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Artificial intelligence as a general-purpose technology: an historical perspective

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Abstract: This paper looks at the impact on productivity of general-purpose technologies such as steam, electricity, and ICT. It finds they had big effects but only with a lag which was substantial in the first two cases. The experience of the First Industrial Revolution is explored and it is found that this is not a template for a general-purpose technology having a major adverse effect on workers' living standards. The essence of that industrial revolution was not rapid productivity growth in the short run, but the 'invention of a new method of invention' which increased technological progress in the long run. Since artificial intelligence is potentially a general-purpose technology that raises the productivity of research and development, it may be the basis for a Fourth Industrial Revolution.

Keywords: artificial intelligence, general purpose technology, industrial revolution, method of invention, total factor productivity growth

JEL classification: N12, N13, O31, O32, O47

I. Introduction

A general-purpose technology (GPT) has been defined as 'a single generic technology, recognizable as such over its whole lifetime, that initially has much scope for improvement and eventually comes to be widely used, to have many uses, and to have many spillover effects' (Lipsey *et al.*, 2005, p. 98). As such, it can be expected to be pervasive and to have a significant impact on aggregate productivity growth, possibly for a long period of time and probably after an initial lag. The classic examples are typically considered to be steam, electricity, and information and communications technologies (ICT). Growth accounting is one way to estimate the productivity impact of these GPTs (section II).

Quite possibly, artificial intelligence (AI) will eventually also be seen as a classic GPT. Indeed, 'techno-optimists' would argue that today's productivity paradox of excitement about AI and robotics combined with slow productivity growth is explained

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by the delay before the potential of this new GPT is realized (Brynjolfsson *et al.*, 2019). Growth accounting estimates for earlier GPTs show that their impact on productivity takes time to develop.

At the same time, new technologies are feared by some for the pressure that may be put on the labour market with adverse implications for workers' living standards. British industrialization in the early nineteenth century is often seen as a prime example of such an outcome. It is well-known that real wages increased very slowly during this period of acceleration in technological progress, which is often seen as an era when the share of wages in national income was squeezed in an early example of workers being replaced by machines. Informed by the account of 'Engels' Pause' in Allen (2009), this interpretation has attracted renewed interest from economists in the context of worries about the impact of AI and robotics on the labour market (Acemoglu and Restrepo, 2019; Frey, 2019). This experience is reviewed in section III to see whether it really is a worrying precedent.

Cheerleaders for AI expect it to be a GPT driving a 'Fourth Industrial Revolution' (Schwab, 2017). Earlier industrial revolutions are also often thought to be associated with classic GPTs: steam with the First Industrial Revolution, electricity with the Second Industrial Revolution, and ICT with the Third Industrial Revolution. For an economic historian, however, this does not do justice to the concept of an 'industrial revolution' which entails a significant change in the methods of generating advances in technology rather than faster technological progress and an acceleration in the rate of productivity growth *per se*.

As Alfred North Whitehead famously remarked, 'the greatest invention of the 19th century was the invention of the method of invention' (1925, p. 120). The First, Second, and Third Industrial Revolutions each saw improved methods of invention and it is helpful to consider the prospects for the impact of AI as a GPT that delivers a Fourth Industrial Revolution in the light of this historical experience (section IV). To achieve this, it needs to be not just a GPT but also the invention of a method of invention (IMI), as some writers think it may be (Cockburn *et al.*, 2019).

In general, IMIs and GPTs are distinct, as Figure 1 describes. IMIs raise productivity in the production of ideas, while GPTs raise productivity in the production of goods

Figure 1: GPTs and IMIs

		General purpose technology	
		No	**Yes**
Invention of a method of invention	**No**	Bessemer converter Industrial robots	Steam power Autonomous vehicles
	Yes	Research laboratory Algorithms	ICT Deep learning

Source: Adapted from Cockburn *et al.* (2019).

and services. However, a subset of GPTs also provide an IMI and have an important role in increasing the productivity of innovative effort. ICT was a case in point. The contribution to productivity growth as an IMI will typically not be attributed directly to the GPT by growth accounting but will show up as an increase in total factor productivity (TFP) growth in the aggregate economy.

II. Implications of growth accounting estimates

The conventional approach to estimating the productivity impact of a GPT is through an elaboration of traditional neoclassical growth accounting which aims to capture the contributions of growth in capital per worker and of the growth of total factor productivity (TFP) on labour productivity growth in the production of GDP.

