What do tests of the relationship between employment growth and technical progress hide?

JESUS FELIPE, DONNA FAYE BAJARO, GEMMA ESTRADA, AND JOHN MCCOMBIE[*]

Abstract:

The debate about whether technical progress causes technological unemployment, as the Luddites argued in the early 19th century, has recently resurfaced in the context of new technologies and automation and the so-called Fourth Industrial Revolution. We review the main issues and then consider in detail the studies of Autor and Salomons (2017, 2018). They find that after both direct and indirect effects are accounted for, technical change is, on the aggregate, employment-augmenting. They find no evidence that technical change (proxied by the growth of productivity) reduces employment growth. We demonstrate that the regressions they estimate are problematic because they approximate an accounting identity. One or two variables in the identity (output growth or both output growth and capital growth) are omitted, which implies that the coefficient of productivity growth suffers from omitted-variable bias. As the omitted variable is known, we can have a good idea of what the statistical results must be. We conclude that, unfortunately, their work does not shed light on the question they address.

Felipe: Asian Development Bank,
email: jfelipe@adb.org
Bajaro: Asian Development Bank,
email: donnafayebajaro@gmail.com
Estrada: Asian Development Bank,
email: gestrada@adb.org
McCombie: University of Cambridge,
email: jslm2@cam.ac.uk

The debate about the impact of mechanization (or, more generally, the role of technical progress) on employment growth goes back to at least the work of David Ricardo (1821), writing in the context of the Luddite movement. This group of English textile workers believed that faster growth of technical progress and the introduction of new machines caused a slower, or even negative, growth of employment, resulting in technological unemployment. For a long time, however, many economists have considered that technical progress does not lead to a reduction in employment growth; their view is that the Luddite arguments (that an economy-

---

wide technical breakthrough enabling production of the same amount of goods with fewer workers will result in an economy with fewer workers) simply involved a fallacy.

In response to the Luddites' destruction of new labor-saving textile machinery over the period 1811 to 1816, Ricardo added the chapter "On Machinery" to the third edition of the *Principles*. Here, he agreed with the opinion prevailing in "the laboring class, that the employment of machinery is frequently detrimental to their interests, is not founded on prejudice and error, but is comfortable to the correct principles of political economy" (Ricardo, 1821, p. 392). This was the first time that the concept of technological unemployment had been provided with a theoretical economic justification. Adam Smith and Karl Marx also discussed the relationship between wages, productivity and (un)employment.

This view has persisted over the years. For example, in an article in the *New York Times* on 26 February 1928, Evan Clark, at a time when the rate of unemployment was 4.2 per cent, predicted automation would lead to a dramatic rise in unemployment.

The term "technological unemployment" was first coined by Keynes (1930), who wrote that "This means unemployment due to our discovery of means of economising the use of labour outrunning the pace at which we can find the new use of labour". But in the next sentence, he dismisses this as a possibility. "But this is only a temporary phase of maladjustment. All this means in the long run *that mankind is solving its economic problem"* (emphasis in the original)*.* Keynes, looking at the next hundred years, considered that what he termed "absolute" needs would be satisfied. He contrasts this with "relative" needs, or positional goods, the satisfaction of which "lifts us above, makes us feel superior to, our fellows". The latter is closely related to Veblen's (1899) concept of conspicuous consumption. Consequently, when absolute needs are satiated, the demand for leisure becomes increasingly important. It goes without saying that history has shown the demand for new absolute goods is insatiable.

The refutation of the Luddite fallacy by some economists derives from the more general belief that long-run growth is, ultimately, determined by the overwhelming importance of *technological change*. In the neoclassical tradition, the aggregate demand curve for labor is downward sloping but technical change shifts the demand curve, leading to an increase in the demand for labor over time. Solow's (1956, 1957) classic papers made it clear that labor-saving technical change was the only way for output per worker to increase in the long run. In simple terms, the Luddite fallacy confuses, the argument goes, the shift of employment from old to new technologies (which has caused, and continues to cause, significant changes in *sectoral* employment and unemployment) with an overall decline in employment or, at least, a significant reduction in its rate of growth. For example, increases and improvements in agricultural machinery have decreased the share of agricultural employment in the U.S. from 40 percent in 1900 to 2 percent today, in spite of a substantial increase in agricultural output. The fall in the relative price of agricultural commodities has increased overall purchasing power, which has led to the increased production of other goods and services. The reality is that advanced economies have not displayed a long-run trend toward increasing aggregate unemployment (Autor, 2016).[1]

The fact that many economists dismiss the Luddite arguments does not mean that these ideas may not have some merit. The mechanism that has enabled real per capita demand in market economies to rise has been the increase in real wages in line with productivity, which

---

[1] Similar arguments were being made during the latter part of the 20th century, with concerns about the information technology revolution putting middle-skilled workers engaged in repetitive activities out of work.

in turn is largely due to technical progress. In these economies, real wages have increased to offset reductions in the growth of labor inputs by supporting a rise in aggregate per capita demand. However, this process can break down: even if wages increase to offset lower labor growth, increased productivity growth does not necessarily lead to higher employment growth. The Luddite argument may be valid if an economy with less-than-full employment is wage-led, that is, if a higher real wage rate, or wage share, induces an increase in employment. In these economies, an increase in labor productivity is unlikely to be followed immediately by a higher real wage rate, especially if some labor is unemployed. Total wage payments will decline as jobs are eliminated, thus reducing consumer demand. Investment and new capacity formation may also decline (Bowles and Boyer, 1995; Taylor, 1996).

In this paper, we undertake a brief and possibly partial review of the recent literature on whether the recent introduction of new technology, including that of robotization, while displacing labor in specific occupations, is causing or is likely to cause increased technological unemployment. It will be argued that some of those studies that come to this conclusion omit the impact of the increased growth of output demand. In particular, we present a detailed consideration of the econometric studies of Autor and Salomons (2017, 2018) on the relationship between employment and technical progress. We show that their work involves a 'catch 22' problem that results from the fact that their regressions are what we refer to as *quasi-accounting identities*. This is because, by adding one variable, e.g., output growth, the equation estimated becomes an identity. The implication is that the coefficient that supposedly measures the impact of technical progress on employment growth suffers from omitted-variable bias, where the omitted variable is known.

The rest of the paper is organized as follows. Section 1 provides a survey of the recent literature on robots, technical change, and technical unemployment. Section 2 discusses Autor and Salomons' (2017) approach (AS hereafter) and comments on its most salient results. Section 3 discusses Autor and Salomons' (2018) approach. We think doing 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 Autor and Salomons' (2018) approach provides a more compelling analysis. The final section offers some conclusions.

1. Robots, technical change, employment growth and technological unemployment

Recently, the debate about the likelihood of technological unemployment has surfaced in the context of the role and impact of the new technologies and the so-called Fourth Industrial Revolution.[2] These technologies include robotics, additive manufacturing, artificial intelligence, the "internet of things" and big data. Some have argued that there are reasons to believe that this time may be different. There is fear that faster technical change will reduce employment growth and will lead to "Robocalypse," the idea that the use of robots will cause a massive destruction of employment opportunities. Brynjolfsson and McAfee (2014) argue that machines are substituting for more types of human labor than ever before. As such, machines replicate themselves; essentially, they create more capital. The implication is that the real winners of the future will not be the providers of cheap labor or the owners of standard capital.

---

[2] This review is necessarily partial. It is impossible to cover the very rich literature on the subject. This would require a full survey.

Rather, the winners will be those who can innovate and create new products, services, and business models. In this view, workers without any special skills will be the most threatened.

Likewise, Harari (2018) argues that workers possess just two kinds of ability: physical and cognitive. Over the course of the 20th century, technological progress was associated with eliminating low-skilled, physically intensive tasks and jobs. These have been replaced with employment requiring cognitive skills that are more difficult to automate. The more recent technological advances, however, are also replacing jobs requiring cognitive skills, raising doubts as to future employment possibilities when machines are more capable than humans at both physical and cognitive tasks.

