Structural dynamics in the era of smart technologies*

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Abstract

This chapter explores established approaches in the economic analysis of structural dynamics, in order to describe observed and potential changes in the economy triggered by automation and digitalisation. In particular, the discussion of mechanisation and computer-based automation by means of Classical Input-Output methods is complemented by an overview of recent empirical evidence on robot deployment. A Neoclassical framework of task-based skill-biased automation is considered in the light of empirical evidence on the routine intensity of tasks. Moreover, the emerging value of digital data is assessed through the lens of the System of National Accounts (SNA). Finally, the changing industry composition of the economy — nuanced by the distinction between immaterial goods and services — is explained by interacting mechanisms of Keynesian inspiration between sectoral productivity, demand and income dynamics.

Keywords: Technical progress; Fixed capital; Robotisation; Technological unemployment; Wage share; Routine intensity of tasks; Data value; Digital output; Sectoral productivity dynamics.

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1 Introduction

Will our jobs be replaced by robots or adapt and complement intelligent machines? How will the share of (human) labour income be affected? Who is entitled to the income generated by a machine learning algorithm? What is the value of data? Will our economy dematerialise as we increasingly digitalise production and consumption?

The economic analysis of structural dynamics may be applied to explore possible answers to these questions. It does so by describing the structure of the economy in terms of its sectoral composition (e.g. primary, manufacturing, services), its production factors (e.g. labour and capital) and their income entitlements (e.g. wages and profits). Sectors of the economy are connected by buyer-supplier relations, factors are part of production techniques and their income entitlements have different origins, depending on the economic perspective considered.

But there is an inherent tension in the term structural dynamics. *Structure* conveys the idea of relations between parts which have a rather pervasive, time-invariant nature. Instead, *dynamics* refers to processes of change within a system. This apparent tension stems from the confusion between a method of enquiry and the phenomena which it intends to analyse.

As has been noted by Frisch (1929), it is our method which is *static* or *dynamic*, economic phenomena being either *stationary* or *evolutionary*. While a static analysis focuses on comparison of alternatives, a dynamic one formulates quantitative relationships between rates of change of economic magnitudes through time. When adopting a dynamic method, structural dynamics may be seen as an offspring of growth theory.

And growth theory has frequently been formulated on the basis of a set of *benchmark* phenomena — Kaldor's 'stylised facts' (Kaldor, 1961, p. 178) — which alternative frameworks try to either comply with, accommodate or challenge: (i) steady trend growth of labour productivity (i.e. output-per-worker), (ii) increasing degree of mechanisation (i.e. capital-to-labour ratio), (iii) steady rate of profits on capital, (iv) steady (or at least no clear long-term trend in) capital intensity (i.e. capital-to-output ratio), and (v) high correlation between income share of profits and (net) output share of investment, implying a steady wage share and a real wage increasing vis-à-vis average labour productivity.

These facts express relationships between growth rates (e.g. of output, capital and employment) and their implied effects on aggregate ratios of the economy (e.g. capital intensity, degree of mechanisation and distributive shares). They are 'stylised' because considered to apply across advanced industrial economies. But as 'facts' they convey quasi-stationary phenomena: growth of all magnitudes proceeds at a uniform rate and distributive shares remain unaltered as accumulation proceeds. They imply a *balanced* growth path.

Unless technical progress is assumed to be 'purely labour-augmenting', i.e. increasing the efficiency of each worker but leaving capital intensity and distributive shares unaltered (if competitive conditions prevail), the evolution (or revolution) in technological possibilities poses a challenge to dynamic analyses based on balanced growth. Smart technologies are no exception.

But the era of smart technologies is ongoing. To pin down an abstract definition and periodisation with respect to previous technological and industrial revolutions is challenging, especially because "ideas about radical technological change are based on *ex-post rationalisations of historical events*" (Kurz et al., 2018, p. 551, italics added). However, by illustrating their character, we may link smart technologies with their representation within economic structure.

Smart technologies cover mechanical, digital and biological realms, and crucially rely on digitalisation of information. Their adoption is triggering changes in production by industries and consumption by households. Following UNIDO (2019), advanced manufacturing comprises: advanced digital production (ADP, hereinafter) technologies, nanotechnology (e.g. nanoelectronics), biotechnology (e.g. genetic engineering) and new materials (e.g. carbon fiber reinforced plastics). Clear-cut distinctions are difficult to make, as these areas intertwine (e.g. new 'nanomaterials' derived from renewable resources) or are interlinked (e.g. nanoscale processes used for quantum computing). In particular, our focus will be on:

> "**Advanced digital production [ADP] technologies**: Technologies that combine hardware (advanced robots and 3D printers), software (big data analytics, cloud computing and artificial intelligence) and connectivity (the Internet of things). Advanced digital production technologies are the latest evolution of digital technologies applied to production, a core technological domain associated with the fourth industrial revolution. They give rise to smart production — also referred as the smart factory, or Industry 4.0." (UNIDO, 2019, p. xvi)

This focus is motivated by the topics we aim to analyse.

Robot deployment, additive manufacturing (i.e. 3D printing) and cloud computing are changing the nature and function(s) of (fixed) capital, whereas the looming scenario of technological unemployment stems from the fear of robotisation. These aspects are considered in Section 2. To explore the degree to which human workers and intelligent machines will complement or compete with each other, section 3 unbundles the task content of labour as a factor of production.

Branches of artificial intelligence — such as machine learning — and big data analytics imply that machines use massive volumes of *human* data as their input. Thus, the valuation of such digital data acquires great relevance. Indeed, digitalisation is blurring the boundaries between material and immaterial output, with an ensuing change in the sectoral composition of the economy. Section 4 explores these issues. Finally, section 5 concludes.

2 Humans and machines: technological unemployment

The emergence and adoption of successive vintages of fixed capital as an input in production has been a key driving force of structural dynamics.[1] This section *conceptually* explores three chronological stages of technical change involving fixed capital: mechanisation, computer-based automation and robotisation, coupled with cloud computing.

2.1 Mechanisation and employment reabsorption

The race between the 'human' and the 'machine' — leading to the (human) fear of technological unemployment — has been present at least since British textile labourers and weavers resisted the adoption of knitting frames and mechanised looms in the XIX century.

Such a fear had been almost immediately labelled (the 'Luddite fallacy') and intellectually counteracted (Babbage, 1832, p. 330): while introducing a machine threw out workers directly involved in a given production process, the increase in demand due to the reduced price of the commodity under the mechanised technique would reabsorb part (or even the whole) of the displaced labour force.

[1] Fixed capital consists in (non-financial) assets used as inputs in production over several accounting periods (more than one year), such as machines, equipment and industrial plants (UN, 2009, p. 8).

The logical steps of the thought experiment leading to the (partial or full) reversal of direct employment losses explicitly relied on the institutional mechanism of capitalist *competition*: under free entry, the generalised diffusion of the labour-saving technique across producers would drive down extra profits, reducing the commodity's price, thereby increasing real incomes, expanding demand, output and employment.

