Working Paper No. 946

The Relationship between Technical Progress and Employment: A Comment on Autor and Salomons

by

Jesus Felipe, Donna Faye Bajaro, Gemma Estrada*
Asian Development Bank

and

John McCombie
University of Cambridge

February 2020

* We acknowledge very useful comments from David Autor and Anna Salomons to a previous version. The usual disclaimer applies and any errors are solely ours.

Levy Economics Institute
P.O. Box 5000
Annandale-on-Hudson, NY 12504-5000
http://www.levyinstitute.org

ISSN 1547-366X

ABSTRACT

We show that Autor and Salomons' (2017, 2018) analysis of the impact of technical progress on employment growth is problematic. When they use labor productivity growth as a proxy for technical progress, their regressions are quasi-accounting identities that omit one variable of the identity. Consequently, the coefficient of labor productivity growth suffers from omitted-variable bias, where the omitted variable is known. The use of total factor productivity (TFP) growth as a proxy for technical progress does not solve the problem. Contrary to what the profession has argued for decades, we show that this variable is not a measure of technical progress. This is because TFP growth derived residually from a production function, together with the conditions for producer equilibrium, can also be derived from an accounting identity without any assumption. We interpret TFP growth as a measure of distributional changes. This identity also indicates that Autor and Salomons' estimates of TFP growth's impact on employment growth are biased due to the omission of the other variables in the identity. Overall, we conclude that their work does not shed light on the question they address.

KEYWORDS: Employment; Labor Productivity; Technical Progress; Total Factor Productivity

JEL CLASSIFICATIONS: E24; O30; O47

1. INTRODUCTION

In two recent papers, David Autor and Anna Salomons (2017, 2018) (AS hereafter) delve into the two-hundred-year-old debate (since David Ricardo) about the impact of the rate of technical progress on employment growth, and the still-widespread belief that faster growth of technical progress causes slower employment growth (i.e., that faster technical change reduces employment growth and leads to a "Robocalypse," or the idea that robots will cause a massive destruction of employment).

Using aggregate and sectoral data for advanced economies, AS (2017) attempted to statistically test the hypothesis that faster technical change reduces employment growth (i.e., the Luddite fallacy). They regressed employment growth on labor productivity growth, plus some controls. They provide what at first sight is compelling evidence that technical progress at the aggregate level of the economy (measured by the growth rate of labor productivity) is employment-augmenting.

AS (2018) is a seemingly more sophisticated piece of work than AS (2017), in that the authors used total factor productivity (TFP) growth (also patent counts and citations) as their measure of technical progress. Likewise, AS (2018) considered several outcome variables besides employment growth, namely, hours, output, wage bill, and labor share. One of the major problems in understanding growth is that there is no independent measure of the rate of technical progress. By independent we mean that the value of the rate of technical change is not dependent upon a particular theory and the assumptions underlying that theory, such as the concept of TFP. Productivity growth may or may not be a good proxy for the rate of technical progress. Acknowledging this, the authors also used patent data as a proxy for technical progress. The test is a regression of different outcome variables (employment, hours, wage bill, nominal value added, real value-added, and labor share) on TFP growth (or patents). AS (2018) concluded that automation displaces employment and reduces the labor share in own industries. In the case of employment, the losses are reversed by the indirect gains in client industries and by induced increases in aggregate demand. They also find that own-industry labor share losses are not compensated for by increases in other industries.

If correct, AS's work and conclusions have important implications for this old debate. Since the 2000s, there has been a rebirth of this debate in the context of the impact of new technologies, artificial intelligence, and computer-based technologies.[1]

This paper provides a critical evaluation of the models estimated by AS (2017, 2018) and of the inferences made based on them. While we acknowledge the authors' commendable attempt at shedding light on the employment-technical progress debate using contemporary data (certainly the two papers contain useful information), in our view, there are fundamental problems with their procedures and the conclusions drawn. Though AS (2018) seems to contain the more conclusive analysis, this work builds on AS (2017). For pedagogical purposes, we briefly sketch the latter's approach and comment on the most salient results. We think this is useful in order to appreciate the differences between the two approaches, and to better explain our arguments. Moreover, as we argue below, we do not think AS (2018) provides a more compelling analysis.

2. AUTOR AND SALOMONS (2017): THE EMPLOYMENT IDENTITY AND THE CATCH 22 PROBLEM

AS's (2017) basic model is:

$$\hat{L}_{ct} = \alpha_0 + \alpha_1 \hat{y}_{ct} + [\textstyle\sum_{k=1}^{m} \alpha_{t-k} \hat{y}_{ct-k} + \theta_c] + \varepsilon_{ct} \tag{1}$$

where $\hat{L}_{ct}$ is the growth rate of aggregate employment in country c at time t; $\hat{y}_{ct}$ is the growth rate of labor productivity; k is the time lag of labor productivity growth; and θ_c is a set of country fixed effects.

[1] Literature reviews of these debates are provided by the authors themselves, so we will not reproduce them here.

The parameter of interest is α_1 in the static regressions, and $\alpha^* = \alpha_1 + \sum_{k=1}^{m} \alpha_{t-k}$ in the dynamic regressions. Note that this is a reduced-form regression not derived from a model. AS (2017) interpret the parameters of interest as elasticities.

Regressions are estimated using ordinary least squares (OLS) and instrumental variables (IV) methods, though the latter are dismissed by the authors (see below). Algebraically, the null hypothesis is H_0: $\alpha_1 < 0$, or, more generally, H_o: $\alpha^* < 0$ (i.e., the impact of the rate of technical progress on employment growth is negative), with the alternative H_1: $\alpha^* \geq 0$. In most cases, the authors find (at the aggregate level) that α_1 is negative, while α^* is positive. This last result is what leads the authors to conclude that technical progress is employment generating.

As noted above, the purpose of this paper is to evaluate the methodology used by AS (2017) to estimate the impact of technical progress on employment growth. We doubt that their estimates are the true elasticities. The reason is that it is not clear what the rationale or theory behind regression (1) is. We elaborate on this point below. As a consequence, we argue instead that, in reality, the estimated parameters of interest are just the coefficients of a *quasi-accounting identity*. As such, they do not convey any relevant information and AS's (2017) work cannot provide an answer to the question they pose.

To facilitate the discussion, we rerun AS's (2017) key regressions. Our results are qualitatively the same as theirs.

2.1 A Model or a Quasi-accounting Identity?

AS (2017) indicate that their regressions yield conditional correlations and interpret the parameters of interest as elasticities. AS (2017) do not present any theory underlying their analysis and merely assert that it is a reduced form of some unspecified model.

To see the problem, consider first the growth rates of aggregate employment and productivity in Australia over the period 1970–80 (see AS 2017, table 2). The exact country and time period is immaterial, as we are using the data to illustrate a general point. Employment growth was 1.44 percent per annum and productivity growth was 1 percent per annum. Compare this with

Germany, where the comparable figures are 0.49 percent and 2.22 percent per annum, respectively. Thus, Germany, with a high rate of productivity growth, had lower employment growth.