One approach adopted in much of the recent literature usually follows that developed by Frey and Osborne (2013, 2017).[3] Frey and Osborne reviewed the literature on machine learning and artificial intelligence and concluded that there seem to be technological bottlenecks corresponding to three main job task categories: perception and manipulation tasks (i.e., recognizing, configurating and manipulating objects), creative intelligence tasks (i.e., finding non-routine solutions to non-routine problems), and social intelligence tasks (i.e., interacting with humans in a social way). They argued that jobs that contain a large degree of tasks in these three categories will not be easily automated in the near future – taken to be 10 to 20 years – but other jobs will be. They then asked a panel of experts (in machine learning) to assess a set of 70 job descriptions in terms of the potential to be automated over the coming decades, with jobs being classified as either automatable or not automatable. Using this information, alongside information on the mix of knowledge, skills and abilities that the jobs require (i.e., based on the identified technological bottlenecks), Frey and Osborne predicted the probability of a job being automatable or not. They classified jobs with a 70 percent or more probability of being automated as jobs at a high risk of automation. Applying these estimates to data on the structure of employment (in their case, for the U.S.), it is then possible to obtain an estimate of the actual distribution of automation for workers – for example, the share of workers at a high risk of automation. Frey and Osborne (2017) estimated the probability of computerization of 702 detailed occupations in the U.S. and concluded that about 47 percent of total U.S. employment is at risk.

This type of analysis and methodology has been extended by, among others, Nedelkoska and Quintini (2018), who used a broader database covering the entire OECD area and also estimated the risk of automation at the level of individuals rather than jobs. They found a smaller share of employment to be in the high-risk group than did Frey and Osborne (2017) but still a median risk of automation of 48 percent. For the OECD as a whole, they found that 16.6 percent of jobs are at a high risk of automation (i.e., greater than a 70 percent chance) and 30.2 percent of jobs had a significant risk of automation (i.e., between 50 percent and 70 percent). The World Bank (2016) applied the methodology to data for a set of around 40 countries, including developing and transition countries. Results indicate that the risk of automation is higher than that found for developing countries by Frey and Osborne (2017) and for developed countries by Nedelkoska and Quintini (2018). Estimates of the share of employment that is susceptible to automation range from around 55 percent in Uzbekistan to more than 80 percent in Ethiopia. The World Bank (2016) study presents a second set of automation risk estimates to account for the fact that technology takes a certain time to diffuse, generally taking longer in poorer countries. This is because of lower technological capability

---

[3] Frey and Osborne (2013) is an earlier version of Frey and Osborne (2017).

and because wages tend to be significantly lower, making technologies initially less competitive. Given these diffusion lags, the risk of jobs being automated in some countries is likely to be delayed, meaning that such employment would not necessarily disappear in the next couple of decades. The World Bank (2016) uses information on diffusion lags to adjust the automation risk estimates. When adjusting for these technological lags, the share of employment at high risk of automation drops significantly. In the case of Uzbekistan, for example, the risk of automation drops to around 35 percent, with the highest rate in Argentina at around 65 percent.

However, the methodology used in these studies has been shown to produce biased estimates of the employment share at risk from automation. An OECD study by Arntz et al. (2016) points out that Frey and Osborne (2013) assumed that automation affects an entire occupation, rather than specific tasks within an occupation. Moreover, there may be economic, legal and ethical reasons why robots do not replace workers, even where this is technically feasible. Arntz et al. (2016) recalculated the share of jobs at risk for 21 OECD countries and found that their corresponding figure is only 9 percent. Furthermore, it should be noted that none of these results necessarily imply that the use of robots leads to a fall in aggregate employment. They find that other effects of non-robotic IT investment either increase employment or are broadly neutral.

Atkinson and Wu (2017, p. 22) describe Frey and Osborne's results as "just plain wrong" and add, "The only problem is that their methodology produces results that make little sense, as when they predict that technologies such as robots will eliminate the jobs of fashion models, manicurists, carpet installers, and barbers". When Atkinson and Wu use corrected data and a very "generous assumption of how tech could eliminate jobs", they find that just about 10 percent of jobs were at risk of automation, a figure very close to that of Arntz et al. (2016).

Atkinson and Wu (2017) consider the impact of technological change and innovation in the U.S. over the period from 1850 to 2015. They argue that the erroneous argument that robotization and current developments in new technology will lead to increasing technological unemployment suffers from being ahistorical. They find that, in all decades over the last 165 years, innovations directly reduced the number of jobs in particular sectors. But, inevitably, the second-order effects due to the growth of demand offset these losses. The level of occupational churn in the last 20 years, for example, is less than 50 percent that found in previous decades. In fact, Atkinson and Wu (2017) consider that the problem in the U.S. today is not too much churn, but too little, reflecting the historically low rate of productivity growth.

Indeed, Robert Solow (1987) famously wrote that "you can see the computer age everywhere but in the statistics", which is equally true today. Atkinson and Wu (2017) provide historical evidence that the view currently expressed, that the pace of technical change is accelerating to such an extent that it will lead to technological unemployment, is just not supported by the facts. As we have noted above, technology creates new jobs as *new* industries arise, just as it destroys jobs that produce goods for which demand falls. It can also destroy jobs in existing industries as the rate of automation outstrips the growth of demand for these goods. Atkinson and Wu (2017) discuss a number of historical case studies of this phenomenon. The pessimistic view of the likely increase in technological unemployment merely confuses this with "structural unemployment". While the latter can have severe consequences in the short run for jobs, especially in local communities, it is an inevitable consequence of economic growth.

A particular influential study is that of Acemoglu and Restrepo (2017, 2020) with, for example, the *Washington Post* (Guo, 2017) and the *New York Times* (Miller, 2017) drawing apocalyptic conclusions from the study for U.S. jobs.[4] The approach Acemoglu and Restrepo (2020) adopted was based on the fact that local labor markets (consisting of 722 commuting zones or CZs) in the U.S. have different exposures to industrial robots. They compare employment and wage changes in the CZs with a large share of employment in industries with a high usage of robots to those CZs with a low share of employment in high-robot-use industries. They then use these results over the period 1990-2007, together with a number of assumptions, to generate estimates of the effect of industrial robots at the national level. While these results were interpreted by the *New York Times* and other media outlets as "large", Mishel and Bivens (2017) are sceptical of this interpretation. The loss according to Acemoglu and Restrepo (2020) is around 45,000 jobs per year over the 17-year period. The effect of the increase in import penetration by China was about two and a half times as great as this. Mishel and Bivens's (2017) own estimates are of a similar magnitude. Moreover, the decline in the employment-to-population ratio "stemming from macroeconomic conditions have utterly swamped any effect of robotic displacement" (Mishel and Bivens, 2017, p. 7). Furthermore, the growth of labor productivity has declined over the periods 2002-2007 and 2007-2016, along with the growth of the capital stock and the growth of capital investment in both hardware and software (Mishel and Bivens, 2017, figure A, p. 10). They argue, for example, that greater income inequality observed over the last three decades or so has little or nothing to do with increased automation or skill-biased technical change. It is due to institutional changes, especially in worker power and the rapid increase in the income share of the top one percent (Bivens and Mishel, 2013).

2. The studies of Autor and Salomons (2017, 2018)

In two recent papers, David Autor and Anna Salomons (2017, 2018) approach the technology-employment relationship by posing a different question and using a different methodology. They try to resolve the issue by testing econometrically whether technical progress leads to lower employment growth. Using aggregate and sectoral data for the advanced economies, AS (2017) statistically tests the hypothesis that a faster rate of technical change (proxied by the growth of labor productivity) reduces employment growth. They regressed employment growth on labor productivity growth, plus some controls. Overall, they rejected the null (Luddite) hypothesis and provided what, at first sight, is compelling evidence that technical progress at the aggregate level of the economy is employment-augmenting.

AS (2018) is a more detailed study than AS (2017), in that the authors used total factor productivity (TFP) growth (and also patent counts and citations) as their measure of the rate of technical progress. Likewise, AS (2018) considered several outcome, or dependent, variables besides employment growth, namely the growth of hours worked, output, the wage bill, and the labor share. Acknowledging that productivity growth may or may not be a good proxy for the rate of technical progress, the authors also used patent data as a proxy for technical progress.

---

[4] An earlier version of this paper was published in 2017 as *NBER Working Paper*, n. 23285.