Insightful as they might be, thought experiments are not flawless. Already Ricardo (1821, chapter XXXI) illustrated how the introduction of a *more mechanised* technique, i.e. a technique with an associated higher fixed capital-labour ratio in value terms (Kurz, 1984, p. 219), could lead to a shrinking *gross* output in the economy, being "injurious to the labouring class" (Ricardo, 1821, p. 390).

Ricardo's conclusion evinced that when a relatively more mechanised technique is introduced in an industry, employment reabsorption is likely to occur in *different* industries than the one which adopted the new technique. By changing the input proportions in an industry, mechanisation activates output from different sectors. And the higher income resulting from productivity increases associated with mechanisation will be spent in different proportions, according to the distribution of the fruits of technical progress between social classes.

2.2 Computer-based automation: Input-Output approaches

Therefore, to assess the comprehensive effects of mechanisation (and automation in general) on employment, an approach based on the interdependence between sectors of the economy is required. This interdependence can be quantified by the *productive* ties between industries and articulated into an Input-Output (I-O, hereinafter) table. An I-O table is the matrix representation of the bilateral flows of commodities in terms of monetary units between industries: "[t]he double-entry bookkeeping of the input-output table thus reveals the fabric of our economy, woven together by the flow of trade which ultimately links each branch and industry to all others" (Leontief, 1986, p. 5).

The analysis of *potential* technological unemployment due to computer-based automation by means of dynamic I-O models pioneered by Leontief and Duchin (1986), and further refined — especially in terms of investment hypotheses — by Kalmbach and Kurz (1990), evince the importance of structural dynamics in projecting societal transformations.

A crucial distinction in this regard is that between *technical progress* and *technological change*. Whilst the former refers to the "emergence of new technical opportunities of production" (Pini, 1997, p. 76), the latter concerns the "progressive adoption and diffusion of these opportunities in the economic system" (Pini, 1997, p. 76). Thus, technical progress is only a necessary – rather than sufficient – condition for technological change: for novel production methods to become widespread, interacting economic and institutional mechanisms involving, for example, profitability, competition, R&D, intellectual property and product standards, need to unfold.

Mindful of this distinction, Leontief and Duchin (1986) devised a set of scenarios differing in the *pace of diffusion* of computer-based automation across industries, quantifying model-implied changes in the sectoral and occupational structure of employment between 1963 and (a projection onto) the year 2000, for the US economy. In the majority of sectors, accelerated diffusion of new technologies would lead to output increases accompanied by employment reductions. Whilst computers would mainly disrupt office work and education, robotisation would affect production workers in manufacturing, and computer-numerically-controlled (CNC) machine tools would mostly affect metal-working human operations. In terms of sectoral composition, automation would decelerate the transfer of employment from manufacturing to services, given the increased production of new vintages of capital goods, coupled with substantial labour-saving trends in services, due to office automation.

Inspired by Leontief and Duchin (1986), ensuing contributions applied a similar framework to other countries (e.g. McCurdy, 1989; Matzner et al., 1990) and/or refined the theoretical structure of the dynamic I-O model (Kattermann and Kurz, 1988).

In particular, given that computer-based automation is diffused through new vintages of capital goods, the dynamics of investment demand is crucial. In this sense, Kalmbach and Kurz (1990, p. 372) introduced a two-step decision process involving an accelerator principle (investment demand is driven by expected sales) and a capacity planning norm, in which the (increasingly automated) 'best practice technique' is gradually diffused. Depicting alternative *diffusion* scenarios for West Germany by means of comparative dynamics (in the sense of Hicks, 1983, p. 109), they suggested that an accelerated diffusion path might affect employment levels to a *lesser* extent than a slower one. Moreover, in line with Leontief and Duchin (1986), the diffusion of micro-electronic-based new technologies increased the economy-wide labour intensity of construction and electronic data processing industries. However, demand compensation effects would be insufficient to revert the overall labour-saving trend in the economy.

While the above-mentioned I-O contributions focus on the changes in the volume and composition of employment due to automation, technological change is also bound to upset relative prices and income distribution.

Under the condition that a uniform rate of profits prevails across industries, the relative price structure emerging from the cost-minimising choice of available techniques guides the assessment of the potential distributive consequences of competing technologies (Cesaratto, 1995). This assessment can be done by depicting the factor price frontier (FPF, hereinafter) associated with each alternative I-O technique. In an economy where prices can be *reduced* into a wage and profit component, the FPF specifies the *inverse* functional relation between the real wage rate (w) and the rate of profits (r), i.e. the map $w(r)$ indicates the real wage rate that may be obtained at the rate of profits r, for a *given* I-O technique (Kurz, 1990).

As a *dual* exercise to Leontief and Duchin (1986), Leontief (1985) compared the FPFs for the US economy between the technique in use at the end of the 1970s and "the economic recipes that could prevail by the year 2000 as a result of the introduction of computer-based automation" (Leontief, 1985, p. 41), evincing that the incentive to switch from the 'old' to the 'new' technology depends on the *actual* configuration of distributive variables.

In fact, the changing shape of the FPF can be used to analyse *historical* forms of technical progress (Schefold, 1976). To illustrate this, we may compare two techniques, α and β, each characterised by alternative skill composition of tasks, labour and capital input requirements. We may assume β represents the new technology, whereas α is the incumbent one.

As depicted in Figure 1, by increasing the fixed capital intensity of production, automation implies a reduction in the maximum rate of profits ($R^\beta < R^\alpha$) but an increase in the maximum real wage rate ($w^\beta(0) > w^\alpha(0)$) which — for a given, fixed composition of the standard of value — means that (skill-adjusted) labour requirements are decreasing. Thus, automation will normally be accompanied by a rise in the degree of mechanisation of the economy.