This allows for different types of capital and distinguished separate components of TFP growth as follows:

$$\begin{aligned}\Delta\,(\mathrm{Y/L})\,/\,(\mathrm{Y/L}) \;&=\; \alpha\Delta\,(\mathrm{K_O/L})\,/\,(\mathrm{K_O/L}) \;+\; \beta\Delta\,(\mathrm{K_{GPT}/L})\,/\,(\mathrm{K_{GPT}/L}) \\ &\quad+\; \omega(\Delta \mathrm{A/A})_{\mathrm{GPT}} + \varphi(\Delta \mathrm{A/A})_{\mathrm{O}}\end{aligned} \tag{1}$$

This equation decomposes the sources of labour productivity growth into contributions from two types of capital, GPT capital and other capital, each weighted by their income shares, β and α, and two types of TFP growth in the production of GPT equipment and in the rest of the economy, each weighted by their shares in gross output, ω and φ. Thus, the GPT has impacts on labour productivity growth both through a capital-deepening effect and through own TFP growth.

It is also possible that a GPT creates externalities from the use of GPT capital through knowledge spillovers. A conventional way to modify equation (1) to include a term for TFP spillovers is as follows:

$$\begin{aligned}\Delta\,(\mathrm{Y/L})\,/\,(\mathrm{Y/L}) \;&=\; \alpha\Delta\,(\mathrm{K_O/L})\,/\,(\mathrm{K_O/L}) \;+\; \beta\Delta\,(\mathrm{K_{GPT}/L})\,/\,(\mathrm{K_{GPT}/L}) \\ &\quad+\; \omega(\Delta \mathrm{A/A})_{\mathrm{GPT}} \;+\; \varphi(\Delta \mathrm{A/A})_{\mathrm{O}} \;+\; \gamma\Delta\,(\mathrm{K_{GPT}/L})\,/\,(\mathrm{K_{GPT}/L})\end{aligned} \tag{2}$$

where $\gamma\Delta(\mathrm{K_{GPT}/L})/(\mathrm{K_{GPT}/L})$, represents the contribution of (unremunerated) TFP spillovers resulting from GPT capital deepening, but a way has to be found to estimate γ and most studies have chosen to omit this item. These TFP spillovers would be counted as part of total TFP growth rather than the capital-deepening contribution of GPT capital and if no attempt is made to measure them they would accrue as part of $\varphi(\Delta \mathrm{A/A})_{\mathrm{O}}$.

As is suggested by the definition, the impact of a GPT on productivity typically is modest initially but then increases over time. This is implied by the arithmetic of growth accounting since β and ω in equation (1) will be very small in the early days. At a deeper level, the reasons for the lags include improvements to the technology over time which increase its range of applications, reductions over time in the quality-adjusted price of the capital equipment in which it is embodied, and the time taken to implement complementary investments in organizational change.

Estimates based on the implementation of equation (1) for the three most famous GPTs, namely, steam, electricity, and ICT, in the leading economy of the time are displayed in Table 1. To place the chronology in perspective, it is worth noting that James Watt's steam engine was patented in 1769, Thomas Edison first distributed electrical

Table 1: GPTs: contributions to labour productivity growth (% per year)

	Capital deepening	TFP	Total	% Whole economy
Steam (UK)				
1760–1830	0.011	0.003	0.014	5.6
1830–1870	0.18	0.12	0.30	19.0
1870–1910	0.15	0.16	0.31	29.2
Electricity (USA)				
1899–1919	0.04	0.06	0.10	5.6
1919–1929 (1)	0.07	0.07	0.14	3.6
1919–1929 (2)	0.07	0.30	0.37	9.5
1929–1941	0.04	0.16	0.20	8.0
ICT (USA)				
1974–1995	0.41	0.36	0.77	49.4
1995–2004	0.78	0.72	1.50	49.0
2004–2012	0.36	0.28	0.64	41.0

Note: In 1919–1929 estimate (1) does not take account of TFP spillovers but they are included in estimate (2).
Sources: Crafts (2004), Byrne *et al.* (2013), Crafts and Woltjer (2021).

power to customers in New York in 1882, and the Intel 4004 microprocessor was introduced in 1971.