The AS (2018) test is to run regressions of the different outcome variables (employment, hours, wage bill, nominal value added, real value added, and labor share) on total factor productivity (TFP) growth (or, alternatively, patents). The authors concluded that automation displaces employment and reduces the labor share in own industries. They also find that own-industry labor share losses are not compensated by increases in other industries. Finally, in the case of employment, the losses are reversed by the indirect gains in client industries and by induced increases in aggregate demand. If correct, the AS (2018) work and conclusions have important implications for this age-old debate. Particularly important is the last point, namely that, overall, the rate of technology does not have a negative impact on employment growth.

We next provide a critical evaluation of the models estimated by AS (2017, 2018) and of the inferences made based on their results. While the authors make a commendable attempt at shedding light on the employment-technical-progress debate using contemporary data (and certainly the two papers contain useful information), in our view, there are fundamental problems with their econometric procedures and hence with the conclusions drawn. Although AS (2018) seems to contain the more comprehensive analysis, this work builds on AS (2017), and we begin by considering this paper. Moreover, as we argue below, it does not seem that AS (2018) provides a more compelling analysis.

2.1. The employment identity and the "catch 22" problem

AS's (2017) approach is to test whether or not a faster growth of productivity reduces the growth of employment. Consequently, they estimate the following basic specification:

$$\hat{L}_{ct} = \gamma_0 + \gamma_1 \hat{P}_{ct} + \left[\sum_{k=1}^{m} \gamma_{1(t-k)} \hat{P}_{c(t-k)} + \theta_c \right] + \varepsilon_{ct} \tag{1}$$

where $\hat{L}_{ct}$ is the growth rate of aggregate employment in country c at time t, $\hat{P}_{ct}$ is the growth rate of labor productivity, k is the time lag of labor productivity growth, θ_c is a set of country fixed effects, and ε is the error term. Here and in the rest of the paper, growth rates are denoted by a circumflex over the corresponding variable.

The parameter of interest is γ_1 in the static regressions (i.e., with no lagged variables included), and $[\gamma_1^* = \gamma_1 + \sum_{k=1}^{m} \gamma_{1\,t-k}]$ in the dynamic regressions. Note that this is a reduced-form regression that is not derived from a specific model. AS (2017) interprets the parameters of interest as elasticities.

The regressions are estimated using either the ordinary least squares (OLS) or the instrumental variables (IV) method, though the latter is dismissed by the authors (see below). Algebraically, the null hypothesis is $H_0: \gamma_1 < 0$ or, more generally, $H_o: \gamma_1^* < 0$ (i.e., the Luddite argument is that the impact of the rate of technical progress on employment growth is negative), with the alternative $H_1: \gamma_1^* \geq 0$. In most cases, the authors find (at the aggregate level) that γ_1 is negative, while γ^* 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. It is problematical that their estimates are the true elasticities. The reason is that it is not clear what is the rationale, or theory, behind equation (1). We elaborate on this point below. As a consequence, it can be seen 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 (2017) cannot provide an answer to the question they pose.

To facilitate the discussion, we rerun the key regressions of AS (2017). Our results are qualitatively the same.

To obtain a broad overview of 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 are immaterial, as we are using the data simply to illustrate a general point. Employment growth was 1.44 percent per annum and productivity growth was 1.00 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 *higher* rate of productivity growth than Australia, had *lower* employment growth.

Now compare these figures with South Korea's growth rates over the same period. Employment growth was 6.30 percent per annum, much *faster* than the rate of Australia or Germany, but productivity growth was 4.11 percent, also much *faster*. South Korea's statistics may seem to suggest that a faster rate of technical progress *increases* the rate of employment growth, in contradistinction to the cases of Australia or Germany. The reason is, of course, that output growth was also much faster in South 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 South Korea. Therefore, running a regression of employment growth on productivity growth and excluding output growth misses the latter's "effect." For convenience, the growth rates are reported in table 1.

Table 1 – *Growth rates* (%) *of Australia, Germany and South Korea, 1970-1980*

	Employment	Productivity	Output
Australia	1.44	1.00	2.44
Germany	0.49	2.22	2.44
South Korea	6.30	4.11	10.41

Given the neoclassical flavor of AS's work, this point (i.e., the role of output growth determining employment growth) may also be seen by considering a neoclassical aggregate production function of the form $Y_t = A_t F(K_t, L_t)$. It should be noted that there are numerous objections that have been raised to the aggregate production function, including insurmountable aggregation problems and the fact that it is nothing more than an isomorphic transformation of a national income accounting identity (Sylos Labini, 1995; Felipe and McCombie, 2013). The literature discussing the unsurmountable aggregation problems within the neoclassical framework goes back to the 1940s and so, consequently, it should be well known (e.g., Fisher, 1993). See Felipe and Fisher (2003) and Baquee and Farhi (2019) for surveys of the aggregation literature.[5]

---

[5] However, the issue is more important than what we may term the *neoclassical aggregation problems*. One only needs to consider the wide variety of production processes and different types of firms and institutions with varying degrees of *x*-efficiency, to question whether they can be adequately represented by a few aggregate variables. Does it make any economic sense to arithmetically sum the inputs and outputs of, say, Amazon, the production of aircraft at Boeing, the output of textile firms, the output of government services, and the finance sector, to give an aggregate production function with the usual neoclassical properties? Furthermore, how are we to view the aggregate elasticity of substitution, which Fisher et al. (1977) persuasively argued in their simulation study is "*non-existent*"?

We stress that the only reason we use the Cobb-Douglas example is that it is surprising that any consideration of the growth of employment and productivity within the neoclassical framework, could ignore the growth of capital. One would be very surprised if any neoclassical economist estimated, say, a Cobb-Doulas, CES or translog production function, omitting the capital stock. Hence, we merely use this to illustrate the problems with AS's argument within a neoclassical production function. AS (2018) use the growth of total factor productivity that, as a measure of the rate of technical progress, depends on the existence of an aggregate production function (Solow, 1957). We will return to this point below (section 3.1) and show that, in fact, one does not need a production function.

For expositional ease, let us further assume 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 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 the Cobb-Douglas in growth rates and rearranging the terms gives us:

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

where a circumflex on L, P, and K again denotes a rate of growth.

Using the Kaldorian stylized fact that the growth rates of output and capital are roughly equal gives us:

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

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 seen in table 1.

From equation (3), as $\hat{L}_t \equiv \hat{Y}_t - \hat{P}_t$ (i.e., employment growth equals the growth of output minus the growth of labor productivity), it can be seen that in this framework the rate of technical change (λ) equals $(1-\alpha)\hat{P}_t$.

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

$$\hat{L}_t = \gamma_0 + \gamma_1 \hat{P}_t + u_t \tag{4}$$

Table 2 – *Employment growth and labor productivity growth*: *equation* (*4*)

	Coefficient Labor productivity growth (γ_1)	R^2	"Bias"
No fixed effects	-0.014	0.001	0.986
Fixed effects	-0.038**	0.145	0.962

Notes: estimates using data from *World Development Indicators* and *Penn World Tables* version 9.1. The estimates are the 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 statistically significant at the 5 percent level.

Estimation results using pooled data (without and with country fixed effects) are shown in the first column of table 2. We use the same sample of 19 industrialized countries as in AS

(2017). These results are qualitatively similar to those of AS (2017). Taken at face value, the results in table 2 indicate that there is a small *negative* relationship between employment growth and labor productivity growth (i.e., the rate of technical progress).