Interestingly, the extent to which $w(0)$ increases depends both on reductions in labour input requirements but, *also*, on how the skill composition of occupations across industries changes with the introduction of new

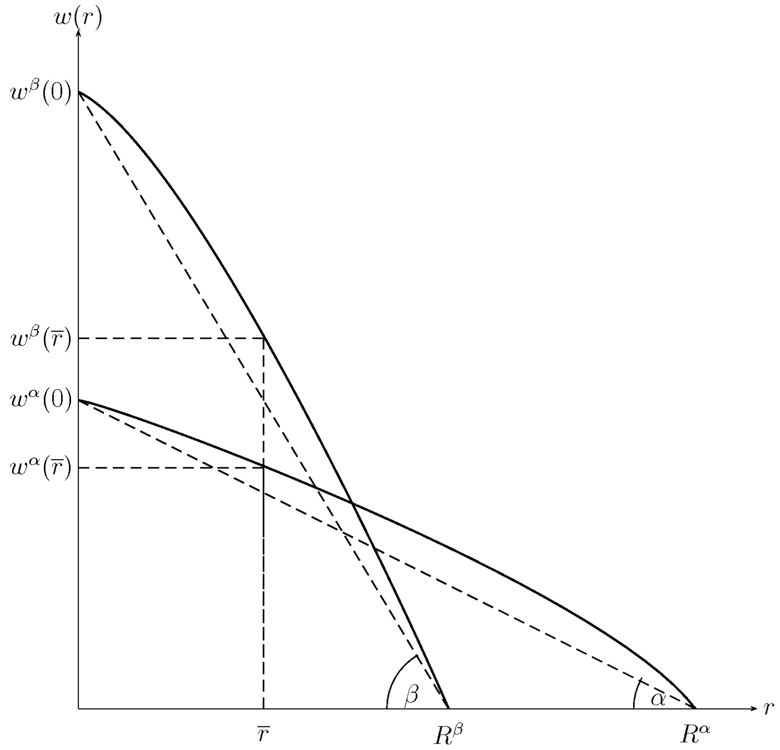

Figure 1: Factor Price Frontiers (FPFs) before (α) and after (β) the introduction and diffusion of relatively more *automated* I-O techniques in the economy

equipment. A sharp increase in the skill content of tasks of automating industries may counteract the fall in labour input requirements, *taming* the expansion of distributive possibilities due to the new technology β.

Moreover, automation renders clear that new technology adoption depends not only on technical conditions, but also on income distribution: the technology providing a higher w for a given r depends on whether the *actual* value of r — $\bar{r}$ in Figure 1 — is to the left (technique β is preferred) or to the right (technique α is preferred) of the intersection point between the two FPFs. And the decrease in $w^{(\beta)}(0)$ due to a higher skill content of labour tasks in automated industries may *widen* the range where the switch between preferred techniques occurs.

2.3 Robotisation: malleable fixed capital

However, there is an important *conceptual* distinction between *mechanisation* of the XIX century, *computer-based-automation* of the 1980s and *robotisation* of this day: they are different forms of automation. Differently from traditional machines and micro-electronic computers, an industrial robot is an "automatically controlled, reprogrammable and multi-purpose manipulator" (UNIDO, 2019, p. xix). It has an autonomy, connectivity, flexibility and functionality which exceeds the *traditional* conception of fixed capital.

By being multi-purpose, the flexibility of an industrial robot diminishes the required pace of fixed capital formation. Multiple automated product lines may be handled by a unique device. Industrial robots – as well as additive manufacturing (i.e. 3D printing) – imply that fixed capital is becoming more "malleable", i.e. interchangeable between production processes and *industries*.

I-O-based analyses are facilitated by the assumption that "machines cannot be transferred from one sector to another, that is, an oven once utilized to produce bread cannot be used during its lifetime to produce biscuits" (Kurz and Salvadori, 1995, p. 250). Multi-purpose robots pose a challenge to such industry-specific conception of fixed capital.

In fact, the attempt by Johansen (1959) to reconcile (dynamic) I-O analysis with smooth neoclassical production functions, by assuming that there are substitution possibilities between capital and labour *ex ante* – before a machine is constructed – but not *ex post* – once a machine has been installed – loses relevance and suggests how multi-purpose fixed capital strengthens the argument for the operation of the principle of 'factor substitution'.[2] Note, however, that this principle may be consistently defined only when the economy produces a *single* output satisfying all final uses (such as consumption and accumulation), as explicitly assumed by Johansen (1959, p. 158). Indeed, the validity of the substitution mechanism in production models has been criticised, both in principle (Pasinetti, 1977) and in practice.[3]

[2]Within a neoclassical system, the principle of 'factor substitution' states that changes in factor prices (r, w) exactly correspond to changes in relative proportions of capital (K) to labour (L), in equilibrium. Therefore, the degree of mechanisation of the economy (the ratio of the value of capital to labour input) is inversely and monotonically related to the factor price ratio (r/w).

[3]As stated by Leontief (1951, p. 39): "the concept of technical substitution and the law of variable proportions — if applied to aggregative industries — have in the main no other function than to conceal the non-homogeneous character of the conventional industrial classification".

2.4 Robotisation: empirical evidence

Pertinent as these conceptual observations might be, at any rate, the most heavily debated aspect of the growth of industrial robots remains its associated effects on employment and the wage share. However, as documented by UNIDO (2019, p. 53), trade in capital goods intensive in ADP took off only around 2002, patenting of ADP intensive technologies started to accelerate only around 2007, and global annual installation of industrial robots took off around 2005 (UNCTAD, 2017, p. 47), making the diffusion of ADP technologies a phenomenon that dates back to less than two decades. Thus, empirical evidence at this early stage may not be considered conclusive.

As evinced by Gort and Klepper (1982), the are lags of variable length between stages in the life cycle of innovations. And while the diffusion (and imitation) time interval has been declining systematically over time, we may not have seen yet a stage in which, due to robotisation, "successful innovators [intended as industrial robot *adopters*] within an industry may be increasing employment but require less employment than unsuccessful firms that contract and exit" (Haltiwanger, 2018, p. 69). Crucially, concerns about job displacement effects of robotisation revolve around the time-path of the *traverse*, the *transitional* dynamics between the old and new technologies (Haas, 2018).

This alerts on the caution needed when presented with evidence on the debate. In fact, two of the most influential empirical studies so far (Acemoglu and Restrepo, 2017; Graetz and Michaels, 2018) cover a period between the early 1990s and 2007, *before* the accelerated growth in industrial robot deployment.

Using a panel of 17 countries across 14 industries from 1993 to 2007, Graetz and Michaels (2018) find that industrial robot densification is associated with *increases* in labour productivity, Total Factor Productivity (TFP, hereinafter)[4] and average wage rates, with a *decrease* in output prices, but *no* statistically significant implications for changes in the wage share and overall employment.

On the contrary, for the same period but focusing on US local labour markets more intensively exposed to industrial robot deployment, Ace-

[4]Within the Neoclassical approach, TFP is assumed to measure "how productively the economy uses all the factors of production" (Aghion and Howitt, 2009, p. 106), its changes being measured as a *residual*: *assuming* factor markets are perfectly competitive, TFP growth rates are obtained by subtracting the growth rate of the degree of mechanisation (the capital-to-labour ratio) from the growth rate of real income (i.e. double-deflated value added).

moglu and Restrepo (2017) find that "one additional robot per thousand workers [...] *reduces aggregate* employment to population ratio by 0.34 percentage points and *aggregate* wages by 0.5 percent" (Acemoglu and Restrepo, 2017, p. 36, italics added).

In between these two contributions, using a long-run distributed lag framework which considers TFP growth (rather than robotisation) and a wider time span (1970-2007), Autor and Salomons (2018) find that automation (proxied by industry-level TFP changes) has been associated with *increases* in *industry* employment (mainly due to TFP growth in supplier sectors) but to an *erosion* of the wage share. Note, though, that by using reduced-form econometric methods, results convey conditional correlations rather than causal effects.