Now compare these figures with Korean growth rates over the same period. Employment growth was 6.30 percent per annum, much faster than that of Australia or Germany, but productivity growth was 4.11 percent, also much faster. This may seem to suggest that a faster rate of technical progress increases the rate of employment growth. The reason is, of course, that output growth was also much faster in Korea. As, *by definition*, output growth equals productivity growth plus employment growth, it follows that the growth rate of output was 2.44 in Australia, 2.71 in Germany, and 10.41 in Korea. Therefore, running a regression of employment growth on productivity growth and excluding output growth misses the latter's "effect."

This point may also be seen by considering an aggregate production function of the form $Y_t = A_t \cdot F(K_t, L_t)$. For expositional ease, let it be a Cobb-Douglas production function with constant returns to scale (i.e., $Y_t = A_0 e^{\lambda t} K_t^{\alpha} L_t^{1-\alpha}$, where A_0 is the level of TFP); λ_t is the constant rate of TFP growth; K is the capital input; L is the labor input; and α and $(1-\alpha)$ are the output elasticities of capital and labor, respectively. Expressing this in growth rates and rearranging we get:

$$\hat{L}_t = -\frac{1}{(1-\alpha)}\hat{\lambda}_t + \frac{1}{(1-\alpha)}\hat{Y}_t - \frac{\alpha}{(1-\alpha)}\hat{K}_t \qquad (2)$$

and using the Kaldorian stylized fact that the growth of output and capital are roughly equal gives:

$$\hat{L}_t = -\frac{1}{(1-\alpha)}\hat{\lambda}_t + \hat{Y}_t \qquad (3)$$

From this perspective it can be seen that employment growth is determined by both the rate of technical progress *and* the growth of output.

As $\hat{L}_t \equiv \hat{Y}_t - \hat{y}_t$ (the growth of output minus the growth of labor productivity), it can be seen that in this framework the rate of technical change $(\hat{\lambda}_t)$ equals $(1-\alpha)\hat{y}_t$.

Let us now discuss AS's (2017) analysis in the light of these comments. For pedagogical purposes, let's start with the static regression:

$$\hat{L}_t = \alpha_0 + \alpha_1^* \hat{y}_t + u_t \tag{4}$$

Estimation results using pooled data (without and with country fixed effects) are shown in the first column of table 1. We use the same sample of advanced countries as in AS (2017). These results are qualitatively similar to those of AS (2017). Taken at face value, the results in table 1 indicate that there is a negative relationship between labor productivity growth (technical progress) and employment growth.

Table 1. Employment Growth and Labor Productivity Growth: Equation (4)

	Coefficient		
	Labor productivity growth (α_1^*)	**R^2**	**"Bias"**
No fixed effects	-0.014	0.001	0.986
Fixed effects	-0.038**	0.145	0.962

Notes: Authors' estimation using data from World Development Indicators and Penn World Table, version 9.1. The estimates are results of pooled regressions with data for 19 advanced countries: Australia, Austria, Belgium, Denmark, Finland, France, Germany, Greece, Ireland, Italy, Japan, Luxembourg, Netherlands, Portugal, Republic of Korea, Spain, Sweden, United Kingdom, and United States

** denotes that the coefficient is significant at the 5 percent level.

What would happen if we add output growth to regression (4)?

$$\hat{L}_t = \alpha_0 + \alpha_1 \hat{y}_t + \alpha_2 \hat{Y}_t + u_t \tag{5}$$

where $\hat{y}_t$ is the growth rate of labor productivity; $\hat{Y}_t$ is the growth rate of GDP; and u_t is an added error term. The problem with this equation is obvious, namely that it is just the tautological definition of employment (L):

$$\mathrm{L_t} = \frac{\mathrm{L_t}}{\mathrm{Y_t}} \cdot \mathrm{Y_t} \tag{6}$$

where $\mathrm{Y_t}$ is GDP. Expression (6) in growth rates is:

$$\hat{\mathrm{L}}_\mathrm{t} = -\hat{\mathrm{y}}_\mathrm{t} + \hat{\mathrm{Y}}_\mathrm{t} \tag{7}$$

where $\mathrm{y_t} = \frac{\mathrm{Y_t}}{\mathrm{L_t}}$ is labor productivity.

It should be self-evident that the estimation of equation (5) will yield coefficients $\alpha_1 = -1$, $\alpha_2 = 1$, and a perfect fit (since there is no actual error) because it is a tautology or definitionally true. No matter what method is used (OLS, IV) to estimate regression (5) and dataset used (i.e., pooled data [without and with fixed effects] or individual-country data), the results must be the same in all cases. Note that the country dummies' coefficients in the fixed effects regression are equal to zero because they are irrelevant variables.

Our argument is that equation (4) can be interpreted as expression (5) with the growth rate of GDP $(\hat{\mathrm{Y}}_\mathrm{t})$ "omitted." We refer to equation (4) as a *quasi-accounting identity*. The implications of this are, first, that even in case one would like to argue that the estimation of (4) produces an elasticity, there is a gray area as to whether this is true or not as a result of the fact that employment and productivity growth are related through the identity. Secondly, we know exactly the value of the estimated coefficient α_1^* in regression (4) by comparing it to its value in expression (5) (i.e., -1). This is akin to the standard econometric problem of omitted-variable "bias," with one important difference: in this case, we know exactly what the omitted variable is. Hence, it is not a statistical problem that calls for IV (or any other method) estimation. The expected value of α_1^* in equation (4) can be calculated as:

$$\mathrm{E}(\alpha_1^*) = \alpha_1 + \alpha_2 \left[\frac{\mathrm{cov}(\hat{\mathrm{Y}}_\mathrm{t}, \hat{\mathrm{y}}_\mathrm{t})}{\mathrm{var}(\hat{\mathrm{y}}_\mathrm{t})}\right] \tag{8}$$

where $\alpha_1 = -1$, $\alpha_2 = 1$, and the "bias" is $\frac{\mathrm{cov}(\hat{Y}_t, \hat{y}_t)}{\mathrm{var}(\hat{y}_t)}$. The latter is shown in the last column of table 1.

We have stressed above the terms "omitted" and "bias." This merits an explanation. First, we are not claiming that we can transform any regression into an identity or tautology by adding (as a regressor) the difference between the left- and right-hand-side variables. It would certainly be more than incorrect to argue that in, for example, the standard export demand function, where exports (X) typically depend on relative prices (RELP) and foreign income (Yw), that the two coefficients of the right-hand-side variables suffer from omitted-variable bias because the regression misses the variable Z, where $\mathrm{Z} = (\mathrm{X} - \mathrm{RELP} - \mathrm{Yw})$. This variable is meaningless. In the case at hand, however, the omitted variable is clearly output growth.

Second, AS (2017) indicate that their regressions yield conditional correlations and interpret them as elasticities. However, because in reality equation (4) is a reduced form, it is very difficult to justify that the estimated coefficient is the true elasticity. From an economic point of view, as we have seen, output growth should also be a determinant of employment growth.