As we argued above, most models, including the neoclassical, would include the growth of output in the regression as a proxy of the growth of demand. As we noted in our brief literature review, the question is often posed as to the extent to which a lower rate of employment growth due to technical change is offset by the increased growth of demand. What would happen, however, if we add output growth to equation (4)? This now becomes:

$$\hat{L}_t = \gamma_0 + \gamma_1 \hat{P}_t + \gamma_2 \hat{Y}_t + u_t \tag{5}$$

where $\hat{P}_t$ is again the growth rate of labor productivity, $\hat{Y}_t$ is the growth rate of output, and u_t is the error term. The problem with this equation is that it is just the tautological definition of employment growth, where the level of employment is given by:

$$L_t \equiv \frac{L_t}{Y_t} Y_t \equiv \frac{1}{P_t} Y_t \tag{6}$$

Equation (6) expressed in growth rates is:

$$\hat{L}_t \equiv -\hat{P}_t + \hat{Y}_t \tag{7}$$

The argument about the need to include output growth in the regression could, misleadingly, give the impression that estimation of equation (5) has a behavioral interpretation. This is that a greater rate of technical progress *causes* the growth of employment to fall, and a faster growth of output (demand) *causes* it to increase. The problem is that by virtue of equation (7), regression (5) must *always* yield coefficients $\gamma_1 = -1$, $\gamma_2 = 1$ and a perfect statistical fit (since there is no actual error), because it is a tautology, or definitionally true.

No matter what method is used (such as OLS, IV) to estimate regression (5) and what dataset is used (i.e., pooled data, without or with, fixed effects or individual-country data), the results must be the same in all cases. Note that the coefficients of the country dummies in a regression including fixed-effects are equal to zero, because they are irrelevant variables.

We note that while identities have a role in the construction of economic models that can then be empirically tested, there is no point in statistically estimating an identity. This applies equally to any mathematical transformation of the identity (e.g., growth rates). It is important to make it clear that a relationship between two variables in an identity can provide a testable hypothesis, but in the case of Autor and Salomons, the implicit full model is effectively an identity.

It follows that equation (4) can be interpreted as equation (5) with the growth rate of GDP $(\hat{Y}_t)$ "omitted." Consequently, equation (4) may be referred to as a *quasi-accounting identity*. The implications of this are, first, that even in case it was argued that the estimation of (4) yields an elasticity, it is problematical as to whether or not this is true. It is just the result of the fact that employment and productivity growth are related through the identity, which ensures the negative relationship. Secondly, while there could seem to be no restrictions on the value that γ_1 in regression (4) can take, the reality is that we know exactly the value that this coefficient would take in regression (5), namely -1. Therefore, equation (4), in fact, suffers from the standard econometric problem of omitted-variable bias. There is, however, an important difference. In this case, we know exactly what the omitted variable is: output growth. Hence,

this is not a statistical problem that calls for the IV (or any other) estimation method. The expected value of γ_1 in equation (4) can be calculated as:

$$E(\gamma_1) = \gamma_1 + \gamma_2 \left[\frac{cov(\hat{Y}_t, \hat{P}_t)}{var(\hat{P}_t)} \right] \tag{8}$$

where $\gamma_1 = -1$, $\gamma_2 = 1$, and the "bias" is $\frac{cov(\hat{Y}_t, \hat{P}_t)}{var(\hat{P}_t)}$. The value of the latter is shown in the last column of table 2.

We have stressed above the terms "omitted" and "bias." This merits further explanation. First, it is not correct that *any* regression can be transformed into an identity or tautology by adding (as a regressor) the difference between the left- and the right-hand-side variables. It would certainly be incorrect to argue that in, for example, the standard export demand function, where the log of exports (lnX) typically depends on relative prices ($lnRELP$) and foreign income (lnY_w), the two coefficients of the right-hand-side variables suffer from omitted-variable bias because the regression does not include the variable lnZ, where $lnZ = (lnX - lnRELP - lnY_w)$. This variable is economically meaningless. In the case under discussion here, however, the omitted variable is clearly output growth.

Secondly, AS (2017) indicates that the regressions yield conditional correlations and interprets 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 including output growth in equation (4) turns the regression into the identity (or a tautology) given by equation (5). This poses a "catch-22" problem in that the better the statistical fit, the closer the results approximate an identity. It also means that γ_1 is a biased estimate of the true coefficient of the rate of technical progress, i.e., labor productivity growth. Therefore, equation (5) tells us that any additional variable in regression (4) increases the goodness of fit and its coefficient tends to 1 if it is correlated with output growth. A corollary is that the coefficient of labor productivity growth tends to -1. The higher the correlation between output growth and the added variable, the closer this regression approximates identity (5).

2.2. Additional variables: what is their role?

AS (2017) tried to improve the explanatory power of their regressions. In particular, they were concerned with the sign of labor productivity growth in equation (4) (i.e., is it truly negative?). To do this, they used lagged values of labor productivity growth, and population growth, as additional explanatory variables in equation (4). They also used the growth rate of the employment-to-population ratio as their dependent variable. We will show 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.

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 can be regarded, in fact, as 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 these 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 3. 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 would reproduce expression (5).[6]

Table 3 – *Regression of employment growth on labor productivity growth* (*current and lagged values*): *equation* (1)

	Coefficient				R^2
	Labor productivity growth	**Labor productivity growth, lag 1**	**Labor productivity growth, lag 2**	**Labor productivity growth, lag 3**	
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: estimates are based on data from *World Development Indicators* and *Penn World Tables* 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.

AS (2017) also added population growth ($\hat{N}_t$) to equation (1) and estimated:

$$\hat{L}_t = \gamma_0 + \gamma_1 \hat{P}_t + \gamma_3 \hat{N}_t + u_t \tag{9}$$

Comparing equation (9) with the identity (5) indicates that the former will yield a close statistical result 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:

$$L_t \equiv \frac{L_t}{Y_t} \cdot \frac{Y_t}{N_t} \cdot N_t \tag{10}$$

where N_t denotes population. In growth rates, equation (10) is:

$$\hat{L}_t \equiv -\hat{P}_t + \hat{P}_t^* + \hat{N}_t \tag{11}$$

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

---

[6] Naturally, if the added variable is not perfectly correlated with output growth, it will not have a coefficient of one. This does not affect the essence of the argument.

$$\hat{L}_t = \gamma_0 + \gamma_1 \hat{P}_t + \gamma_3 \hat{N}_t + \gamma_4 \hat{P}_t^* + u_t \tag{12}$$

would yield $\gamma_1 = -1$, $\gamma_3 = 1$, $\gamma_4 = 1$. It should be emphasized that these coefficients (unity) and signs are predetermined by construction (i.e., from the identity).

However, AS (2017) estimated equation (9). In this case, the omitted variable is the growth rate of income per capita ($\hat{P}_t^*$). The effect is, again, to introduce a bias in the coefficients of the included variables. The expected value of γ_1 is:

$$E(\gamma_1) = \gamma_1 + \gamma_4 \left[\frac{cov(\hat{P}_t, \hat{P}_t^*) var(\hat{N}_t) - cov(\hat{N}_t, \hat{P}_t^*) cov(\hat{N}_t, \hat{P}_t)}{var(\hat{N}_t) var(\hat{P}_t) - [cov(\hat{N}_t, \hat{P}_t)]^2} \right] \tag{13}$$

with $\gamma_1 = -1$ and $\gamma_4 = 1$. The estimation results of equation (9) and the bias in equation (13) are reported in table 4. AS (2017, table 3a, column 6) found a coefficient of population growth of 1.013, which the authors consider "noteworthy" (AS 2017, p. 58). Their interpretation is that employment rises equiproportionally with population. In our case, we obtain a coefficient of 1.145 (with no fixed effects) and 0.794 (with fixed effects), and neither is statistically different from one. Clearly, the coefficient of unity is the result of the nature of the exercise, that is, results are driven by identity (11). The results are not perfect because equation (9) omits income per capita growth as a regressor. Nevertheless, the coefficient of population growth is close to what the identity predicts. It should be noted that the growth of labor productivity (the growth of output per worker) very closely correlates with the growth of income per capita. Consequently, omitting the latter from equation (11) will cause the coefficient of labor productivity to be subject to a significant downward bias, which is precisely what happens (see table 4).

Table 4 – *Employment growth, productivity growth, and population growth: equation* (9)

	Coefficient		R²	"Bias" (γ_1)
	Labor productivity growth (γ_1)	Population growth (γ_3)		
No fixed effects	-0.045**	1.145***	0.140	0.955
Fixed effects	-0.054***	0.794***	0.184	0.946

Notes: estimates use data from *World Development Indicators* and *Penn World Tables* 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 reported here, 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).