In assessing the employment effects of robotisation, the employment to population ratio is often used (e.g. Acemoglu and Restrepo, 2017). A key related debate concerns the denominator — rather than the numerator — of such ratio, for the long-period trend of a demographic decline in advanced industrial economies paves the way for the deployment of robots. Declining working-age populations alert on the need for an acceleration of labour productivity growth to sustain current standards of living in advanced countries (Leitner and Stehrer, 2019). Thus, a positive correlation between robot deployment and labour productivity growth would provide a rationale for robot densification.

Interestingly, using a panel for 60 countries between 1993 and 2013, Abeliansky and Prettner (2020) find that a faster pace of population growth tends to be related to a reduction in the growth rate of robot deployment. It would be important, though, to be careful when interpreting such correlation. A declining population and the scale of robot deployment might be complementary in advanced countries, but this may not be the case in developing economies, where traditional *mechanisation* is still the prevalent form of automation (UNCTAD, 2017, p. 39).

2.5 Cloud computing and capital services: outsourcing fixed capital

The diffusion of ADP technologies leads to rethink the role of capital as a factor of production beyond robotisation. Cloud computing, i.e. renting a computing environment and associated storage space hosted in equipment operating elsewhere, crystallises the approach in the latest System of National Accounts (SNA, hereinafter) to measuring 'productive' capital using capital *services* (UN, 2009, chapter 20): the sum across capital goods weighted by their rental price, i.e. by the price that would have to be paid to hire the asset for a period. By rendering the hiring process explicit, cloud computing avoids imputation difficulties when valuing capital services for owners and users of Information and Communication Technology (ICT, hereinafter) equipment.

If cloud computing becomes generalised, we may expect a redistribution of gross fixed capital formation by *destination* industry: rather than investing in ICT equipment themselves, industries will purchase an *intermediate* service to data processing, hosting, renting and leasing activities.[5] These service industries will, thus, increase their relative importance as activating demand sources of physical ICT infrastructure, having as a counterpart a whole new stream of intermediate consumption transactions with users of cloud computing services.

Interestingly, this (potential) process of fixed capital *outsourcing*, may resemble (or at least be analysed as) the process of outsourcing of labour from manufacturing into business-related service industries during the 1980-1990s (see, e.g. Franke and Kalmbach, 2005).

3 Tasks, jobs and occupations: the content of labour content

The asymmetry between process and product innovations (Pini, 1997, pp. 65-6) maintains its relevance when assessing the introduction and diffusion of ADP technologies. The labour-saving, cost-reducing potential of process innovations should be weighed against potential job-creation effects of product innovations, which involve, at least, two channels: (i) employment induced by new product markets (e.g. smart devices) which require a whole range of supporting functions (via I-O linkages), and (ii) human-robot complementarity in the workplace requiring *new* occupations (e.g. software developers, data analysts).

But assessing the potential for human-robot complementarity requires to unbundle the *content* of labour as a factor of production. To begin with, there are conceptual differences between the notions of task, job and occupation. Tasks represent granular activities at the workplace. A job may be seen as a set of tasks, whereas an occupation represents a set of jobs whose main tasks have a high degree of similarity. Empirical

[5]ISIC Rev. 4 categories 66 and 77. See UN (2008) for details.

work rendering operational these distinctions has been made possible by the Occupational Information Network (O*NET) programme, which has developed a *granular* database mapping tasks to occupations for the US economy,[6] as well as by the European classification of Skills, Competences and Occupations (ESCO), a database identifying, describing, codifying and classifying occupations and skills across the European Union (EU).[7]

3.1 Task-based, skill-biased theory of automation

It is by no means simple, and in many ways arbitrary, to *classify* tasks. The analytical taxonomy introduced by Autor et al. (2003) distinguishes, first, between 'routine' and 'non-routine' tasks. A 'routine' task is "sufficiently well understood that [it] can be fully specified as a series of instructions to be executed by a machine" (Acemoglu and Autor, 2011, p. 1076). Essentially, a routine task is highly *codifiable*. Non-routine tasks, instead, can be sub-classified as 'manual' or 'abstract'. The former require "situational adaptability, visual and language recognition, and in-person interactions" (Acemoglu and Autor, 2011, p. 1077), whereas the latter require "problem-solving, intuition, persuasion, and creativity" (Acemoglu and Autor, 2011, p. 1076).

The rationale for this taxonomy is that of associating a *skill set* to each of these three categories, allocating the *highest* skill set to non-routine abstract tasks and the *lowest* skill set to routine tasks. Thus, if ADP technologies (such as robots) were substitutes to (human) routine tasks but complementary to non-rountine abstract tasks, increased relative labour demand for occupations intensive in the latter task type would widen the wage gap between workers with highest and lowest skill sets. Therefore, there would be a 'skill bias' associated with ADP technology adoption (and recent automation in general) explaining widening wage inequalities.

The unequal skill profile of labour demand associated with automation triggers a 'race between education and technology'. In particular, Acemoglu and Restrepo (2018a,b) have applied the idea of a mismatch between skill requirements and their availability to formulate a 'task-based' theory of technological unemployment and declining wage share.

[6]For details, please see: https://www.onetcenter.org. The ONET database is based on the US-BLS Standard Occupational Classification (SOC), which may be converted into the ILO's International Standard Classification of Occupations (ISCO).

[7]For details, please see: http://https://ec.europa.eu/esco/portal. The current version at the time of writing (ESCO v. 1.1) articulated 2,942 occupations and 13,485 skills linked to them across the EU.

In their framework, services embodying a range of tasks are combined to produce aggregate final output, used both for consumption and accumulation. Rather than purely labour-augmenting innovations, they assume that machines and labour are perfect substitutes to produce (a range of) tasks, so that cost-minimisation implies that labour will be selected for those tasks in which it has a higher relative productivity (with respect to machines), i.e. tasks in which humans have a *comparative advantage*. Automation, thus, is represented by an expansion in the set of tasks autonomously performed by (intelligent) machines.

Equilibrium conditions imply that automation will *always* be wage-share-reducing, and its impact on labour demand (and wages) depends on how the *displacement* effect of workers from automated tasks is counteracted by a *productivity* effect, given by the gap between the productivity-to-input-price ratios of machines and labour: only when the 'benefit-to-cost' ratio of machines is notoriously higher than for labour, automation will increase labour demand (see Acemoglu and Restrepo, 2018a, p. 19, for details).[8]

Moreover, by restricting the range of tasks that low-skill workers may perform, while assuming that the share of high-skilled workers in the economy is *lower* than the share of tasks that only they can produce (i.e. high-skilled workers are relatively *scarce*), the labour demand profile triggered by automation is biased towards higher skill sets, increasing the wage gap between worker types.