The problem is that adding output growth to equation (4) turns the regression into the identity (tautology) (5). This poses a "catch-22" problem. It also means that α_1^* is a biased estimate of the true impact of technology on employment. Therefore, equation (5) tells us that any additional variable in regression (4) would work (add explanatory power, and its coefficient would tend to 1) if it is correlated with output growth; the coefficient of labor productivity growth would tend to -1. The higher the correlation between output growth and the added variable, the closer this regression will approximate identity (5).[2]

We close this section with a comment on AS's (2017) justification for dismissing the IV estimates. They argue as follows: "our instrumental variable approach will likely exaggerate the causal effect of own-country productivity growth on own-country employment because productivity growth will affect employment both through own-productivity gains and from

[2] In the light of our analysis, we question Harhoff's (2017) comments praising AS (2017).

simultaneous growth of export demand from trading partners." They add that: "A further limitation of the IV approach is that, by using each country as an instrument for every other country, it is asymptotically equivalent to using the time-series average of cross-country productivity growth as the instrument for each country simultaneously" (AS 2017: fn 31). These comments are based on the fact that some of their IV estimates (AS 2017: table 3a) are difficult to explain. Our view is that, since the estimation of the full identity equation (5) is not affected by the method (i.e., OLS and IV will yield the same estimated coefficients), the different results obtained estimating regression (4) with OLS and IV are due to the fact that IV introduces—on top of not including output growth as an explanatory variable—another "source of error" (i.e., instrumenting labor productivity growth), to the extent that the problem is not the regressors' endogeneity.

2.2 Additional Variables: What Is Their Role?

AS (2017) tried to improve their results, in particular they were concerned with the sign of labor productivity growth in regression (4) (i.e., is it truly negative?). To do so, they lagged values of labor productivity growth and population growth as additional explanatory variables to equation (4). They also used the growth rate of the employment-to-population ratio as their dependent variable. We argue that all these variants of equation (4) can also be explained in terms of the definitional identity equation (5) and the omission of a variable in it.

2.2.1 Adding Lagged Values of Productivity Growth

What would happen if we add lagged values of labor productivity growth to regression (4), effectively estimating equation (1)? It should be self-evident that these variables will have a positive sign in the regression to the extent that they are positively correlated with GDP growth $(\hat{Y}_t)$. They are in fact proxying it. Indeed, the correlations between $(\hat{Y}_t)$ and the first three lags of labor productivity growth are 0.460, 0.327, and 0.368, respectively. Since correlations are not perfect (and they decline with time), the coefficients are less than one and only the first lag is statistically significant. The results are shown in table 2. To make the point clear: the inclusion into regression (4) of any variable that is perfectly correlated with GDP growth would have a coefficient of one and it would reproduce expression (5).[3]

Table 2. Employment Growth and Labor Productivity Growth (current and lagged values): Equation (1)

	Coefficients				
	Labor productivity growth	**Labor productivity growth, lag 1**	**Labor productivity growth, lag 2**	**Labor productivity growth, lag 3**	R^2
No fixed effects	-0.073***	0.126***	-	-	0.030
Fixed effects	-0.089***	0.115***	-	-	0.170
No fixed effects	-0.075***	0.121***	0.031	-	0.035
Fixed effects	-0.091***	0.112***	0.024	-	0.171
No fixed effects	-0.075***	0.123***	0.032	0.012	0.037
Fixed effects	-0.089***	0.114***	0.024	0.012	0.170

Notes: Authors' estimation using data from World Development Indicators and Penn World Table, version 9.1. The correlation between GDP growth and: (i) labor productivity growth lagged 1 period is 0.460; (ii) labor productivity growth lagged 2 periods is 0.327; and (iii) labor productivity growth lagged 3 periods is 0.368.
*** denotes that the coefficient is significant at the 1 percent level.

2.2.2 Adding Population Growth

AS (2017) also added population growth to regression (1) and estimated:

$$\hat{L}_t = \alpha_0 + \alpha_1^* \hat{y}_t + \alpha_3^* \hat{P}_t + u_t \quad (9)$$

Comparing equation (9) to the identity (5) indicates that the former will yield good results if population growth is a good proxy for output growth. In our dataset, both variables are positively correlated with a value of 0.31.

The problem can also be stated as follows. We can write the definition:

$$L_t = \frac{L_t}{Y_t} \cdot \frac{Y_t}{P_t} \cdot P_t \quad (10)$$

[3] Naturally, if the added variable is not perfectly correlated with output growth, it will not have a coefficient of one.

where $\frac{Y_t}{P_t}$ is income per capita and P_t is population. In growth rates, equation (10) is:

$$\hat{L}_t = -\hat{y}_t + \hat{y}_t^* + \hat{P}_t \tag{11}$$

where $\hat{y}_t^*$ is the growth rate of income per capita and $\hat{P}_t$ is the growth rate of population. As above, estimation of this regression as:

$$\hat{L}_t = \alpha_0 + \alpha_1\hat{y}_t + \alpha_4\hat{y}_t^* + \alpha_3\hat{P}_t + u_t \tag{12}$$

would yield $\alpha_1 = -1$, $\alpha_4 = 1$, $\alpha_3 = 1$. We must stress that these coefficients (unity) and signs are ensured by construction (the identity).

However, AS (2017) estimated equation (9). In this case, the omitted variable is the growth rate of income per capita ($\hat{y}_t^*$). The effect is, again, to introduce a bias in the coefficients of the included variables. The expected value of α_1^* is:

$$E(\alpha_1^*) = \alpha_1 + \alpha_3\left[\frac{cov(\hat{y}_t,\hat{y}_t^*)var(\hat{P}_t) - cov(\hat{P}_t,\hat{y}_t^*)cov(\hat{P}_t,\hat{y}_t)}{var(\hat{P}_t)var(\hat{y}_t) - [cov(\hat{P}_t,\hat{y}_t)]^2}\right] \tag{13}$$

with $\alpha_1 = -1$ and $\alpha_3 = 1$. Estimation results of equation (9) and the bias in (13) are shown in table 3. AS (2017: table 3a, column 6) found a coefficient of population growth of 1.013, which they thought it was "noteworthy" (AS 2017, 58). Their interpretation was that employment rises equiproportionately with population. In our case, we obtain a coefficient of 1.145 (no fixed effects) and 0.794 (fixed effects), both statistically not different from one. In our view, the unit coefficient is the result of the nature of the exercise, that is, results are driven by identity (11). Results are not perfect because regression (9) omits income per capita growth as a regressor. Yet, the coefficient of population growth is close to what the identity predicts.

Table 3. Employment Growth, Labor Productivity Growth, and Population Growth: Equation (9)

	Coefficients		R^2	"Bias" (α_1^*)
	Labor productivity growth (α_1^*)	Population growth (α_3^*)		
No fixed effects	-0.045**	1.145***	0.140	0.955
Fixed effects	-0.054***	0.794***	0.184	0.946

Notes: Authors' estimation using data from World Development Indicators and Penn World Table, version 9.1. *** denotes that the coefficient is significant at the 1 percent level and ** denotes significance at the 5 percent level.