2.3. Using the growth rate of the employment-to-population ratio as the dependent variable

To corroborate their results, the authors of AS (2017) substituted the growth rate of employment on the left-hand side by the growth rate of the employment-to-population ratio $\left(\frac{L_t}{N_t}\right)$. Once again, the tautological nature of the exercise is clear. One can express the ratio of employment to population definitionally as follows:

$$E_t \equiv \frac{L_t}{N_t} \equiv \frac{L_t}{Y_t} \cdot \frac{Y_t}{N_t} \tag{14}$$

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

In growth rates, equation (14) is:

$$\hat{E}_t \equiv -\hat{P}_t + \hat{P}_t^* \tag{15}$$

The estimation of the regression:

$$\hat{E}_t = \gamma_0 + \gamma_5 \hat{P}_t + \gamma_6 \hat{P}_t^* + u_t \tag{16}$$

would yield the estimates of $\gamma_5 = -1$ and $\gamma_6 = 1$.

The estimated regression by AS (2017) in this case is:

$$\hat{E}_t = \gamma_0 + \gamma_5 \, \hat{P}_t + u_t \tag{17}$$

and so it appears that AS (2017) "omitted" the growth rate of income per capita $(\hat{P}_t^*)$, 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 5. Again, the lagged values of labor productivity growth proxy the growth rate of per capita income (results available upon request).

Table 5 – *Employment-to-population growth and productivity growth: equation* (17)

| | Coefficient | | |
	Productivity growth (γ_5)	R^2	"Bias"
No fixed effects	-0.041**	0.005	0.959
Fixed effects	-0.058	0.054	0.942

Notes: estimates use data from *World Development Indicators* and *Penn World Tables* version 9.1.
** denotes that the coefficient is significant at the 5 percent level.

2.4. 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:

$$\hat{L}_{ict} = \gamma_0 + \gamma_1 \hat{P}_{ict} [+\delta_t + \theta_c + \tau_i] + \varepsilon_{ict} \tag{18}$$

where i denotes the industry, c the country, and t once again is a time variable; and δ_t, θ_c, and τ_i are a set of year, country, and industry fixed effects, respectively.

The problem is that this regression suffers from the same concerns discussed above. Theoretically, output growth needs to be included, but this will again result in estimating an identity. The coefficient of labor productivity growth takes a negative sign, but this is implicit in the identity (the results of estimating 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 above.

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

$$\hat{L}_{ict} = \gamma_0 + \gamma_1 \hat{P}_{ict} + \sum_{k=0}^{m} \gamma_{7(t-k)} \tilde{P}_{c(t-k),j\neq i} \left[+\delta_t + \theta_c + \tau_i \right] + \varepsilon_{ict} \qquad (19)$$

where $\hat{L}_{ict}$ is the growth rate of employment in own-industry i, country c, at time t; $\hat{P}_{ict}$ is the growth rate of labor productivity in own-industry; $\tilde{P}_{c(t-k),j\neq i}$ 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, θ_c, and τ_i are 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 (and positive in the aggregate). AS (2017) argues that this is due to the effect of spillovers. An alternative, and more plausible, view is that this is because the growth rates of other sectors' labor productivity growth 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): The use of total factor productivity (TFP), and its problems, as an explanatory variable

As noted above, AS (2018) offers a more detailed analysis of the relationship between technical progress and employment growth, although this does not avoid the criticisms outlined above. In this paper, the authors focus on whether or not technological progress is employment-displacing and the direct and indirect factors behind this. Unlike AS (2017), here they used the neoclassical concept of total factor productivity growth, instead of labor productivity growth, as a measure of the rate of technical progress (with a number of caveats acknowledged as to whether this is the correct measure or indicator). They also used several outcome, or dependent, variables besides employment growth. These are: the growth of hours worked, the growth of the wage bill, the growth of nominal and real output, and the shares of labor. Finally, their econometric analysis is more sophisticated than that of AS (2017) in two respects. First, they use other countries' TFP growth rates in the same industry in lieu of own-country-industry TFP growth; and, secondly, a time lag is introduced to account for the effects of TFP growth impacts on the outcome variables. We show below that these two refinements do not solve the problems we highlight.

The question in this case is that, as we elaborate below, TFP growth is not an 'independent' or theory-neutral 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 economic theory and the assumptions underlying that theory. TFP growth is a theory-dependent concept, unlike, say, the growth of employment or productivity.[7]

---

[7] Productivity growth is, of course, calculated as the difference between the growth of output and the growth of employment, but this is the result of a definition, not a theory.

Focusing on the authors' initial estimates, AS (2018, table 5) finds: 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 growth, which is offset by the indirect effects arising from the input-output linkages, as well as from the overall positive impact of increasing TFP on aggregate value-added and final demand.

We find it again somewhat surprising that AS (2018) does not refer explicitly to a neoclassical aggregate production function in its analysis, although this is implicit in the use of the primal measure of TFP growth. As in AS (2017), the entire empirical analysis is a series of reduced-form equations. Hence, the results are conditional correlations at best. Also, the measure of TFP growth (taken from the KLEMS database; see O'Mahony and Timmer, 2009) seems to assume Hicks-neutral technical progress (AS 2018, footnote 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.[8] Finally, if AS (2018) had started from an explicit production function, then it would have had to account for the effects of the growth of capital and output, the other two variables in the production function.

The explicit consideration of a production function takes us to a more fundamental problem with AS's (2018) analysis, namely the use of TFP growth as a measure of technical progress. As we shall see, the problem with the use of TFP growth is that it is, in fact, not an *opaque* measure of technical progress (as AS, 2018, refers to it). This is because, even though TFP growth is most often calculated as a residual, its interpretation, nevertheless, is unambiguous. The problem is that it cannot be considered as a measure of exogenous or endogenous technical progress. This has been known for a long time, but it has been ignored by the literature (Felipe and McCombie, 2013, 2020).[9] What TFP growth actually measures and captures is key for understanding the problems with the AS (2018) analysis. The reason for focusing on TFP growth is that we show it is not an independent measure of technical progress. Hence, our point is that the many regressions estimated do not capture what the authors think they do. AS (2018) raises questions about the relevance of TFP growth, as do the two discussants of the paper, Haltiwanger (2018) (much of his discussion is about TFP) and Rogerson (2018). However, their criticisms are very different from those in this paper. Given this, we think it is worth explaining our arguments in detail.

---

[8] Nelson (1973) noted 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).

[9] It is worth noting that the two discussants of AS (2018) – Haltiwanger (2018) and Rogerson (2018) – questioned at length the soundness of the AS (2018) exercise and concluded that it 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 the AS (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 U.S. industries. He referred to issues such as mismeasurement error and misallocation problems as possible explanations.

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, without loss of generality, that technical progress is Hicks-neutral. Totally differentiating the production function with respect to time, the growth rate of output is given by:

$$\hat{Y}_t = \widehat{TFP}_t + \delta_t \hat{L}_t + \beta_t \hat{K}_t \tag{20}$$

where, as before, a circumflex over the variables denotes the growth rate; δ_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., λ or 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 to the rate of growth of the factor inputs. Growth accounting derives an estimate of $\widehat{TFP}_t$ residually as $\widehat{TFP}_t \equiv \hat{Y}_t - \delta_t \hat{L}_t - \beta_t \hat{K}_t$, given values for the right-hand-side variables.

The problem, however, is that there are very few reliable estimates of the output elasticities from statistical 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 perfectly competitive 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, and equal their marginal products). Under these circumstances, the factor elasticities equal the shares of labor and capital in total output – namely, $\delta_t = a_t = (W_t/Y_t)$ 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.

Output growth can be written as:

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

And, consequently, the TFP growth rate is calculated as:

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

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 some sort of a mystery, a residual or *measure of our ignorance*, which is how TFP growth is often referred to. However, even though this is noted, it is, nevertheless, commonly interpreted as the rate of technical progress (Solow, 1957). As the derivation above shows, TFP growth is a theory-dependent measure.