This renders clear the predicted outcomes of automation 'at the extensive margin', i.e. through expansion of the share of tasks produced by machines. However, it is also possible for automation to work 'at the intensive margin', i.e. when machine productivity increases in tasks which had already been automated. In this case, employment should expand and the wage share should remain unaltered.

Interestingly, this distinction between *extensive* and *intensive* margins of automation *echoes* the Marxian extraction of *absolute* and *relative* surplus value from a (human) worker, but applied to a robot. Hence, unless robot 'exploitation' is sufficiently high, extensive automation will reduce

[8]The compensation between the 'displacement' and 'productivity' effects operates as follows: if the gap between the productivity of machines ('benefit') and their rental rate ('cost') is *sufficiently high* with respect to the gap between the productivity of labour ('benefit') and the wage rate ('cost') for the same set of *automated* tasks, the substitution of machines for labour — under competitive conditions — reduces production costs *and* prices, increasing per-capita real incomes channeled towards higher demand for products, triggering further demand for labour. This demand for labour exceeds the originally displaced workers substituted by machines performing the automated tasks.

the wage share, displace workers and increase wage gaps between workers with different skill sets. To partially revert this trend, Acemoglu and Restrepo (2018a, p. 22) assert that technological advances ought to bring about the creation of new tasks in which human labour has a comparative advantage. In this way, with extensive robot deployment displacing low-skill workers and the emergence of new tasks for high-skilled workers (i.e. human-robot complementarity), the economy is predicted to reach a *balanced* growth path (provided the high-skill worker supply adjusts accordingly).

3.2 Changes in the labour process: routine intensity of tasks

The creation of new tasks alerts on the importance of studying the (potential) effect of ADP technology adoption beyond employment levels, focusing also on changes in the labour process itself, in the *content* of labour content.

A first challenge, though, is to empirically distinguish between routine and non-routine tasks (of both manual and abstract types). In an attempt to address it, Marcolin et al. (2016) introduce a 'routine-task intensity index' (RII, hereinafter), quantifying the degree to which a task can be routinised and — after aggregating across tasks for each occupation — identify occupation × industry combinations particularly intensive in routine-based tasks.[9]

Table 1 suggests that the RII is generally higher for manufacturing industries, and highest in food processing, textiles/apparel and transport equipment, which evinces the importance that cross-country structural differences — in terms of the sectoral composition of the economy — may have in assessing potential effects of automation.

Equally relevant, the RII by occupation (Marcolin et al., 2016, p. 17, Table 3a) is highest for elementary occupations, plant operators and services/sales workers (ISCO-08 categories 9, 8 and 5, respectively) which, again, evinces the relevance of the occupational structure *supporting* the sectoral composition of the economy.

The RII was highest in occupations with lowest *skill levels*, according to ILO's ISCO-08 classification (ILO, 2012, p. 14, Table 1). This raises a key

[9]The four dimensions used to capture the routine-intensity of a task concern "the frequencies with which individuals may, respectively: [(i)] choose the sequence of the tasks involved by the job; [(ii)] change the content of work or how this is carried out; [(iii)] plan their own work activities; and [(iv)] organise their own working time" (Marcolin et al., 2016, p. 9). Data has been obtained from the OECD Programme for the International Assessment of Adult Competencies (PIAAC) survey.

Table 1: Routine Intensity Index (RII) by industry

(22 OECD countries; years 2011-2012)

Sector	*ISIC Rev. 4*	*Mean*	*SD*
Agriculture	01-03	2.26	1.14
Mining	05-09	2.29	1.00
Food, Beverages & Tobacco	10-12	2.75	1.28
Textiles, Apparel & Leather	13-15	2.66	1.29
Wood & Paper	16-18, 58	2.31	1.13
Chemicals	19-23	2.37	1.17
Basic & Fabricated Metals	24, 25	2.40	1.16
Machinery n.e.c.	28	2.22	1.07
Electrical Equipment	26, 27	2.35	1.15
Transport Equipment	29, 30	2.61	1.22
Manufacturing n.e.c	31-33	2.35	1.16
Utilities	35, 36	2.12	0.91
Construction	41-43	2.25	1.04
Trade & Hotels	45-47, 55, 56, 95	2.41	1.12
Transport & Telecom	49-53, 61, 79	2.59	1.20
Finance	64-66	1.99	0.88
Business services	62, 63, 68, 69-78, 80-82	2.00	0.95
Personal services	37-39, 59, 60, 84-88, 90-94, 96	2.17	0.95

Notes: column ISIC Rev. 4 reports the 2-digit classes composing the reported sectors.

Source: Adapted from Marcolin et al. (2016, p. 17, Table 3b).

issue: what is the relationship between (non-)routine tasks and the skill content of occupations?

If we take at face value the skill content of occupations as allocated by the ISCO-08 classification, Table 2 suggests that non/low-routine intensive tasks are predominantly done by workers with the highest skill level. Instead, medium/high-routine intensive tasks are predominantly carried out by workers with *medium*-level skills. Interestingly, it is medium — rather than low — skill-level workers currently employed in routine-based tasks.

Thus, a point open to debate is whether ADP technologies will be accompanied by a generalised increase in the *skill threshold* of the workforce *or*, instead, we will see a job *polarisation* process, with the hollowing out

Table 2: Employment by skill and routine intensity

(22 OECD countries; years 2011-2012)

Routine intensity	NR	LR	MR	HR
	Non-routine	Low routine	Medium routine	High routine
Skill level				
Low	0.00	0.01	0.07	0.24
Medium	0.09	0.30	0.68	0.73
High	0.91	0.69	0.25	0.03

Notes: Skill levels correspond to one-digit ISCO-08 categories
1 to 3: managers, professionals, technicians and associate professionals (High),
4 to 8: clerical support/services/sales, skilled agriculture, crafts, machine operators (Medium)
9: elementary occupations (Low)

Source: Adapted from Marcolin et al. (2016, p. 20, Table 5).

of human occupations in the middle range of skills,[10] and at the same time, a proliferation of complementary low-skill and high-skill jobs functional to the deployment of intelligent machines.

3.3 Skill content of a task or skill level of a worker?

So far, though, we have not enquired into how skill levels are allocated to workers. For one thing is to measure the *skill content* of a task within an occupation, and another is to measure the *skill level* of the worker performing the task. The most diffused *proxy* of skill level for the latter is the level of educational attainment, *assuming* that individuals awarded a higher education qualification possess the *skill content* of high-skill tasks. But this can be misleading.

First, because while a higher education qualification might be a *sufficient* condition to perform certain high-skill tasks, it may not be a *necessary* one. For example, tasks requiring "factual, technical and procedural knowledge in a specialized field" (ILO, 2012, p. 13, ISCO-based Skill Level 3) can be performed by university graduates, but may often be proficiently carried out by workers who have completed specialised vocational education and on-the-job training.