The effect of adding lagged values of labor productivity growth in regression (9) is to proxy the growth rate of income per capita. To the extent that this variable and the lags are positively correlated (which they are), these variables will have a positive sign in the regression. This extended regression (not shown but available upon request) also yields a coefficient of population growth in the neighborhood of one, with the coefficient of labor productivity growth statistically significant (and statistically insignificant further lags).

2.2.3 Using the Growth Rate of the Employment-to-Population Ratio as the Dependent Variable

To corroborate their results, AS (2017) substituted the growth rate of employment on the left-hand side by the growth rate of the employment-to-population ratio $\left(\frac{L_t}{P_t}\right)$. Once again, the tautological nature of the exercise is obvious. One can write the definition:

$$N_t = \frac{L_t}{P_t} = \frac{L_t}{Y_t} \cdot \frac{Y_t}{P_t} \tag{14}$$

where $N_t = \frac{L_t}{P_t}$ is the employment-to-population ratio.

In growth rates, equation (14) is:

$$\hat{N}_t = -\hat{y}_t + \hat{y}_t^* \tag{15}$$

The regression:

$$\widehat{N}_t = \alpha_0 + \alpha_1 \hat{y}_t + \alpha_4 \hat{y}_t^* + u_t \qquad (16)$$

would yield $\alpha_1 = -1$ and $\alpha_4 = 1$.

The estimated regression in this case is:

$$\widehat{N}_t = \alpha_0 + \alpha_1^* \hat{y}_t + u_t \qquad (17)$$

and so it appears that AS (2017) "omitted" the growth rate of income per capita ($\hat{y}_t^*$), which would yield a biased estimate of the coefficient of labor productivity growth. Estimation results for equation (17) and the computed bias are shown in table 4. Again, the lagged values of labor productivity growth proxy the growth rate of per capita income (results available upon request).

Table 4. Employment-to-Population Growth and Labor Productivity Growth: Equation (17)

	Coefficient		
	Labor productivity growth (α_1^*)	**R^2**	**"Bias"**
No fixed effects	-0.041**	0.005	0.959
Fixed effects	-0.058	0.054	0.942

Note: Authors' estimation using data from World Development Indicators and Penn World Table, version 9.1.
** denotes that the coefficient is significant at the 5 percent level.

2.3. Industry-level Evidence and the Effect of Other Sectors' Productivity Growth

To assess the effect of productivity growth at the industry level, AS (2017) estimated:

$$\widehat{L}_{ict} = \alpha_0 + \alpha_1 \hat{y}_{ict}[+\delta_t + \beta_c + \gamma_i] + \varepsilon_{ict} \qquad (18)$$

where $\widehat{L}_{ict}$ is the growth rate of employment in industry i, country c, at time t; $\hat{y}_{ict}$ is the growth rate of labor productivity; and δ_t, β_c, and γ_i is a set of year, country, and industry fixed effects, respectively.

Our view is that this regression suffers from the same problem discussed above. Theoretically, output growth needs to be included, but this will again result in estimating an identity. The labor productivity growth's coefficient carries a negative sign, and we argue that this is implicit in the identity (the results of regression [18] are available upon request). AS (2017) also added population growth to this specification. The coefficient of this variable in our regression is 1.099, statistically not different from 1, for the reasons discussed in section 2.2.2.

Finally, to assess the effect of other sectors' productivity growth, AS (2017) estimated:

$$\hat{L}_{ict} = \alpha_0 + \alpha_1 \hat{y}_{ict} + \sum_{k=0}^{m} \alpha_{t-k} \tilde{y}_{ct-k,j\neq i} \, [+\delta_t + \beta_c + \gamma_i] + \varepsilon_{ict} \tag{19}$$

where $\hat{L}_{ict}$ is the growth rate of employment in own-industry i, country c, at time t; $\hat{y}_{ict}$ is the growth rate of labor productivity in own-industry i; $\tilde{y}_{ct-k,j\neq i}$ is the average growth rate of labor productivity in all other industries (i.e., except own-industry i), country c, at time t (including current and lagged values); and δ_t, β_c, and γ_i is a set of year, country, and industry fixed effects, respectively.

Results (also available upon request) indicate that own labor productivity growth has a negative sign, and that most of the growth rates of other sectors' labor productivity growth carry a positive sign. This is because the latter are correlated with the growth rate of GDP. Finally, the coefficient of population growth is again statistically not different from 1.

3. AUTOR AND SALOMONS (2018): TFP IS NOT A MEASURE OF TECHNICAL PROGRESS

As noted in the introduction, AS (2018) offers a more technically sophisticated analysis of the relationship between technical progress and employment growth. In this paper, the authors focus on whether or not technological progress is employment displacing and the direct and indirect factors behind this. Unlike in AS (2017), here they used TFP growth as a measure of technical progress (with plenty of caveats acknowledged as to whether this is the correct measure or indicator) instead of labor productivity growth. They also used several outcome variables besides employment growth (hours, wage bill, nominal and real output, and labor shares). Finally, their econometric analysis is substantially more sophisticated than that of AS (2017) in two directions: (i) the use of other countries' TFP in the same industry in lieu of own-country-industry TFP; and (ii) the acknowledgement that there is a time lag to account for the effects of TFP impacts on the outcome variables. We argue below that these two refinements do not solve the problems we highlight.

Focusing on their initial estimates, AS (2018, table 5) find: a negative relationship between TFP growth and the growth rates of employment, hours, the wage bill, nominal output, and the labor share; and a positive relationship between TFP growth and real output. The main finding for employment growth is that there is an own-industry negative impact of increasing TFP, which is offset by the indirect effects arising from the input-output linkages, as well as from the overall positive impact of rising TFP on aggregate value-added and final demand.

We find it again somewhat surprising that AS (2018) do not refer explicitly to a production function in their analysis, although this is implicit in their use of the primal measure of TFP growth. Again, as in AS (2017), their entire empirical analysis is a series of reduced-form equations; hence, results are conditional correlations at best. Also, their measure of TFP growth (taken from the KLEMS database; see O'Mahony and Timmer [2009]) seems to assume Hicks-neutral technical progress (AS 2018: fn 15). However, if technical progress is, for example, labor saving, and the elasticity of substitution is different from one, the standard TFP growth calculations are incorrect insofar as, under these circumstances, technical progress affects the factor shares and this effect has to be eliminated.[4] Finally, if AS had started from an explicit production function, then they would have had to account for the effects of capital and output, the other two variables in the production function.

[4] Nelson (1973) argued that the purpose of growth accounting is to separate the contribution of technological progress from that of factor accumulation. In doing this, the factor shares that multiply the growth rates of capital and labor should be those that would have occurred *if there had been no technical change*. However, the factor shares actually used in these exercises are the *observed* ones, taken from the national accounts, which incorporate the effect of technical progress. If the latter is labor saving, purging this effect would reduce the capital share. See also Ferguson (1968) and Felipe and McCombie (2001).