From the National Income and Product Accounts (NIPA) we have the accounting identity for GDP:

$$Y_t \equiv W_t + S_t \tag{23}$$

where Y is real (i.e., deflated) GDP, or value-added (e.g., dollars measured in base-year prices), W is the real total wage bill (in dollars of a base year), and S is the operating surplus (in dollars of a base year). It is important to emphasize that identity (23) (note the symbol $\equiv$) 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 necessary 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, either production or 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 (in dollars of a base year per worker), L is total employment (number of workers), r is the *ex post* average profit rate (in dollars of operating surplus per dollar of capital stock, a pure number), and K is the stock of capital (in practice, dollars of a base year, not a physical quantity). [10] Note that, by construction, $W_t = w_t L_t$ is the wage bill and $S_t = r_t K_t$ is total profits (the gross operating surplus).[11]

Now one can simply express the accounting identity (24) in growth rates as:

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

or

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

Rearranging the terms yields:

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

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). It will be noted that equations (26) and (27) are identical to equations (21) and (22) and, consequently, $\lambda_t \equiv \lambda_t^D \equiv \widehat{TFP}_t$. 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 aggregate production and cost functions and their associated concepts, such as TFP (Felipe and McCombie, 2013, 2020).

The neoclassical tradition acknowledges identity (24) but argues that the aggregate production function, together with the usual neoclassical assumptions and Euler's theorem, provides a *theory* of the income side of the NIPA. This line of reasoning is incorrect.[12] Identity

---

[10] 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 user 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.

[11] While it is self-evident that the wage bill (W_t) is split into the product of a price (w_t is measured in, say, dollars [\$] per 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 pure numbers 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 $\left(\frac{\partial Y}{\partial K}\right) \equiv r_t$.

[12] This seems to be the view of, for example, Jorgenson and Griliches (1967, pp. 252-253). 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

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

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

(i)   Identity (27) makes it clear that the residually calculated TFP growth, $\widehat{TFP}_t \equiv \hat{Y}_t - a_t \hat{L}_t - (1-a_t)\hat{K}_t \equiv \lambda_t$, is numerically equivalent to $\lambda_t^D \equiv a_t \hat{w}_t + (1-a_t)\hat{r}_t$. This means that TFP growth is not a "measure of our ignorance." We know precisely what it is. It is a weighted average of the growth rates of the wage and profit rates. This is the result of how the accounting identity (23) was split into identity (24), namely $W_t = w_t L_t$ and $S_t = r_t K_t$ (which is unrelated to an aggregate production function). This self-evident, yet important, point seems to have been missed by those who regard $\widehat{TFP}_t$ as derived from a production function, because they do appreciate its direct dependence on the accounting identity. It is important to point out the resemblance between λ_t^D and the dual of TFP growth, which in neoclassical theory is 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 omit here.[13]

(ii) The identity given by equation (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 $\widehat{TFP}_t$ 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 $\lambda_t \equiv \hat{Y}_t - a_t \hat{L}_t - (1-a_t)\hat{K}_t \equiv \lambda_t^D \equiv a_t \hat{w}_t + (1-a_t)\hat{r}_t$ as 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.[14] Arguing that neoclassical production and cost theories explain what $\lambda_t \equiv \lambda_t^D \equiv \widehat{TFP}_t$ measures 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 non-event (Felipe and Fisher, 2003). Nadiri (1970, p. 1144), in a survey on the topic, already realized that the aggregation problem matters because "without proper aggregation we cannot interpret the properties of an

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, p. 4). Solow's (1957) contribution was to provide the economic structure that the approach lacked.

[13] 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 (2020). Empirically, the primal (from the production function) and the dual (from the cost function) tend to be very close and are statistically not different.

[14] It could be argued that the growth of the wage 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, this provides the link with the production function (and similarly the profit rate and capital productivity), and this is what λ_t^D captures. The problem with this argument is that the relationship between the growth of the wage 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: $\hat{w}_t \equiv \hat{a}_t + \hat{P}_t$ (where $P \equiv \frac{Y}{L}$). This relationship will always be true. For short periods of time, $\hat{w}_t \simeq \hat{P}_t$, as factor shares vary little and slowly.

aggregate production function, which rules the behavior of total factor productivity."[15] The Cambridge Capital Theory Controversies of the 1960s and early 1970s, which centered around the theoretical problems in the measurement of capital (Cohen and Harcourt, 2003), have also been described as essentially an aggregation problem. However, Harcourt (1976) argues to the contrary, that there is more to the controversies than that.

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

(iv) Labor productivity growth and TFP growth are directly related through the accounting identity, given by equation (26), since the former can be written as $\hat{P}_t \equiv \lambda_t^D + (1 - a_t)(\hat{K}_t - \hat{L}_t)$. This is true always by construction. This means that the formulations (regressions) in AS (2017) and AS (2018) are intrinsically related.

Given that the AS (2018) measure of technical progress is just $\lambda_t \equiv \lambda_t^D \equiv a_t \hat{w}_t + (1 - a_t)\hat{r}_t$, a weighted average of the growth rates of the wage rate and profit rate, a question arises concerning 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 $\lambda_t \equiv \lambda_t^D$, given the identity given by equation (27), which links all these variables. Naturally, the fact that AS (2018) uses 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.[16] This is because these procedures do not solve any putative endogeneity, or other econometric, problem. The identity argument also applies to the AS (2018) cross-sectoral linkage analysis, as it is self-evident that the identity holds for each cross-section.

This analysis also helps understand the well-documented finding in the literature of very low and negative TFP growth rates in many U.S. industries (Haltiwanger, 2018, pp. 66-68). Given our arguments and understanding of what TFP truly captures, the low TFP growth rates have been the result of: (*i*) very low wage growth because a great deal of employment has been generated in non-tradable services, activities which, in general, experience low wage increases; and (*ii*) the well-documented decline in the U.S. labor share (Dao et al., 2017; Stockhammer, 2017). This means that $a_t \hat{w}_t$ was approximately zero, or even negative, in some industries and was not compensated for by an increase in $(1 - a_t)\hat{r}_t$.[17] Very importantly, this result (finding) follows directly from the accounting identity, and, at best, says something only about distributional changes.

---

[15] It is worth quoting Nadiri 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" (Nadiri, 1970, pp. 1145-1146).

[16] After several exchanges, our disagreements with David Autor and Anna Salomons remain on two points: (i) the interpretation of TFP growth, and how it is derived; and (ii) their belief that their leave-out-mean approach and use of lags solve the problem. We dispute this. We acknowledge that the use of patents is a different identification approach, but this is not trouble-free either and it is a minor part of their work.

[17] While it is true that the capital share has increased (the mirror image of the decline in the labor share), the profit rate has not increased. Often the variable is about flat or shows decline, with the consequence that its growth rate is either zero or even negative.

3.1. An example

Apart from the conceptual problem discussed above, it should now be clear that the AS (2018) regressions with TFP growth as regressor are also problematic. The focus of attention is on equations (25), (26), and (27), namely the accounting identity expressed in growth rates. A series was constructed for output growth, employment growth, capital growth, and TFP growth so that they satisfy the identity. The purpose of the regressions in table 6 is to show that one can reinterpret the AS (2018) regressions of employment growth on TFP growth in terms of the accounting identity. We do not report the regressions for all outcome variables, and only show the one for employment growth. This regression is run separately for five countries, Austria, Belgium, Italy, Netherlands, and Sweden.

We start with the regression of output growth on $\lambda_t \equiv \lambda_t^D$, together with the growth rates of labor and capital (equation 26). $\lambda_t \equiv \lambda_t^D$ was constructed from the data and the coefficients of labor and capital growth were estimated in unrestricted form. The regressions for the five countries are shown in the first four columns of table 6. It is known from equation (26) that the coefficients of the growth rates of labor and capital will be positive and will have to be close to the corresponding factor shares (and consequently add up to unity) if these do not show great variation. The coefficient of λ_t^D will be positive and should be close to unity. Naturally, since the regression assumes that the coefficients of labor and capital growth are constant, there is an "error" to the extent these two coefficients are not exactly constant. As their variation is very small (see footnote to table 6), the statistical fits and t-values are very high (as it is a quasi-accounting identity). Overall, results indicate that, in the five countries, factor shares are sufficiently constant so that the regressions give almost a perfect statistical fit. 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 6 – *Employment growth and TFP growth regressions* (*I*)

Regressand	$\hat{Y}_t$: 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: all coefficients in regressions (26) and (28) are statistically significant at the 1 percent level, with extremely high t-values. Coefficients with ** in regression (29) are statistically significant at the 5 percent level. NS stands for not statistically 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.