The examples of electricity and steam illustrate some of the reasons why it takes time for the impact of GPTs to build up. The big impact of electricity in the United States came in the 1920s, about 40 years after Thomas Edison first distributed electrical power in New York in 1882. The productivity gains came from the redesign of American factories which electricity facilitated but took time to be recognized and implemented and were realized through TFP spillovers (David, 1991).[1] The impact of steam power on productivity growth in Britain was negligible prior to 1830, when only 165,000 horsepower was in use (Crafts, 2004). Even in 1870 about two-thirds of steam power was used in coal mining, cotton textiles, and metal manufactures (Kanefsky, 1979). The cost effectiveness and diffusion of steam power was held back by the high coal consumption of the original low-pressure engines, and the move to high pressure—which benefited not only factories but railways and steam ships—was not generally accomplished until the second half of the nineteenth century. The science of the steam engine was not yet developed and the price of steam power fell very slowly, especially before about 1850.

The estimates in Table 1 reflect delays before the maximum impact of a GPT on productivity growth rates. Table 1 reveals both that the impact of ICT was relatively large and also that it came through very quickly. ICT was unprecedented in its rate of technological progress. In the context of Solow's productivity paradox—'you can see the computer age everywhere except in the productivity statistics'—it is worth noting that by historical standards the growth contribution of ICT in the late 1980s, when Solow made his famous comment, was already quite stunning. Arguably, western societies have been getting better at exploiting new technological opportunities so that the impacts are felt more quickly. This would perhaps not be surprising in the context

[1] In principle, unremunerated TFP spillover effects are distinct from the capital-deepening contribution to labour productivity growth from investment in new forms of capital goods which embody the GPT. They essentially represent externalities, for example, in the form of learning effects which enhance TFP. In practice, they are hard to measure and are omitted from nearly all growth accounting studies, hence their appearance in only one row of Table 1.

Table 2: Contributions to US labour productivity growth, 1974–95 (% per year)

	1974–1995	1995–2004	2004–2012
ICT capital	0.41	0.78	0.36
TFP in ICT	0.36	0.72	0.28
Other capital	0.38	0.44	0.38
Other TFP	0.20	0.90	0.20
Labour quality	0.26	0.22	0.34
Total	1.61	3.06	1.56

Note: Based on implementing equation (1) with an additional component for labour quality growth weighted by labour's share in national income. Estimates are for private non-farm economy.
Source: Byrne *et al.* (2013).

of superior scientific and technological capabilities, greater expenditure on R&D, and more sophisticated capital markets.[2]

In view of this history, it is quite reasonable to think that we are at the point with AI as a GPT when it is early in its lifetime and its significant impact on macroeconomic productivity performance lies in the future . . . but possibly relatively soon compared with the time that it took for steam and electricity to make a noticeable difference. This is indeed the argument of Brynjolfsson *et al.* (2019) who expect implementation and restructuring lags but emphasize that machine-learning systems will advance rapidly, not least because they are designed to improve themselves over time.

If GPTs have major implications for productivity growth, and 'great inventions' are the basis of strong overall productivity performance (Gordon, 2016), then an interval between them will entail a productivity slowdown. A good example of this is taken by the GPT literature to be the hiatus between steam and electricity in the later nineteenth century (Lipsey *et al.*, 1998), echoing the well-known hypothesis of Handfield-Jones and Phelps-Brown (1952) to explain the so-called 'climacteric' in British economic growth. This might be seen as a precedent for a similar slowdown today between the impacts of ICT and Artificial Intelligence (AI) on productivity growth.[3]

Viewing the history (and future) of productivity growth primarily in terms of the waxing and waning of GPTs is, however, not warranted, as is suggested by the estimates in Tables 1 and 2. ICT did loom very large, but while electricity and steam made important contributions to productivity growth, they were certainly not dominant. Indeed, the suggestion that the Victorian climacteric was a result of the end of the steam age is not borne out by the evidence. The slowdown in trend labour productivity growth started in the early 1870s and continued through the 1880s, with a decline from 2.2 per cent per year in 1869 to 0.8 per cent by 1890 according to recent estimates in Crafts and Mills (2020), but the growth accounting contribution of steam to productivity growth was about the same in 1870 to 1910 as in 1830 to 1870 (Table 1). As Musson pointed out a long time ago, 'steam-powered mechanization . . . [was] still proceeding at a tremendous pace . . . the 1870s did not witness the end of the "massive

[2] Section IV, below, examines the new and improved methods of invention which characterized successive 'industrial revolutions'.