The explicit consideration of a production function takes us to a more fundamental problem with AS's (2018) analysis, namely the use of the primal TFP growth as a measure of technical progress. As we shall see, the problem with the use of TFP growth is that it is not an opaque measure of technical progress. We will argue that, even though TFP growth is most often calculated as a residual, its interpretation is clear. The problem is that it is hardly a measure of technical progress. This has been known for a long time, but it has been ignored by the literature (Felipe and McCombie 2013, 2019).[5] Our emphasis in this comment on what TFP growth truly measures and captures is key to understanding AS's (2018) analysis. The reason for focusing on TFP growth is that we show it is not a measure of technical progress. Hence, our point is that the many regressions estimated do not capture what the authors think they do. AS (2018)—as well as the two discussants of their paper, Haltiwanger (2018) (much of his discussion is about TFP) and Rogerson (2018)—also raised questions about the relevance of TFP growth. However, their reasons are very different from ours. Given this, we think it is worth explaining our arguments in detail.

3.1 Total Factor Productivity Growth

Since Solow (1957), the neoclassical approach starts with the assumption that there is a well-behaved aggregate production function: $Y_t = A_t F(L_t, K_t)$. This assumes that technical progress is Hicks-neutral. By totally differentiating it with respect to time, the growth rate of output is:

$$\widehat{Y}_t = \widehat{TFP}_t + \alpha_t \widehat{L}_t + \beta_t \widehat{K}_t \qquad (20)$$

where a circumflex hat over the variables denotes the growth rate; α_t and β_t denote the elasticities of output with respect to labor and capital, respectively; and $\widehat{TFP}_t$ denotes what is often interpreted as the rate of technological progress (i.e., the growth rate of A_t). This is referred to as TFP growth, or the residual, a variable that supposedly captures all output growth not due

[5] It is worth noting that the two discussants of AS (2018)—Haltiwanger (2018) and Rogerson (2018)—questioned at length the soundness of AS's (2018) exercise and concluded that they had failed to provide compelling evidence of the causal effects of technical progress on employment. Haltiwanger and Rogerson offered discussions of different TFP-related issues in the context of AS's (2018) results, but neither one ventured to even suggest that TFP growth might capture something very different from technical progress. This is more so in the case of Haltiwanger, who argued at length about the negative TFP growth rates for many US industries. He referred to issues such as mismeasurement error or misallocation problems as possible explanations.

to increases in factor inputs. Growth accounting derives an estimate of $\widehat{TFP}_t$ residually as $\widehat{TFP}_t = \hat{Y}_t - \alpha_t \hat{L}_t - \beta_t \hat{K}_t$, given values for the right-hand-side variables.

The problem, however, is that there are very few reliable estimates of the output elasticities from econometric estimations because of the econometric issues that plague the latter. To solve this problem, growth accounting exercises assume that: (i) production is subject to constant returns to scale, (ii) the objective function of the firms in the economy is to maximize profits, and (iii) labor and capital markets are perfectly competitive (wage and profit rates are given by the first-order optimizing conditions). Under these circumstances, the factor elasticities equal the shares of labor and capital in total output—namely, $\alpha_t = a_t = (W_t/Y_t)$ and $\beta_t = (1 - a_t) = (S_t/Y_t)$, where a_t and $(1 - a_t)$ denote the labor and capital shares in output (W is the total wage bill and S is the total surplus), respectively. Then output growth can be written as:

$$\hat{Y}_t = \widehat{TFP}_t + a_t \hat{L}_t + (1 - a_t)\hat{K}_t \quad (21)$$

and consequently, the TFP growth rate is calculated as:

$$\widehat{TFP}_t = \hat{Y}_t - a_t \hat{L}_t - (1 - a_t)\hat{K}_t \quad (22)$$

given that data for all the right-hand-side variables are now readily available (the shares of labor and capital in total output can be obtained from the national accounts). The residually measured TFP growth in equation (22) is referred to as the primal measure of TFP growth. This is probably the most widely used method for calculating the TFP growth rate. Since the calculation involves two subtractions, it gives the impression that the resulting figure is sort of a mystery, a residual, or measure of our ignorance, which is how TFP growth is often referred to.

3.2 The Problems Interpreting TFP Growth as a Measure of Technical Progress

Let's start by writing how the data appear in the National Income and Product Accounts (NIPA) identity:

$$Y_t \equiv W_t + S_t \quad (23)$$

where Y is real (i.e., deflated) GDP or value-added (e.g., dollars of a base year), W is the real total wage bill (dollars of a base year), and S is the operating surplus (dollars of a base year).[6] It is very important to stress that identity (23) (note the symbol ≡) is true at any level of aggregation, including at the firm level. NIPA statisticians construct the identity by arithmetic summation (aggregation) from individual firm-level data and government institutional data. This aggregation is logically consistent, and unrelated to the problem of the conditions to aggregate production functions (Felipe and Fisher 2003). We will nevertheless return to this important issue below when we discuss the interpretation of TFP. Equation (23) is theory-free (e.g., it does not depend on the zero profits assumption) and it is not related to or derived from production/cost theory.

We now dichotomize the wage bill and operating surplus into the products of a price times a quantity as:

$$Y_t \equiv w_t L_t + r_t K_t \tag{24}$$

where w is the average real wage rate (dollars of a base year per worker), L is total employment (number of workers), r is the ex post average profit rate (dollars of operating surplus per dollar of capital stock, a pure number), K is the stock of capital (dollars of a base year). Note that by construction $W_t = w_t L_t$ is the wage bill and $S_t = r_t K_t$ is total profits (operating surplus).[7]

One can simply now express the accounting identity (24) in growth rates as:

[6] We note that it makes no difference whatsoever to our argument writing equations (23) and (24) by splitting the surplus into the cost of capital and monopolistic profits, namely, $S_t \equiv r_t K_t \equiv \rho_t K_t + Z_t$, where ρ is the use cost of capital and Z denotes pure profits. Consequently, $Y_t \equiv C_t + Z_t \equiv w_t L_t + \rho_t K_t + Z_t$, where $C_t \equiv w_t L_t + \rho_t K_t$ is the total cost.