Secondly, and as argued above, it is difficult to understand the omission of the growth rates of output and capital in the AS (2018) employment growth regressions, to the extent that, as it is essentially a neoclassical analysis, an aggregate production function *should* underlie these

regressions. The problem is that adding these two variables to the regression leads, again, to the identity given by equation (26), now with employment growth on the left-hand side, that is:

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

AS (2018) again faces the "catch-22" problem. The estimation results of regression (28) are reported in the middle four columns of table 6. It is worth emphasizing that the coefficients are, both in size and sign, as predicted by equation (28), and is $-\left(\frac{1}{a_t}\right)$ in the case of λ_t^D. These are the result of the accounting identity and not of estimating any behavioral relationship. This regression has no behavioral implications at all.

We argued in section 2.1 that the neoclassical example with the Cobb-Douglas production function was for expositional ease, introduced to show that output growth is a determinant of employment growth. We also mentioned that we could show that we do not need a production function. Indeed, equation (28) is the general form of equation (2) above. There, it was written with constant factor elasticities (while equation (28) is written with the factor shares with the time subscript, and without making any neoclassical assumptions) and with a constant rate of weighted factor prices (λ, the neoclassical measure of productivity growth). This is because it is derived from a Cobb-Douglas 'production function' with a constant rate of 'technical progress' (λ). As the derivation from the identity shows, equation (28) is simply an identity; there is no underlying aggregate production function. What does the identity with the growth rate of employment on the left-hand side tell us? 'Nothing' beyond the self-evident definition. Can it be used to *test*? Clearly the answer to this is 'no'.

Moreover, *if output and capital happen to grow at the same rate* (i.e., $\hat{Y}_t = \hat{K}_t$), then equation (28) reduces to $\hat{L}_t \equiv \hat{Y}_t - [\frac{a_t\hat{w}_t + (1-a_t)\hat{r}_t}{a_t}]$, which will also be an accounting identity under these circumstances. Moreover, *if factor shares happen to be constant*, and this does not imply a Cobb-Douglas function (Fisher 1971), the expression will reduce to $\hat{L}_t \equiv \hat{Y}_t - [\hat{w}_t + \frac{(1-a)}{a}\hat{r}_t]$. We emphasize that it makes no difference whether one refers to the more general expression for $\hat{L}_t$, or to the one where $\hat{Y}_t = \hat{K}_t$ happens to hold, and additionally factor shares are constant. They are accounting identities derived with no reference to a Cobb-Douglas production function.[18]

---

[18] Our arguments do not depend either on the assumption of Hicks-neutral technical progress (although it is true that this is how we specified the Cobb-Douglas production function). The reason is that our arguments and criticisms are based on an accounting identity. Because of this, our arguments hold for any mathematical specification that resembles a 'production function', including one of the form:

$$Y_t = F(A_L L_t, A_K K_t)$$

where A_L and A_K are interpreted to represent factor-augmenting technical change. In growth rates this becomes (imposing the standard assumption in growth accounting, that elasticities equal the factor shares):

$$\hat{Y}_t = a_t\hat{\lambda}_L + (1-a_t)\hat{\lambda}_K + a_t\hat{L}_t + (1-a_t)\hat{K}_t$$

where $\hat{\lambda}_L$ and $\hat{\lambda}_K$ are the growth rates of factor-augmenting technical change (which might or might not be constant – we assume they are constant here to simplify the exposition). It should be self-evident that what is calculated as total factor productivity growth is the weighted average of the growth rates of labor and capital-augmenting technical change, that is,

$$TFP_t = \hat{Y}_t - a_t\hat{L}_t - (1-a_t)\hat{K}_t = a_t\hat{\lambda}_L + (1-a_t)\hat{\lambda}_K$$

Now recall the accounting identity is $\hat{Y}_t \equiv a_t\hat{w}_t + (1-a_t)\hat{r}_t + a_t\hat{L}_t + (1-a_t)\hat{K}_t$, or equation (25) above, and that it always holds. This implies that:

Thirdly, the growth rates of output and capital in regression (28) are omitted and we estimate the same regression that AS (2018) estimated. This is given by equation (29) below:

$$\hat{L}_t = c + \rho \lambda_t^D + u_t \tag{29}$$

Results are shown in the right-hand-side two columns of table 6. It may be seen that the coefficient of λ_t^D changes, both in magnitude and sign, compared with that of equation (28). This is straightforwardly the result of omitting the growth rates of output and capital, which causes a significant bias in the estimate of the coefficient γ. Given that we have argued that λ_t^D is effectively a measure of distributional changes, and the interpretation of equation (29) as equation (28) with two variables omitted, it is not clear that the leave-out-mean approach of AS (2018) yields an estimate of ρ that can be interpreted with any confidence to be the impact of technical progress on employment growth.

Finally, table 7 shows the regressions of employment growth on two of the three regressors in identity (28): on λ_t^D and $\hat{Y}_t$, the results of which are reported on the left-hand side of the table; and on λ_t^D and $\hat{K}_t$, reported on the right-hand side of the table. The results of the first set (i.e., with output growth as the added regressor) are much better. They are not far, in fact, from the results in table 6 for the full equation (28), in terms of the magnitude, sign, and statistical significance of the coefficients. This means that omitting the capital stock's growth rate when output growth is included together with λ_t^D (left-hand side of the table) causes a small bias. The opposite happens when output growth is the omitted variable and instead the growth rate of the capital stock is added as a regressor (right-hand side of the table). The correlation between λ_t^D and $\hat{Y}_t$ is higher than that between $\hat{K}_t$ and these two variables.

Table 7 – *Employment growth and TFP growth regressions* (II)

Regressand	$\hat{L}_t$			$\hat{L}_t$		
	λ_t^D	$\hat{Y}_t$	R^2	λ_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: all coefficients in the first regression are statistically significant at the 1 percent level. Coefficients in the second regression marked with ** are significant at the 5 percent level; those marked with * are significant at the 10 percent level; and NS stands for not statistically significant.

$$TFP_t \equiv a_t \hat{\lambda}_L + (1 - a_t)\hat{\lambda}_K \equiv a_t \hat{w}_t + (1 - a_t)\hat{r}_t \equiv FR_t$$

that is, the weighted average of the growth rates of labor and capital-augmenting technical change must be identical to the weighted average of the growth rates of the wage and profit rate given by the identity. This is correct, although the precise interpretation of the results is open to question for the same reasons advanced earlier. We do not consider, *pace* Autor and Salomons, that the changing distribution of factor shares into payments to labor and capital informs the question of whether technological change is factor-augmenting or labor task-displacing can be statistically tested (i.e., the possibility of the data rejecting a null hypothesis).

4. Conclusions

The last decade has brought to the forefront the discussion of the role of technical progress on employment growth, in the context of the technologies being associated with the Fourth Industrial Revolution. The specific questions asked by researchers and the statistical methods used are different, but overall, there is a sense that these new technologies may have a negative impact on employment.

AS (2017, 2018), however, show that once one takes into account both the direct and indirect effects, technical progress is not detrimental to employment growth at the economy-wide level. The attempt to shed light on the old question of the impact of innovation and productivity growth on employment is important. The assessment in this paper of AS (2017; 2018) studies, however, leads to the conclusion that their methods are problematical and ultimately do not answer their research questions in a satisfactory way. The equations of AS (2017) *should* include the growth rate of output as a determinant of employment growth. However, we have shown that adding this variable would transform the equations into tautologies. It is a "catch-22" problem that has no solution within the framework used.

AS (2018) 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, and not necessarily of technical progress. Hence, the regressions with TFP growth as the explanatory variable miss the point. The authors' analysis with patents as a proxy for technical progress is perhaps more promising, although it is not clear whether patents have a large effect on productivity. See, in particular, Boldrin and Levine (2013), who question the use of patents. 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.

These problems appear as a result of the fact that the proxy for technical progress is productivity (labor or TFP), which is not an *independent* measure.

Summing up, the question Autor and Salomons intend to answer cannot be addressed with the regressions they ran in the two papers. It transpires that the old, and important, question about the impact of technical progress on employment growth cannot be answered by this approach.