Second, because it validates the conception that education *mostly* rep-

[10] Occupations such as plant and machine operators, assemblers, services and sales workers, involving tasks such as operating mechanical machinery/electronic equipment, as well as information manipulation, ordering and storage.

resents an *investment* with an expected return, to be reflected in a wage premium. But this seems to confuse the true source of extra income (the high-skill content of a task) with the *commodity* that is perceived to command it (a higher education qualification). It is institutional specificities (and historical trajectories) of advanced industrial societies which have led high-skill occupations to be remunerated relatively more than low-skill ones, not an explicit societal consensus about the 'discounted present value' of expected income streams of a human asset who enrolled into university.

In fact, when high-skill occupations are confused with the advanced educational attainment of the worker who performs them, there is a risk of interpreting tasks performed *by* university graduates as necessarily *knowledge*-intensive, because of the length of formal instruction of their degree.

The structural transformation in the skill content of tasks is prone to widen wage inequalities if the correlation between skill content and remuneration across occupations continues to be strongly positive, in a context where routine-intensive tasks with medium-skill requirements disappear. But can we be sure that high-skill tasks can be safeguarded from automation? Machine learning techniques have improved robot performance in both non-routine *abstract* tasks, such as natural language processing, image/video/speech recognition, as well as in non-routine *manual* tasks involving robot dexterity (UNIDO, 2019, p. 75).

4 Physical and digital: the value of data and the changing composition of output

By means of machine learning techniques, robots are beginning to perform non-routine *abstract* tasks, automating decision-making. Beyond robotics, computer-aided design and manufacturing (CAD-CAM) are automating the production not only of physical goods (by controlling machine tools) but also of *immaterial* goods (such as drafting industrial designs).

However, robots need data as input to learn from experience and improve their performance. Thus, while humans use robots as a fixed capital input in the production process, robots use *human* data as *their* input. In fact, "data are a *productive resource* that fuels the learning of machines" (Kurz et al., 2018, p. 571, italics added).

Therefore, a key question associated with the structural dynamics of prices triggered by the diffusion of ADP technologies is: what is the *value* of the productive resource labelled as 'data'? A single sentence may contain multiple (and often contrasting) views on the underlying source(s) of data value:

> "[D]ata can be used multiple times (e.g. in different contexts) without *inherently diminishing their value.* In principle, data can be exploited and re-exploited infinitely at low *marginal cost*; it is *data infrastructure and analytics* that are the *primary costs* related to data re-use."(OECD, 2019, p. 240, italics added)

The sentence above implies, at least, three alternative conceptions for data value: (i) value as a substance embodied in commodities, (ii) value deriving from scarcity and (iii) value as interdependence.

Claiming that the inherent value of data is not consumed through repeated usage conveys the idea of data as a substance transferred to products. The low marginal cost of extremely abundant data exploitation relates to its consideration as a scarce resource. Finally, data value may derive from the *structure of interdependence* between fixed capital ('data infrastructure') and labour ('data analytics') requirements to reproduce it.

4.1 Data as a non-produced asset

Given the difficulty to reconcile contrasting theoretical perspectives, one interesting route is to explore current proposals (Ahmad and van de Ven, 2018; Mitchell, 2018; OECD, 2019; Mitchell, 2020) and discussions within international statistical organisations (mainly the OECD and the UN Statistics Division) aimed at building a specific digital economic account. Starting from digital data measurement within the SNA may prove enlightening to distil how alternative conceptions of value underpin such proposals.

Currently, digital data is considered as a *non-produced asset* in the SNA, i.e. while it appears in the balance sheet of firms, its very production, does not increase GDP. Data in itself, will only be valued when a *market transaction* occurs, recording the monetary amount under the category of a non-financial, non-produced asset.

This convention has implications for both the production and asset boundaries of the SNA. Crucially, it is argued that "not to treat the data, in and of itself, as produced does not mean that data has no value" (Ahmad and van de Ven, 2018, p. 5). But where does this 'value' derive from?

From a *Classical* perspective, value derives from *production*, whereas from a *Marginalist* (or Neoclassical) viewpoint, it derives from *exchange* under conditions of relative *scarcity*. In fact, the (relatively) undisputed character of GDP as an *observable* indicator of economic value derives from its being *exchanged production*. So how may data be a 'productive resource' without being itself produced? The Neoclassical reconciliation guiding the SNA framework could be that data can have value as it is exchanged, but does not contribute to GDP because it is not produced.

This, however, overlooks whether digital data may be considered a *substance* embodied in commodities. Just as human labour is measured in *hours*, data is measured in *bytes*. It would be difficult, though, to discern value differences between two products based on the *volume* of bytes used for their (re)production. In essence, the underlying value of data reflects its *knowledge* content. But while knowledge is embodied in data, it is not *apparent* just by accessing data. Hence, the value of data is separated from the reproduction costs of its storage medium, a database, for example.

But, then, if it is the underlying knowledge content of data that has value, its *digital* nature cannot be a necessary condition for rendering data valuable. For instance, physical record files in an archive would possess a similar knowledge content, albeit in a different storage medium. Thus, it still remains an open question how to distil the *uniqueness* of *digital* data stored electronically as a source of economic value.

Probably, as convincingly argued by Ahmad and van de Ven (2018, p. 13, italics added): "the decision not to treat data as produced was in large part a function of the fact that to do so would lead to an *implicit recognition that all knowledge was produced*, and as such should be valued as contributing to GDP". This would significantly expand the *production* boundary of the SNA, generating new income entitlements derived from knowledge creation.

Indeed, even before national accounts acknowledge it, machine learning methods are already disrupting the idea that the entitlement to shares in income are distributed in proportion to factor contributions. When an algorithm learns *by itself* how to exploit new arbitrage opportunities, who should be rewarded with the additional value added or net product generated? Is it the labourer who designed and codified the algorithm? Is it the owners of the computing equipment on which the algorithm runs, learning from experience? Alternative theories of value would reply differently to these questions (Savona, 2019).

Keeping data with its embodied knowledge out of income *generation* avoids having to discuss whether intelligent machines should be granted (human) agency. Being considered a non-produced asset renders *data* similar to *land* as a production factor. In fact, land made available for productive uses generates *rents* rather than *rentals.* The former are part of the primary income *distribution* account of the SNA, and need not be financed out of value added. The latter, instead, belong to the income *generation* account of the SNA, being part of the added value of the economy.

In a nutshell, current practice in the national accounts implies that when digital data is created there is no immediate impact on GDP, effects may be indirectly traced when data is used to produce other products within the production boundary.

In order to trace these indirect effects through a network of money flows, a framework of 'Digital Supply-Use Tables (SUTs)' has been proposed (Mitchell, 2018, 2020). In this way, an economy-wide digital economic account would articulate data-related money flows into a cross-tabulated classification of digital industries and products. Such a classification would codify data circulation, and the circulation of mutually dependent flows allows to derive economic value.

