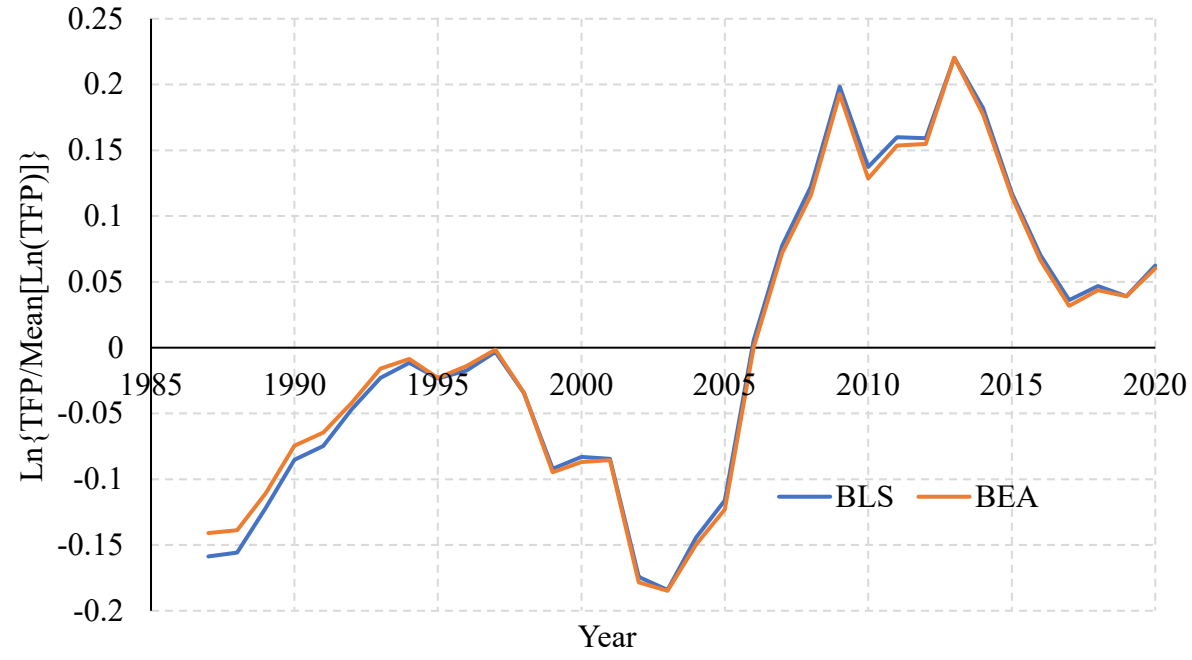


Figure A2. Illustration of a consistent pair of TFP series (outcome "Y.N.Y"): BLS and BEA series for industry {59} Water Transportation.