[7] We just note that while it is self-evident that the wage bill (W_t) is split into the product of a price (w_t is measured in $/worker) times a quantity (L_t is measured in number of workers), it is much less obvious that this is also the case of the operating surplus (S_t). This is because the units of r_t and K_t are a percentage and dollars of a base year, respectively. This does not mean that writing $S_t = r_t K_t$ is incorrect, as the product still yields dollars. Also, it should be obvious that w_t and r_t may or may not be the marginal products of labor and capital, respectively, in the sense of being derived from a production function, even though this is what equation (24) will always indicate, namely, $\left(\frac{\partial Y}{\partial L}\right) \equiv w_t$ and $\left(\frac{\partial Y}{\partial K}\right) \equiv r_t$.

$$\hat{Y}_t \equiv a_t\hat{w}_t + (1 - a_t)\hat{r}_t + a_t\hat{L}_t + (1 - a_t)\hat{K}_t \tag{25}$$

or

$$\hat{Y}_t \equiv \hat{\lambda}_t^D + a_t\hat{L}_t + (1 - a_t)\hat{K}_t \tag{26}$$

where a_t and $(1 - a_t)$ are the labor and capital shares in GDP. Rearranging the terms yields:

$$\hat{\lambda}_t \equiv \hat{Y}_t - a_t\hat{L}_t - (1 - a_t)\hat{K}_t \equiv a_t\hat{w}_t + (1 - a_t)\hat{r}_t \equiv \hat{\lambda}_t^D \tag{27}$$

where the superscript D is used to refer to the right-hand side of the identity (i.e., the weighted average of the growth rates of the wage and profit rates). The reader will note that equations (26) and (27) are identical to equations (21) and (22), and consequently, $\hat{\lambda}_t \equiv \hat{\lambda}_t^D \equiv \widehat{TFP}_t$. This is true by construction. Since (27) is an identity, it poses insurmountable problems for the interpretation of (22) as a measure of technical progress. More generally, it poses a problem for all empirical work using production and cost functions and their associated concepts, such as TFP (Felipe and McCombie 2013, 2019).

The neoclassical tradition acknowledges identity (24) but argues that the production function, together with the usual neoclassical assumptions and Euler's theorem, provides a theory of the income side of the NIPA. We consider that this line of reasoning is incorrect.[8] Identity (24) holds by itself and is not dependent upon any conditions from production theory. It is also important to note that while the weights of the growth rates (the factor shares) in equation (22) are theoretically derived by imposing the first-order conditions, the shares in the identity are simply

[8] This seems to be the view of, for example, Jorgenson and Griliches (1967, 252–53). From $Y = F(K, L)$, one can write $Y = F_K K + F_L L$ (Euler's theorem), and from the first-order conditions, $F_K = r$ and $F_L = w$. Hence $Y_t = r_t K_t + w_t L_t$ is taken to be identity (24). That is, the neoclassical framework considers that the production function through Euler's theorem *implies* the identity. While this derivation is mathematically correct, it does not mean that the production function provides a theory of the accounting identity. See also Hulten (2009), who traces the history of growth accounting from the 1930s through the 1950s, with the identity as starting point. This formulation was "atheoretical" (Hulten 2009, 4). Solow's (1957) contribution was to provide the economic structure that the approach lacked.

the result of taking the derivative with respect to time. This means that they are the true weights of whether factor markets are perfectly competitive or not. Identity (27) is not a model.

To understand the problems AS (2018) face in using TFP growth as a measure of technical progress, we make four clarifications:

(i) Identity (27) makes it clear that the residually calculated TFP growth, $\widehat{\mathrm{TFP}}_t \equiv \hat{Y}_t - a_t\hat{L}_t - (1-a_t)\hat{K}_t \equiv \hat{\lambda}_t$, is numerically equivalent to $\hat{\lambda}_t^D \equiv a_t\hat{w}_t + (1-a_t)\hat{r}_t$. This means that TFP growth is not a "measure of our ignorance." We know what it is: *a weighted average of the growth rates of the wage and profit rates*. This is the result of how identity (23) was split into identity (24)—namely, $W_t = w_tL_t$ and $S_t = r_tK_t$ (unrelated to a production function). This self-evident yet important point seems to have been missed by those who think of $\widehat{\mathrm{TFP}}_t$ as derived from a production function, because they do not see the immediate link with the accounting identity. It is important to point out the resemblance between $\hat{\lambda}_t^D$ and the dual of TFP growth, which in neoclassical theory is the derived from the cost function. What our analysis shows is that so-called primal and dual measures of TFP growth are essentially the same, except for some issues that we skip here.[9]

(ii) Identity (25) can certainly be used to apportion growth in an accounting sense into the various components of the identity (the same way it is often done with the identity from the demand side). However, interpreting $\widehat{\mathrm{TFP}}_t$ as a measure of the growth in efficiency or of the rate of technical progress (or rate of cost reduction) is problematic. Nothing in the identity identifies $\hat{\lambda}_t \equiv \hat{Y}_t - a_t\hat{L}_t - (1-a_t)\hat{K}_t \equiv \hat{\lambda}_t^D \equiv a_t\hat{w}_t + (1-a_t)\hat{r}_t$ with the rate of technical progress. After all, identity (25) is just $\hat{Y}_t \equiv a_t\hat{W}_t + (1-a_t)(\hat{S}_t) \equiv a_t(\hat{w}_t + \hat{L}_t) + (1-a_t)(\hat{r}_t + \hat{K}_t)$, *a measure of distributional changes*.[10]

[9] The neoclassical dual uses cost shares instead of revenue shares and the user cost of capital instead of the average profit rate; see the discussion in Felipe and McCombie (2019). Empirically, primal (from the production function) and dual (from the cost function) tend to be very close, and are statistically not different.

[10] It could be argued that the wage rate's growth rate is the consequence of productivity growth, where both variables are related through the first-order condition $\left(w = \frac{\partial Y}{\partial L}\right)$, hence the link with the production function (and similarly the profit rate and capital productivity), and this is what $\hat{\lambda}_t^D$ captures. The problem with this argument is

Arguing that neoclassical production and cost theories explain what $\hat{\lambda}_t \equiv \hat{\lambda}_t^D \equiv \widehat{TFP}_t$ is, is an act of faith. The literature on aggregation of production functions is clear: the conditions under which aggregate production functions with neoclassical properties exist, in the sense that it can be generated from micro-production functions, are so stringent that they are not met by actual economies. This makes the existence of aggregate production functions in real economies a nonevent (Felipe and Fisher 2003). As far back as 1970, Nadiri (1970, 1144), in a survey on the topic, already claimed that the aggregation problem matters because "without proper aggregation we cannot interpret the properties of an aggregate production function, which rules the behaviour of total factor productivity."[11]

(iii) The wage rate's growth rate tends to be mildly procyclical (wages are sticky), whereas that of the profit rate is markedly so. This means that most of the variation in $\hat{\lambda}_t \equiv \hat{\lambda}_t^D$ is, in fact, induced by $\hat{r}_t$.

(iv) Labor productivity growth and TFP growth are directly related through the accounting identity (26), since it can be written as $\hat{y}_t \equiv \hat{\lambda}_t^D + (1 - a_t)\hat{k}_t$, where $\hat{k}_t$ is the growth rate of the capital–labor ratio. This is true always and by construction. This means that the formulations (regressions) in AS (2017) and AS (2018) are intrinsically related.