4.2 Immaterial goods are not services

The emphasis on digital over physical outputs, pervasive in conceptualising ADP technologies, echoes the divide between material and immaterial (or intangible) products, prominent in decades-long discussions on the transition towards a 'service economy' (Walker, 1985). Material production was associated with manufacturing, whereas immaterial output with services. Hence, the increasing share of services in (nominal) value added and employment suggested that the economy was gradually 'dematerialising' as it was 'deindustrialising' (in relative terms).

At least two points emerge from these debates. First, the need to conceptually clarify the notions of digital (as immaterial) and physical (as material) production in terms of structural analysis. Second, the need to explain the changing sectoral income shares in the economy.

On the first point, Parrinello (2004) insightfully clarified the difference between goods and services in relation to (im)material production: "commodities include goods and services, goods can be material or immaterial, but services are not immaterial goods" (Parrinello, 2004, p. 389). By analytically dissecting a uniform production-consumption period into a series of independent processes at a sufficiently granular level, he singled out two relationship types between processes, *serial* and *parallel* I-O relations.

Serial I-O relations mean that today's outputs are tomorrow's inputs. This time-lag in production also implies that an inventory of inputs can be maintained and restored. On the other hand, in parallel I-O relations, the output of a provider process 'serves' as input to the user process, during the *same* period. Quantities resulting from serial relations, albeit dated, have no intrinsic time dimension and may be accumulated. They represent *goods*. Instead, those from parallel relations may only be defined during a time period and cannot be accumulated. They represent *services*.[11]

This distinction might be useful to show that 'service' industries produce both services *and* immaterial goods, whereas 'manufacturing' industries generate a sizeable amount of services in the process of production of physical goods. As an example of the former, the output of a firm in a service industry consisting of a patented industrial design represents an immaterial good, whilst if the same firm provides time for analytical activities to another one — without generating vendible intellectual property as an output — then it is supplying a service. As an example of the latter, consider specialised repair services across manufacturing firms.[12]

Conceptual distinctions between product types become relevant to avoid the commonplace (mis)conception that the increasing weight of service industries will necessarily render the economy more knowledge-intensive. As lucidly put forward by Parrinello (2004, p. 396): "[t]he myth [of a *post-industrial* economy] rests upon a sort of deduction from two spurious premises: (i) services are immaterial goods (ii) immaterial goods are fragments of knowledge and information; hence (iii) more services reflect more knowledge and more information".

Just as was argued — in section 3 — that tasks are not necessarily knowledge-intensive due to the length of formal instruction of the university graduates who perform them, service activities are not necessarily knowledge-intensive due to their being confused with immaterial goods.

Thus, digital products involve both immaterial goods and services. Services are functional to the production of both physical and immaterial goods. And the changes in relative shares between manufacturing and services should not be seen as a direct consequence of increasing digitalisation, as evinced by the fact that ADP technology development is, to a

[11] Parrinello (2004, p. 389) also distinguishes a service from a pure perishable good, as the latter — though not storable — is first produced through a *serial* I-O relation, before its consumption.

[12] Interestingly, the latest ISIC Rev. 4 classification (UN, 2008, p. 161), has moved "Repair and installation of machinery and equipment", which consist of a *service* output, within the umbrella of manufacturing industries.

great extent, conditioned by human learning within manufacturing industries (UNIDO, 2019, p. 61).

4.3 Sectoral income shares: Baumol's cost disease

Debates around the underlying cause(s) and measurement of the changing sectoral income shares of manufacturing and service industries have been a long-standing feature of structural dynamics, especially since Baumol (1967). In his framework, faster productivity growth in manufacturing vis-à-vis services under *competitive* conditions imply: (i) a *relative* unit labour cost and price increase for services, and (ii) labour-displacement in manufacturing and labour-absorption in services, *if* demand for the latter is (sufficiently inelastic to be) maintained (despite a higher relative price).

As a consequence, while the manufacturing-to-services output ratio may remain constant, the nominal income share of services will increase, as well as its share in employment. Thus, '*balanced growth* in a world of *unbalanced productivity*' requires a progressive slowdown of aggregate labour productivity, labelling the predicted dynamics as Baumol's 'cost-disease'.

Under this view, manufacturing industries represent *progressive* activities, whereas service industries *stagnant* ones. Baumol et al. (1985) empirically confirmed model-implied trends for the US (between 1947 and 1976). They did so by extending the original framework through the introduction of *asymptotically stagnant* industries, i.e. sectors using inputs from progressive and stagnant industries in fixed proportions. In such sectors, the stagnant labour-intensive component gradually assumes a greater share of the unit cost, eventually rendering the activity stagnant.

This third industry type becomes particularly relevant when considering ADP technology diffusion, as the authors argue precisely that 'data processing (computing services)' represents a prime example of an asymptotically stagnant sector: *software* takes over *hardware* in unit costs and "[s]oftware development remains essentially a handicraft activity, and is, *so far*, a stagnant service" (Baumol et al., 1985, p. 813, italics added). It remains an open question whether the automation of non-routine abstract tasks, such as component-driven software development through machine learning methods, will overcome the *predicted* asymptotically stagnant character of (at least, some) digital industries.

4.4 Interacting productivity, demand and income: mechanisms of structural dynamics

Baumol's cost disease suggests that widespread adoption of ADP technologies would deepen the uneven dynamics of sectoral productivities, slowing down aggregate labour productivity growth, if relative *output* shares remain (approximately) constant, i.e. if a balanced growth path prevails.

A challenge to a world in which there is convergence towards a balanced growth path is the approach of structural economic dynamics introduced by Pasinetti (1981, 1993). By means of a dynamic I-O model with uneven sectoral dynamics of per-capita consumption and labour productivities, Pasinetti specifies a *normative* benchmark in which technological unemployment and unbalanced growth are the normal state of the economy.

The mechanism of *structural* dynamics implied by the benchmark configuration of this approach may be framed as follows: uneven sectoral productivity changes modify *relative* production costs, but if average productivity gains accrue to labour, (aggregate) price dynamics is slower than nominal income expansion, increasing real incomes. As real income increases, consumption patterns change — as predicted by Engel curves (Moneta and Chai, 2014) — altering the compositional structure of household expenditure. Hence, gross output induced by household expenditure has a changing commodity composition. This generates a potential mismatch between activating sources of demand and activated sources of employment, as sectors for which consumption demand is growing faster (slower) than productivity will expand (contract) employment.

Therefore, if the adoption of ADP technologies accelerates productivity growth in branches of the economy for which the corresponding demand for its final output is stagnant (such as traditional motor vehicles), or if the expansion rate of household demand for digital outputs is short of productivity increases in its supplying sectors, technological unemployment is bound to increase.