[3] This idea was put forward by Ben Broadbent, Deputy Governor of the Bank of England, in an interview with the *Daily Telegraph* in 2018.

application" of steam power' (1963, p. 530). Steam horsepower in use rose from 2.1 million in 1870 to 9.7 million in 1907 (Kanefsky, 1979).

Similarly, the idea that 'great inventions' dominated the rise and fall of American productivity growth in the twentieth century, popularized but not quantified by Gordon (2016), is surely oversold. The sectors which embody the technology clusters which he sees as at the heart of the Second Industrial Revolution and propelling TFP growth to new heights by the 1940s accounted for only 36 per cent of labour productivity growth and 38 per cent of TFP growth in the private domestic economy during 1899 to 1941 (Bakker *et al.*, 2019).[4] Impressive but not by any means the whole story. And, in the recent past, the speeding up and slowing down of productivity growth in the United States around the turn of the twenty-first century is only partly (about half) explained by the acceleration and deceleration of the ICT contribution (Table 2).

III. The First Industrial Revolution

The term 'First Industrial Revolution' is often used to describe economic development in Britain between the 1760s and the 1830s. It is well-known that real wages increased very slowly during this period of acceleration in technological progress, which is often seen as an era when the share of wages in national income was under downward pressure in an early example of workers being replaced by machines. It should be clear from the previous section, however, that steam-powered productivity growth only started to have a significant impact after 1830.

Acemoglu and Restrepo (2019) set out a model where automation has a displacement effect as tasks are taken over by machines, which leads to job losses and reduces labour's share of national income. The displacement effect is offset in the long run by productivity and reinstatement effects. The former works through employment resulting from the demand created by higher incomes, and the latter comes from the creation of new tasks in which labour has a comparative advantage over machines, which leads to new jobs and a recovery in labour's share. If the displacement effect dominates the reinstatement effect, labour's share of national income falls and vice versa. Even if in the long run the reinstatement effects are larger, this may take a long time to materialize. Based on the estimates in Allen (2009), Acemoglu and Restrepo (2019) suggest that, although productivity growth accelerated, real wages stagnated, and labour's share fell for a period of 80 years from 1780 at the start of the industrial revolution. In other words, for a long time, displacement effects outweighed reinstatement effects.

The key diagnostic here is the share of labour in national income. This can be written as $wL/pY = (w/p)/(Y/L)$ where w is money wages, p is the GDP deflator, L is labour input, and Y is real GDP. When this formula is implemented using the new and improved dataset developed by Broadberry *et al.* (2015), labour's share shows only a

[4] Following Gordon (2016), 'great inventions' comprise technology clusters around electricity, the internal combustion engine, re-arranging molecules, and communications and entertainment. The distribution sector (which had a large share of value added but which might not be accepted by everyone as qualifying for inclusion in this list) accounts for a substantial part of the productivity growth.

Table 3: Factor shares (% GDP) and implied profit rate (%)

	Labour	Land	Capital	Profit rate
1770	61.0	21.8	17.2	9.8
1780	56.8	21.4	21.8	12.6
1790	57.1	19.8	23.1	13.1
1800	55.8	18.3	25.9	15.3
1810	56.4	16.3	27.3	16.0
1820	59.0	15.8	25.2	14.3
1830	60.7	15.1	24.2	14.1
1840	59.2	12.5	28.3	15.9
1850	65.3	10.5	24.2	12.9
1860	62.0	8.5	29.5	17.2

Note: Profit rate obtained by dividing capital share by the capital–output ratio using capital stock estimates in Feinstein (1988, p. 454).
Sources: Crafts (2020).

very short and modest decline at the beginning of the nineteenth century, as is reported in Table 3.[5]

The modest increase in labour's share of national income reported in Table 3 does not mean that the displacement effects highlighted by Acemoglu and Restrepo (2019) were absent. On the contrary, for some workers the impact of mechanization was devastating. The most notorious example is that of the handloom weavers who initially gained a lot from the prior mechanization of spinning but were then swept away by the invention of the power loom. They numbered 37,000 in 1780, 240,000 in 1820, but only 43,000 in 1850 (Allen, 2018). Their money wages were 75d per week in 1770, 276d in 1805 (the peak year), but were back to 75d by 1830 (Wood, 1910). That said, the overall trajectory of the labour market saw a proliferation of new tasks and this was reflected in the expansion of lower-middle class occupations (Allen, 2019); 253,000 families (8.6 per cent) were in this group in 1798, but 649,000 (15.4 per cent) in 1846. However, the redeployment of labour was left to market forces at the time and adjustment costs may have been quite high—this is an issue that deserves more research.