Given that AS's (2018) measure of technical progress is just $\hat{\lambda}_t \equiv \hat{\lambda}_t^D \equiv a_t\hat{w}_t + (1 - a_t)\hat{r}_t$, a weighted average of the growth rates of the wage rate and profit rate, one wonders about the meaning of regressions of the growth employment $(\hat{L}_t)$, hours, the wage bill $(\hat{W}_t)$, output $(\hat{Y}_t)$, and the labor share $(\hat{a}_t)$ on $\hat{\lambda}_t \equiv \hat{\lambda}_t^D$, given identity (27), which links all these variables.

---

that the relationship between the wage rate's growth rate and labor productivity growth is definitional, and hence cannot be tested. Indeed, as the labor share is $a_t \equiv \frac{(w_t L_t)}{Y_t}$, in growth rates: $\hat{w}_t \equiv \hat{a}_t + \hat{y}_t$ (where $y \equiv \frac{Y}{L}$). This relationship will always be true. For short periods of time, $\hat{w}_t \simeq \hat{y}_t$, as factor shares vary little and slowly.

[11] It is worth quoting Nadiri (1970, 1145–46) on this: "The conclusion to be drawn from this brief discussion is that aggregation is a serious problem affecting the magnitude, the stability, and the dynamic changes of total factor productivity. We need to be cautious in interpreting the results that depend on the existence and specification of the aggregate production function… That the use of the aggregate production function gives reasonably good estimates of factor productivity is due mainly to the narrow range of movement of aggregate data, rather than the solid foundation of the function. In fact, the aggregate production function does not have a conceptual reality of its own."

Naturally, the fact that AS (2018) use other countries' TFP growth rates (the leave-out-mean approach) to measure within-industry-by-country TFP growth, as well as a complex lag structure of TFP growth, is beside the point, as these procedures do not solve any putative problem. The identity argument also applies to AS's (2018) cross-sectoral linkage analysis, as it is self-evident that the identity holds for each cross-section.

This analysis also helps in understanding the well-documented finding of very low and negative TFP growth rates in many US industries (Haltiwanger 2018, 66, 68). Given our arguments and understanding of what TFP truly captures, this has been low as a result of: (i) very low wage growth because a great deal of employment has been generated in nontradable services, activities which, in general, experience low wage increases; and (ii) the well-documented decline in the US labor share (Dao et al. 2017; Stockhammer 2017). This means that $a_t\hat{w}_t$ was probably zero or negative in some industries and was not compensated for by an increase in $(1 - a_t)\hat{r}_t$. Very importantly, we stress that this result (finding) follows directly from the accounting identity, and, at best, it only says something about distributional changes.

3.3 Example

Apart from the conceptual problem discussed above, it should be self-evident that AS's (2018) regressions with TFP growth as regressor are also problematic. We focus our attention on equations (25), (26), and (27), the accounting identity in growth rates. We have constructed the series to satisfy the identity. The purpose of the regressions in table 5 is to show that one can reinterpret AS's (2018) regressions of employment growth on TFP growth in terms of the accounting identity. Obviously, we do not run the regressions for all outcome variables. We only show the one for employment growth. We run this regression for five countries.

We start with the regression of output growth on $\hat{\boldsymbol{\lambda}} \equiv \hat{\lambda}_t^D$ and on the growth rates of labor and capital (equation 26). $\hat{\boldsymbol{\lambda}} \equiv \hat{\lambda}_t^D$ was constructed from the data and the coefficients of labor and capital growth were left unrestricted. The regressions for the five countries are shown on the left-hand side of table 5. We know from equation (26) that the coefficients of the last two variables will be positive and will have to be close to the corresponding factors *if* these do not show great variation, and that the coefficient of $\hat{\lambda}_t^D$ will be positive and would have to be close to one.

Naturally, since we assume that the coefficients of labor and capital growth are constant, there is an "error" (to the extent that coefficients are not exactly constant). As their variation is very small (see footnote in the table), the fits and t-values are very high (it is a quasi-accounting identity). Overall, results indicate that in the five cases, factor shares are sufficiently constant so that the regressions "work." Some researchers have traditionally confused these results and thought that they are driven by an underlying production function. It should be obvious that it is just the identity.

Table 5. Employment Growth and TFP Growth Regressions (I)

	$\hat{Y}_t$: Eq. (26)				$\hat{L}_t$: Eq. (28)				$\hat{L}_t$: Eq. (29)	
	$\hat{\lambda}_t^D$	$\hat{L}_t$	$\hat{K}_t$	R^2	$\hat{Y}$	$\hat{\lambda}_t^D$	$\hat{K}_t$	R^2	$\hat{\lambda}_t^D$	R^2
Austria	1.000	0.586	0.435	0.999	1.683	-1.681	-0.733	0.991	0.177**	0.299
Belgium	1.012	0.639	0.376	0.999	1.562	-1.580	-0.587	0.999	0.078**	0.027
Italy	1.004	0.677	0.380	0.999	1.472	-1.478	-0.555	0.998	0.081^{NS}	0.060
Netherlands	1.012	0.599	0.433	0.999	1.666	-1.686	-0.719	0.998	-0.002^{NS}	0.000
Sweden	1.007	0.495	0.519	0.999	2.012	-2.026	-1.042	0.997	0.136^{NS}	0.126

Notes: Coefficients are statistically significant at the 1 percent level, except those with ** are significant at the 5 percent level, * are significant at the 10 percent level, and NS means not significant.
Mean, Min, Max labor shares are, respectively:
Austria: 0.578,0.523, 0.648; Belgium: 0.622, 0.588, 0.657; Italy: 0.650, 0.612, 0.716; Netherlands: 0.581, 0.519, 0.640; and Sweden: 0.482, 0.449, 0.552
Mean, Min, Max capital shares are, respectively:
Austria: 0.422, 0.352, 0.477; Belgium: 0.378, 0.343, 0.412; Italy: 0.350, 0.284, 0.388; Netherlands: 0.419, 0.360, 0.481; and Sweden: 0.518, 0.448, 0.551

As argued above, it is difficult to understand the omission of the growth rates of output and capital in AS's regressions, to the extent that a production function should underlie these regressions. The problem is that adding these two variables to the regression leads, again, to the identity equation (26), now with employment growth on the left-hand side, that is:

$$\hat{L}_t \equiv -\frac{1}{a_t}\hat{\lambda}_t^D + \frac{1}{a_t}\hat{Y}_t - \frac{(1-a_t)}{a_t}\hat{K}_t \tag{28}$$

AS (2018) again faces the "catch-22" problem. We show the estimation results of regression (28) in the middle of table 5. It is worth emphasizing both the size of the coefficients (as predicted in equation [28]) and the negative sign of $\hat{\lambda}_t^D$. These are the result of the identity and not of estimating any behavioral relationship. It proves nothing.

We now omit the growth rates of output and capital in regression (28) and we estimate the same regression that AS (2018) estimated. This is equation (29):

$$\hat{L}_t = \gamma\hat{\lambda}_t^D + u_t \tag{29}$$

Results are shown on the right-hand side of table 5. It is immediately obvious that the coefficient of $\hat{\lambda}_t^D$ changes, both in magnitude and sign. This is, in our view, simply the result of "omitting" output and capital growth, which causes a significant bias.