But whilst Pasinetti (1981) considers a system where sector-specific per-capita consumption and labour productivity are continuously changing at uneven rates, these are considered to be exogenously given. In particular, no explicit link is specified between final demand expansion and productivity growth. However, at an *aggregate* level, Verdoorn (1949) already documented an empirical, positive relationship between labour productivity growth and output expansion, whereas Kaldor (1966) argued that the relationship is particularly associated with 'secondary' activities, especially with manufacturing. More importantly, Kaldor emphasised that it is labour productivity growth which is a *positive function* of the growth rate of manufacturing output, and argued against the reverse direction of causality, which would mainly operate through relative price adjustments.

In this way, the Kaldor-Verdoorn mechanism allows to (partly) *endogenise* productivity dynamics based on the evolution of demand-induced output. Lorentz and Savona (2008) take this *aggregate* relationship to firm and industry-level dynamics, formulating a simulation model — calibrated with German data — in order to study *tertiarisation* patterns. More in general, the logic of the Kaldor-Verdoorn mechanism implies that shifts in the composition of final expenditures, as well as *autonomous* determinants of *both* technical progress — such as advances in scientific and technological knowledge — *and* the level of aggregate demand — such as public expenditures — shape the evolution of productivity growth.

And not only of productivity growth, but also of productivity *decline*. Because a symmetric application of the Kaldor-Verdoorn mechanism suggests that a slow growth of actual output is conducive to a labour productivity slowdown. This might help explain the 'productivity puzzle' (ONS, 2020) facing some advanced industrial economies since the Great Recession of 2008-09.

5 Conclusion

This chapter has explored how advanced digital production (ADP) technologies disrupt three main axes of economic structure: (i) the changing nature and function of fixed capital in relation to (human) job displacement, (ii) the changing content of labour tasks complementing automated production, and (iii) the evolving distinction between physical and digital output and assets.

From mechanisation debates in the XIX century to the Input-Output (I-O) studies of computer-based automation of the 1980s, job displacement effects due to the diffusion of automated production techniques were not fully compensated by mechanisms of capitalist competition. And while preliminary evidence on the employment and distributive consequences of robotisation since the 1990s is still not conclusive, industrial robots and cloud computing are accelerating a trend towards multi-purpose, malleable and outsourced fixed capital.

Hence, the degree of human-robot complementarity — and the extent of job displacement — depends on the skill set required by tasks which characterise those occupations interacting with new vintages of fixed capital goods. By mapping the skill content of tasks to their relative codifiability, the empirical application of a 'routine-task intensity index' across selected advanced economies suggests that transport equipment, food processing and textiles/apparel are industries with highest *routinisation* potential. Note that the latter two sectors are amongst those with lowest labour share and highest share of female workforce in the economy (UNIDO, 2019, p. 81). Crucially, as routinisation potential predicts the technical feasibility of robotisation, industry-level differences suggest that the impact of robot deployment on the economy's wage share depends on its structural composition (UNCTAD, 2017, p. 41).

But will non-routine, high-skill tasks be safeguarded from automation? The improvement of robot performance in abstract and manual tasks by means of machine learning techniques cast doubts. A key novelty brought about by ADP technologies is a potential reversal of roles in human-machine complementarity. Traditionally, humans have used fixed capital as a productive input. Instead, machine learning allows for robots to use *human data* as their *input*. Hence, the valuation of *data* is a crucial (still open) question for the structural dynamics of prices. The current practice in the System of National Accounts (SNA) considers data as a *non-produced* asset, i.e. data is not part of value added generation in the economy. Keeping data with its embodied knowledge out of income generation avoids having to discuss whether intelligent machines should be granted (human) agency. Being considered a non-produced asset renders data similar to land as a production factor.

Despite the fact that data is not considered an output in itself, digital products based on data have been pervasive to conceptualise ADP technologies. In fact, the ongoing changing sectoral composition of the economy requires to go beyond the dichotomy between manufacturing and service industries. This is because digital products involve both immaterial goods (such as an industrial design or a software package) and services (such as cloud computing), whilst manufacturing industries remain at the core of human learning conducive to novel ADP technologies, resulting in new digital products (UNIDO, 2019, p. 61).

In hindsight, to understand the unfolding dynamics of economic structure, it is worthwhile to glimpse at its historical development. We have traditionally described the structure of the economy in terms of its sectoral composition (e.g. primary, manufacturing, services), its production factors (e.g. land, capital and labour) and their income entitlements (e.g. rent, profits and wages). The assumption that one factor is more intensively employed in each sector has been instrumental to identify the *privileged* income entitlement in each stage of structural transformation.

In this way, the primary sector, reliant upon *biological* processes on land, has privileged rent. Manufacturing took over, articulated around the *transformative* power of machines, privileging profits. Finally, services, anchored in active *human* labour, have privileged wages (with compounding hierarchies and widening gaps across occupations).

But technological change has increasingly blurred the neat mapping between factors of production and sectors of the economy, as well as the clear-cut entitlement to factor payments. With the mechanisation of agriculture, profits became prominent in the primary sector. With the servicification of manufacturing, the physical transformation of goods has been bundled with labour-intensive tasks.

So how will ADP technologies *and* digital outputs alter these mappings? Rent payments to grant the mining of digital (identity and footprint) human data may represent a new cycle in the loop, making *data rentiers* a prominent social group owning 'lands' of data. Moreover, if the income streams attributable to a machine learning algorithm operating on an industrial robot accrue to owners of robots as profits and rents to owners of the embodied intellectual property, we may head into an era of 'automated inequality'.

At a deeper level, what is called into question is what might be the role of *human activity* in value generation and its share in income. In an *extreme* scenario, data resulting from human *consumption* may become a *productive input* into robotised processes, which require a tiny fraction of the workforce to run. And while consumers may embrace a 'rentier' future of digital existence, in which they are remunerated for the data they generate, doing without the *indispensable* role of labour in production (Zalai, 1989) is not without consequences.

Several research avenues remain open. For example, the role of digitalisation in deepening financialisation deserves to be explored, as financial services have 'leveraged on' digital media beyond any other sector of the economy (Mitchell, 2018, p. 28).

Moreover, global robot production is currently highly concentrated,[13]

[13]To the extent that "China, Germany, Japan and Republic of Korea [...] accounted for about 83 per

and so is the *capitalisation* of digital assets (Tambe et al., 2020). This dichotomy between (i) the highly *centralised* production of industrial robots and accumulation of data assets and (ii) the highly *decentralised* consumption of smart devices and digital outputs, alerts on the need to carefully analyse the market structure implications of current trends.

Finally, the international dimension. ADP technology adoption has been sharply uneven across countries (Ghodsi et al., 2020). Deepening asymmetries in *functional* specialisation of labour might hinder wage upgrading through Global Value Chain participation, whereas a *robotised reshoring* of internationally fragmented production might not boost employment in advanced economies, while lowering income in developing ones. Thus, wider implications of ADP technologies for *global* structural change are still awaiting to be drawn.

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Subject Index