The share of profits in GDP rose over time from 17.2 per cent in 1770 to 29.5 per cent in 1860, but this was associated with a decline in the share of land rents rather than that of labour. This is hardly surprising in an industrializing economy where capital was being accumulated but agricultural land acreage was barely growing. The rate of profit increased but only slowly over most of this period. It is, however, fair to say that income inequality described a Kuznets Curve. The Gini coefficient has been estimated as 0.53 in 1759, 0.60 in 1798, 0.58 in 1846, and 0.48 in 1867 (Allen, 2019).

As Table 4 shows, the defining characteristic of the First Industrial Revolution is slow growth of labour productivity rather than pro-rich growth, especially in the first 50 years. In 1820, real GDP per worker had risen by about 16 per cent compared with

[5] Allen (2009) used a cost of living index rather than the GDP deflator to make his estimates. This distinction matters because in the first half of the nineteenth century real product wages grew much faster than real consumption earnings, reflecting differences between the rate of inflation as measured by the GDP deflator and a cost of living index. Technological progress had a bigger impact on the former than the latter. Estimates of the GDP deflator have only become available since Allen wrote his paper.

Table 4: Real GDP/worker and real wages (1770 = 100)

	Real GDP/ worker	Real consumption earnings	Real product wages
1770	100.0	100.0	100.0
1780	104.0	105.2	97.0
1790	104.2	109.3	97.6
1800	113.8	109.3	104.2
1810	118.7	109.6	109.8
1820	115.9	111.6	112.2
1830	124.7	114.3	124.3
1840	143.9	127.1	139.8
1850	154.3	148.9	165.3
1860	164.1	154.7	167.1

Note: Columns 2 and 3 are 5-year averages centred on year stated.
Sources: Derived from Thomas and Dimsdale (2017, Table A8 Column B and Table A49 Column AI, Table A48 Column X, Table A47 Columns B and R).

Table 5: Growth accounting estimates, UK 1700–1913 (% per year)

	Labour productivity growth	Capital deepening contribution	Labour quality contribution	TFP growth
1700–1760	0.25	0.10	0.01	0.14
1760–1780	–0.01	–0.06	–0.01	0.06
1780–1800	0.46	0.19	–0.01	0.28
1800–1830	0.29	0.10	0.01	0.18
1830–1856	1.11	0.65	0.08	0.38
1856–1873	2.06	0.72	0.32	1.02
1873–1913	1.06	0.38	0.58	0.10

Note: The growth accounting estimates are obtained using a standard neoclassical formula.
Source: Crafts (2021).

1770 and real consumption earnings by about 12 per cent. The increase in labour productivity outstripped that of real consumption earnings by a larger margin over the period 1770–1840, by 44 per cent to 27 per cent. Over the same period, real product wages increased by 39 per cent, so it is not surprising that labour's share of national income was little changed compared with 1770.[6]

The industrial revolution was a time of famous inventions including those of Richard Arkwright, Henry Cort, Samuel Crompton, George Stephenson, and James Watt. *Prima facie*, this 'wave of invention' seems to suggest that TFP growth and labour productivity growth would both speed up dramatically. However, the striking feature of the growth accounting estimates in Table 5 is that TFP growth was modest rather than spectacular, especially before 1830; the famous inventions did not promote a dramatic acceleration of TFP growth during the industrial revolution.[7]

[6] The estimates of real consumption earnings taken from the compilation in Thomas and Dimsdale (2017) are based on Feinstein (1998) and Allen (2007).

[7] The estimates of TFP growth in Table 5 do not allow for land inputs. Taking account of them would raise TFP growth during the Industrial Revolution slightly but would not change the basic picture (see Crafts, 2020).