A. BLS and BEA series.



B. Difference between BLS and BEA series.

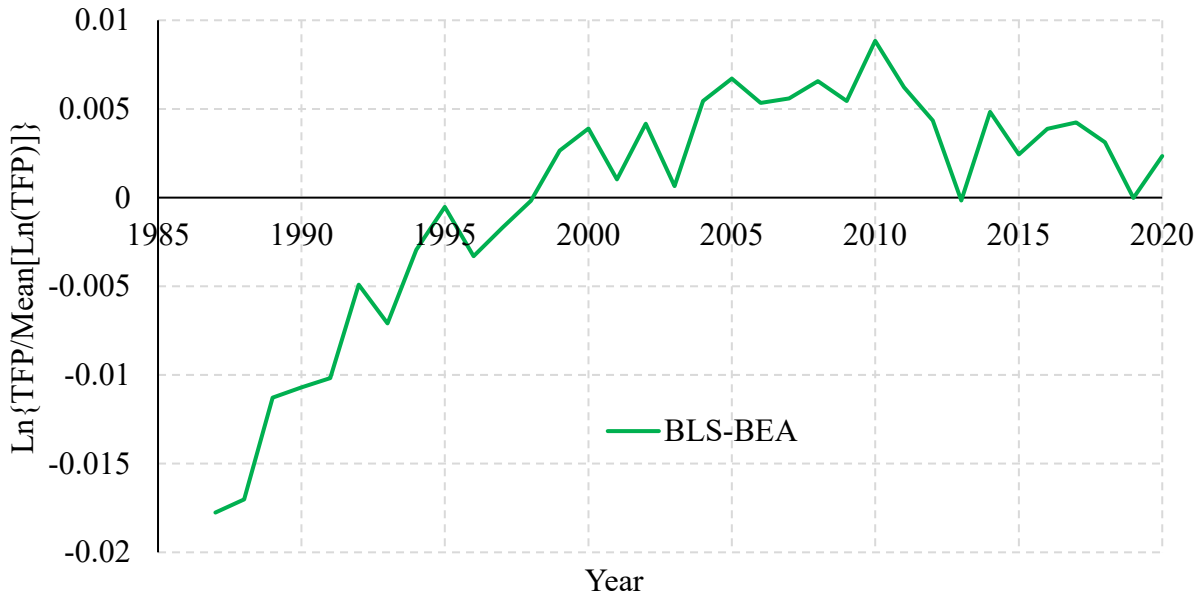
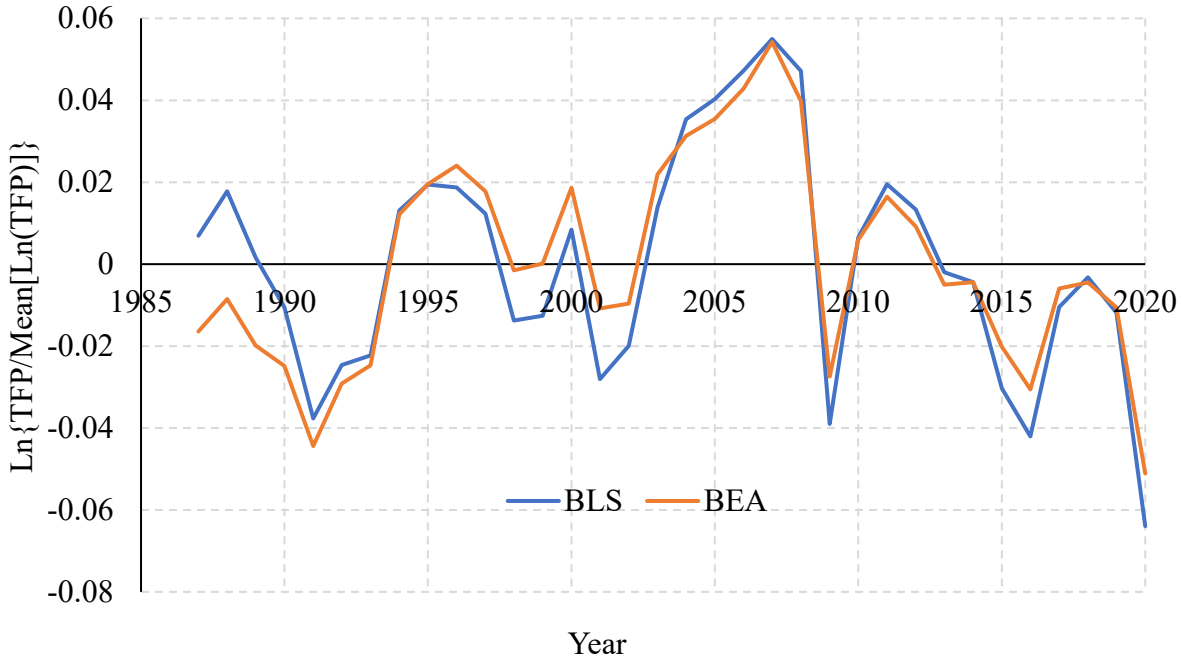


Figure A3. Illustration of a consistent pair of TFP series (outcome "Y.Y"): BLS and BEA series for industry {16} Fabricated Metal Products.