References

Acemoglu D. and Restrepo P. (2017), "Robots and jobs: Evidence from U.S. labor markets", *NBER Working Paper*, n. 23285, Cambridge (MA): National Bureau of Economic Research.

Acemoglu D. and Restrepo P. (2020), "Robots and jobs: Evidence from U.S. labor markets", *Journal of Political Economy*, 128 (6), pp. 2188-2244.

Arntz M., Gregory T. and Zierahn U. (2016), "The risk of automation for jobs in OECD countries: A comparative analysis", *OECD Social, Employment and Migration Working Papers*, n. 189, Paris: OECD.

Atkinson R.D. and Wu J.J. (2017), "False alarmism: Technological disruption and the U.S. labor market, 1850–2015", *Information Technology & Innovation Foundation @Work Series*, May.

Autor D. (2016), "Why are there still so many jobs? The history and future of workplace automation", *Journal of Economic Perspectives*, 29 (3), pp. 3-30.

Autor D. and Salomons A. (2017), "Robocalypse now—Does productivity growth threaten employment?", ECB Forum on Central Banking, *Investment and Growth in Advanced Economies*, Sintra (Portugal), June 26-28.

Autor D. and Salomons A. (2018), "Is automation labor share-displacing? Productivity growth, employment, and the labor share", *Brookings Papers on Economic Activity*, 49 (1), pp. 1-63.

Baquee D., Rezza D. and Farhi E. (2019). "JEEA-FBBVA Lecture 2018: The Microeconomic Foundations of Aggregate Production Functions", *Journal of the European Economic Association*, 17 (5), pp. 1337–1392.

Bivens J. and Mishel L. (2013), "The pay of corporate executives and financial professionals as evidence of rents in top 1 percent incomes", *Journal of Economic Perspectives*, 27 (3), pp. 57-78.

Boldrin M. and Levine D.K. (2013), "The case against patents", *Journal of Economic Perspectives*, 27 (1), pp. 3-22.

Bowles S. and Boyer R. (1995), "Wages, aggregate demand, and employment in an open economy: An empirical investigation", in Epstein G.A., Gintis H.M. (eds.), *Macroeconomic policy after the conservative era: Studies in investment, saving and finance*, pp. 143-171, Cambridge (UK): Cambridge University Press.

Brynjolfsson E. and McAfee A. (2014), *The second machine age*, New York, London: W.W. Norton & Company.

Cohen A.J. and Harcourt G.C. (2003), "Retrospectives: Whatever happened to the Cambridge capital theory controversies?", *Journal of Economic Perspectives*, 17 (1), pp. 199-214.

Dao M.C., Das M., Koczan Z. and Lian W. (2017), "Understanding the downward trend in labor income shares", *World Economic Outlook April 2017*, Washington (DC): International Monetary Fund.

Felipe J. and Fisher F.M. (2003), "Aggregation in production functions: What applied economists should know", *Metroeconomica,* 54 (2-3), pp. 208-262.

Felipe J. and McCombie J.S.L. (2001), "Biased technical change, growth accounting, and the conundrum of the East Asian miracle", *Journal of Comparative Economics*, 29 (3), pp. 542-565.

Felipe J. and McCombie J.S.L. (2013), *The aggregate production function and the measurement of technical change: "Not even wrong"*, Cheltenham (UK) and Northampton (MA): Edward Elgar.

Felipe J. and McCombie J.S.L. (2020), "The illusions of calculating total factor productivity and testing growth models: From Cobb-Douglas to Solow and to Romer", *Journal of Post Keynesian Economics*, 43 (3), pp. 470-513.

Ferguson C.E. (1968), "Neoclassical theory of technical progress and relative factor shares", *Southern Economic Journal*, 34 (4), pp. 490-504.

Fisher F.M. (1971), "Aggregate Production Functions and the Explanation of Wages: A Simulation Experiment", *The Review of Economics and Statistics*, 53 (4), pp. 305–25.

Fisher F.M., Solow R.M. and Kearl J.M. (1977), "Aggregate Production Functions: Some CES Experiments", *Review of Economic Studies*, vol. 44(2), pp. 305-320.

Fisher F.M. (1993), *Aggregation: Aggregate Production Functions and Related Topics*, edited by Monz J., Cambridge (MA): The MIT Press.

Frey C.B. and Osborne M.A. (2013), "The future of employment: How susceptible are jobs to computerisation?", *Oxford Martin Programme on Technology and Employment Working Paper*, Oxford (UK): Oxford Martin School, University of Oxford.

Frey C.B. and Osborne M.A. (2017), "The future of employment: How susceptible are jobs to computerisation?", *Technological Forecasting and Social Change,* 114 (C), pp. 254-280.

Guo J. (2017), "We're so unprepared for the robot apocalypse", *The Washington Post*: *Wonkblog*, March 30.

Haltiwanger J. (2018), "Comment", *Brookings Papers on Economic Activity,* 49 (1), pp. 64-71.

Harari Y.N. (2018), "Why technology favors tyranny", *The Atlantic* (October).

Harcourt G.C. (1976), "The Cambridge controversies: Old ways and new horizons—or dead end?", *Oxford Economic Papers*, 28 (1), pp. 25-65.

Hulten C.R. (2009), "Growth accounting", *NBER Working Paper*, n. 15341, Cambridge (MA): National Bureau of Economic Research.

Keynes J.M. (1930), "Economic possibilities for our grandchildren (1930)", in *Essays in persuasion*, London: Palgrave Macmillan.

Jorgenson D.W. and Griliches Z. (1967), "The explanation of productivity growth", *The Review of Economic Studies*, 34 (3), pp. 249-283.

Miller C.C. (2017), "Evidence that robots are winning the race for American jobs", *The New York Times: The Upshot,* March 28.

Mishel L. and Bivens J. (2017), *The zombie robot argument lurches on*: *There is no evidence that automation leads to joblessness or inequality,* Washington (DC): Economic Policy Institute, May 24.

Nadiri M.I. (1970), "Some approaches to the theory and measurement of total factor productivity: A survey", *Journal of Economic Literature*, 8 (4), pp. 1137-1177.

Nedelkoska L. and Quintini G. (2018), "Automation, skills use and training", *OECD Social, Employment and Migration Working Paper*, Paris: OECD, March 14.

Nelson R. (1973), "Recent exercises in growth accounting: New understanding or dead end", *The American Economic Review,* 63 (3), pp. 462-468.

O'Mahony M. and Timmer M. (2009), "Output, input and productivity measures at the industry level: The EU KLEMS database", *Economic Journal*, 119 (538), pp. F374-F403.

Ricardo D. ([1817-1821] 1951), *Principles of political economy and taxation*, Sraffa P. (ed.), 3rd ed., Cambridge (UK): Cambridge University Press.

Rogerson R. (2018), "Comment", *Brookings Papers on Economic Activity,* 49 (1), pp. 71-87.

Solow R. (1956), "A contribution to the theory of economic growth", *The Quarterly Journal of Economics,* 70 (1), pp.

65-94.

Solow R. (1957), "Technical change and the aggregate production function", *The Review of Economics and Statistics,* 39 (3), pp. 312-320.

Solow R. (1987), "'We'd better watch out', review of *Manufacturing Matters*: *The myth of the post industrial economy* by Cohen S. and Zysman J., New York: Basic Books", *The New York Times Book Review*, July 12.

Stockhammer E. (2017), "Determinants of the wage share: A panel analysis of advanced and developing economies", *British Journal of Industrial Relations,* 55 (1), pp. 3-33.

Sylos-Labini P. (1995), "Why the interpretation of the Cobb-Douglas production function must be radically changed", *Structural Change and Economic Dynamics*, 6 (4), pp. 485-504.

Taylor L. (1996), "Stimulating global employment growth", in Eatwell J. (ed.), *Global Unemployment*, Armonk (New York): M.E. Sharpe, pp. 143-172.

Veblen T. (1899), *The theory of the leisure class: An economic study of institutions,* New York: Macmillan.

World Bank (2016), *World development report 2016: Digital dividends*, Washington (DC): The World Bank Group.