Finally, table 6 shows the regressions of employment growth on two out of the three regressors in identity (28): on $\hat{\lambda}_t^D$ and $\hat{Y}_t$ on the left-hand side of the table; and on $\hat{\lambda}_t^D$ and $\hat{K}_t$ on the right-hand side of the table. The first set of results (i.e., with output growth as the added regressor) yields much better results, close in fact to the results in table 5 for the full equation (28). This means that omitting the capital stock's growth rate when output growth is included together with $\hat{\lambda}_t^D$ (left-hand side of the table) causes a small bias. The opposite is the case when output growth is the omitted variable, and instead the capital stock's growth rate is added as a regressor (right-hand side of the table). $\hat{\lambda}_t^D$ and $\hat{Y}_t$ are highly correlated, while the correlation between $\hat{K}_t$ and these two variables is low.

Table 6. Employment Growth and TFP Growth Regressions (II)

	$\hat{L}_t$: $\hat{\lambda}_t^D$ and $\hat{Y}_t$			$\hat{L}_t$: $\hat{\lambda}_t^D$ and $\hat{K}_t$		
	$\hat{\lambda}_t^D$	$\hat{Y}_t$	R^2	$\hat{\lambda}_t^D$	$\hat{K}_t$	R^2
Austria	-1.271	1.286	0.800	0.183**	-0.112^{NS}	0.305
Belgium	-0.930	0.944	0.783	0.073^{NS}	0.304^{NS}	0.172
Italy	-1.141	1.134	0.953	0.031^{NS}	0.989	0.455
Netherlands	-1.278	1.276	0.899	0.015^{NS}	0.693^{NS}	0.170
Sweden	-1.046	1.118	0.754	0.150*	0.420^{NS}	0.231

Notes: Coefficients are statistically significant at the 1 percent level, except those with **, which are significant at the 5 percent level, * are significant at the 10 percent level, and NS are not significant.

It is important to note that most of what the variable $\hat{\lambda}_t \equiv \hat{\lambda}_t^p \equiv a_t \hat{w}_t + (1 - a_t)\hat{r}_t$ reflects is simply $\hat{r}_t$ (i.e., the growth rate of the profit rate), as factor shares vary little (they show no cyclical fluctuations) and the wage rate is mildly procyclical. Consequently, AS (2018) effectively used the profit rate's growth rate as their measure of the rate of technical progress. As the profit rate is markedly procyclical, it is highly correlated with output growth.

4. CONCLUSIONS

We do acknowledge Autor and Salomons' (2017, 2018) attempt to shed light on the old question of the impact of innovation and productivity growth on employment. Our assessment, however, leads us to the conclusion that their methods are problematic and ultimately do not answer their research questions in any satisfactory way. AS's (2017) equations *should* include the growth rate of output as a determinant of employment growth. However, we have shown that adding this variable would transform their equations into tautologies. It is a "catch-22" problem that has no solution with the framework used.

AS (2018) also suffers from a similar, though more complex, problem. The measure of technical progress used in this case, total factor productivity (TFP) growth, is simply a weighted average of the growth rates of the wage and profit rates, i.e., a measure of distributional changes, not of technical progress. Hence, their regressions with TFP growth as the explanatory variable miss the point. The analysis with patents as a proxy for technical progress is much more promising, although it is not clear whether patents have a large effect on productivity. The problem is also that one needs a model to justify and interpret the regressions with the selected outcome variables and the results. Unfortunately, this is not the core of their analysis.

Summing up, in our view, the question AS intend to answer cannot be addressed with the types of regressions they ran in their two papers. In our view, the old and important question about the impact of technical progress on employment remains unanswered.

REFERENCES

Autor, David, and Anna Salomons. 2018. "Is Automation Labor Share–Displacing? Productivity Growth, Employment, and the Labor Share." *Brookings Papers on Economic Activity* 49(1): 1–63.

———. 2017. "Robocalypse Now—Does Productivity Growth Threaten Employment?" In the ECB Forum on Central Banking *Investment and Growth in Advanced Economies*., June 26–28, Sintra, Portugal.

Dao, Mai Chi, Mitali Das, Zsoka Koczan, and Weicheng Lian. 2017. "Understanding the Downward Trend in Labor Income Shares." World Economic Outlook. Washington, DC: International Monetary Fund. April.

Felipe, Jesus, and John S. L. McCombie. 2019. "The Illusions of Calculating Total Factor Productivity and Testing Growth Models: From Cobb-Douglas to Solow and to Romer." Available at SSRN: https://ssrn.com/abstract=3377758

———. 2013. *The Aggregate Production Function and the Measurement of Technical Progress: "Not Even Wrong."* Cheltenham, UK and Northampton, MA: Edward Elgar.

———. 2001. "Biased Technical Change, Growth Accounting and the Conundrum of the East Asian Miracle." *Journal of Comparative Economics* 29(3): 542–65.

Felipe, Jesus, and Franklin M. Fisher. 2003. "Aggregation in Production Functions: What Applied Economists Should Know." *Metroeconomica* 54(2–3): 208–62.

Ferguson, Charles Elmo. 1968. "Neoclassical Theory of Technical Progress and Relative Factor Shares." *Southern Economic Journal* 34(4): 490–504.

Haltiwanger, John. 2018 "Comment." *Brookings Papers on Economic Activity* 49(1): 64–71.

Harhoff, Dietmar. 2017. "Comment on 'Does Productivity Growth Threaten Employment' by David Autor and Anna Salomons." In the ECB Forum on Central Banking *Investment and Growth in Advanced Economies*., June 26–28, Sintra, Portugal.

Hulten, Charles R. 2009. "Growth Accounting." NBER Working Paper No. 15341. Cambridge, MA: National Bureau of Economic Research.

Jorgenson, Dale W., and Zvi Griliches. 1967. "The Explanation of Productivity Growth." *The Review of Economic Studies* 34(3): 249–83.

Nadiri, M. I. 1970. "Some Approaches to the Theory and Measurement of Total Factor Productivity: A Survey." *Journal of Economic Literature* 8(4): 1137–77.

Nelson R. 1973. "Recent Exercises in Growth Accounting: New Understanding or Dead End." *The American Economic Review* 63(3): 462–68.

O'Mahony, Mary, and Marcel Timmer. 2009. "Output, Input and Productivity Measures at the Industry Level: the EU KLEMS Database." *Economic Journal* 119(538): F374–503.

Rogerson, Richard. 2018. "Comment." *Brookings Papers on Economic Activity* 49(1): 71–87.

Solow, Robert. 1957. "Technical Change and the Aggregate Production Function." *The Review of Economics and Statistics* 39 (3): 312–20.

Stockhammer, Engelbert. 2017. "Determinants of the Wage Share: A Panel Analysis of Advanced and Developing Economies." *British Journal of Industrial Relations* 55(1): 3–33.