A. BLS and BEA series.



B. Difference between BLS and BEA series.

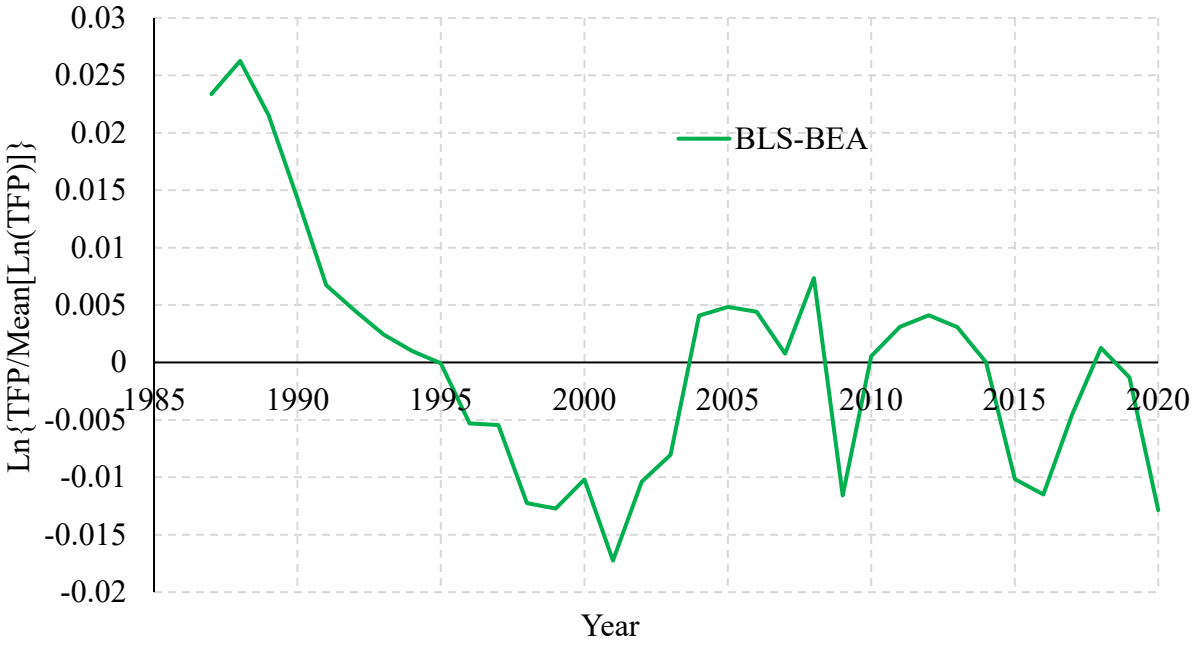
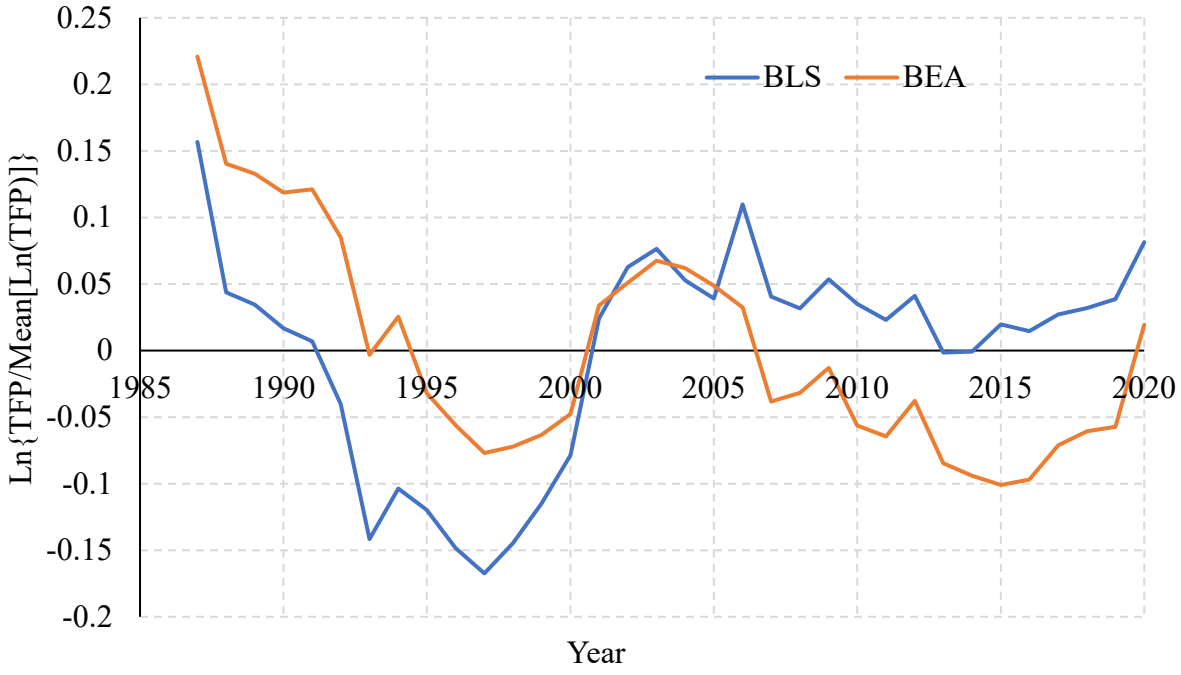


Figure A4. Illustration of an inconsistent pair of TFP series (outcome "N.N"): BLS and BEA series for industry {20} Forestry Fishing and Related Activities.

A. BLS and BEA series.



B. Difference between BLS and BEA series.

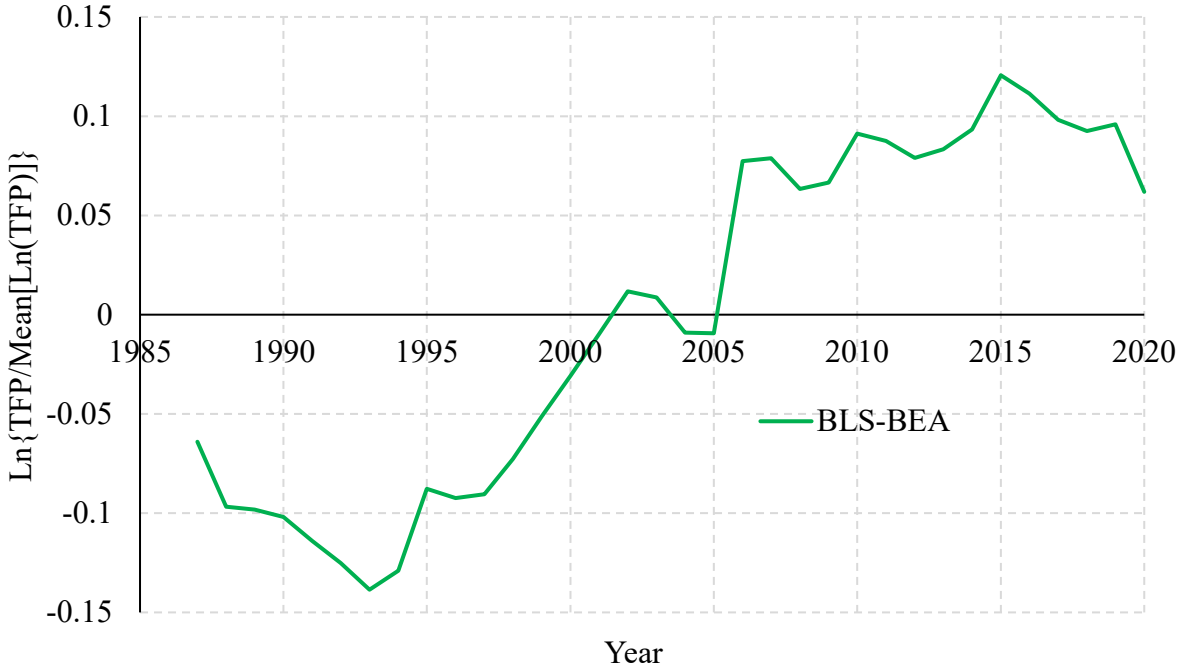
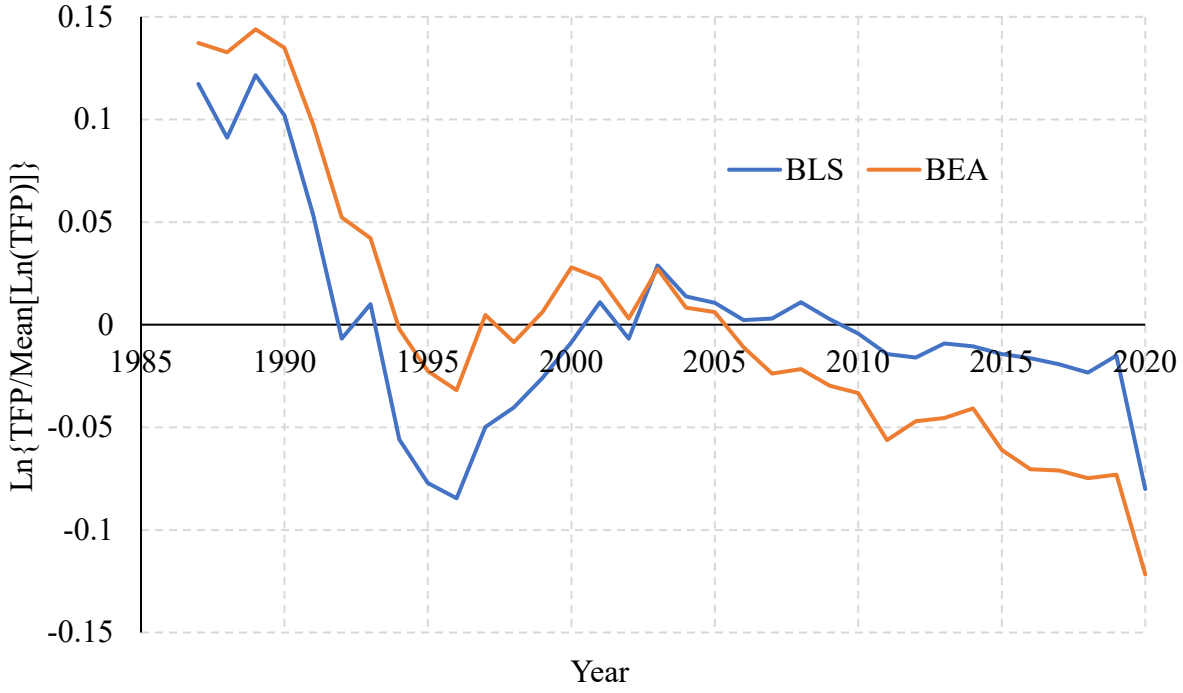


Figure A5. Illustration of an inconsistent pair of TFP series (outcome "Y.N.N"): BLS and BEA series for industry {51} Social Assistance.

A. BLS and BEA series.



B. Difference between BLS and BEA series.