How can the paradox of famous inventions but modest TFP growth be resolved? First, the impact of technological progress was very uneven. Agriculture and most of the service sector other than transport was largely unaffected. Sectors which we think of as the embodiment of the industrial revolution, namely, textiles, metals, and machine-making, accounted for less than a third of industrial employment—or 13.4 per cent of total employment—even in 1851 (Shaw-Taylor, 2009), while much industrial employment was still in 'traditional' sectors. Second, the process of technological advance was characterized by many incremental improvements and learning to realize the potential of the original inventions. This took time in an era where scientific and technological capabilities were still very weak by later standards. Steam technology is an excellent example and its impact was delayed until after 1830.

Looking at the industrial revolution with a view to finding a precedent for traumatic labour market shocks from labour-saving technological progress in the manner of Frey (2019) is misguided. Labour's share of national income did not decrease significantly as displacement effects were offset by reinstatement effects. The steam age only came quite late in the day (cf. Table 1). The story of the industrial revolution is surely not one of a new GPT boosting productivity growth at the expense of a big shift in the distribution of income, as is the current fear about AI.

IV. Industrial revolutions as the invention of a new method of invention

As we have seen, the industrial revolution is not a template for studying the impact of technological change that gives a rapid and substantial boost to productivity at the expense of a significant and prolonged decline in labour's share of national income. The experience of the industrial revolution is more one of productivity paradox than pro-rich growth.[8] Nevertheless, it does mark a transition to modern economic growth based on a new era of technological progress.

The concept of the industrial revolution as essentially the invention of a new method of invention which for the first time could deliver sustained technological progress is an idea which has been documented in detail by Mokyr (2009). The new method of invention was based on systematic empiricism and experimentation that established what worked and which accumulated and made accessible useful knowledge which could promote further technological advance.

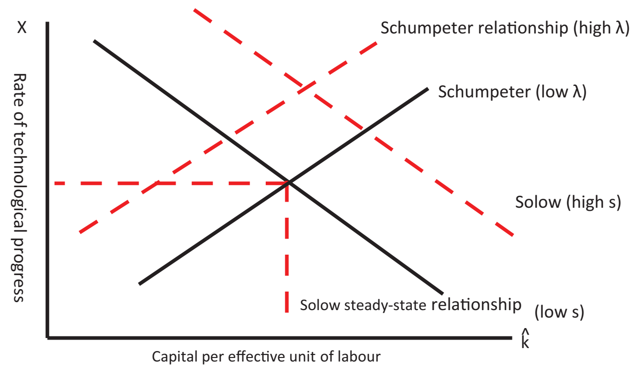
This interpretation fits naturally into the basic model of endogenous growth outlined by Carlin and Soskice (2006) which is represented in Figure 2. Here the equilibrium rate of technological progress is determined by the intersection of the Schumpeter and Solow lines (see the Appendix). The former can be written as:

$$\mathrm{X} = \lambda\sigma\mathrm{q} \tag{3}$$

where the rate of technological progress, x, depends on the amount of innovative effort or research intensity, q, the probability of successful innovation per unit of effort,

[8] Steam could be thought of as a precursor of Solow's ICT productivity paradox except that you couldn't see the steam age everywhere except in the productivity statistics in 1800.

Figure 2: Endogenous growth



Source: Carlin and Soskice (2006).

λ, and the extent to which each innovation raises productivity, σ. Innovative effort increases with market size, *inter alia*, hence the upward slope of the Schumpeter line.

The implications of the new method of invention of the First Industrial Revolution were to increase each of the variables on the right-hand side of (3). The probability of successful innovation was raised by the availability and accessibility of more knowledge, this encouraged more innovative effort since expected returns increased, and the impact of innovations was enhanced by a greater capability of improving initial designs and through more effective diffusion of new technology.

Central to this accumulation and diffusion of an evidence-based method of invention were 'knowledge access institutions' (KAIs), organizations whose objectives were to produce and disseminate scientific and technological knowledge, of which the first was the Royal Society (1660) and which included the Lunar Society (1765), the Manchester Literary and Philosophical Society (1781), the British Association for the Advancement of Science (1831), and Mechanics Institutes from 1823. The total number of KAIs was only three in 1761 but had risen to 1,014 by 1851. KAIs had a strong causal impact on patenting in their localities (Dowey, 2017). A further important component was the spread of skills in applied mathematics which underpinned measurement and calculation (Kelly and O'Grada, 2020). Here a key implication was the development of machine tools that were required to convert inventions into working machinery.

The First Industrial Revolution was based on empiricism rather than scientific understanding. The example of steam-engine technology is a good case in point. Nuvolari and Verspagen (2009) detail the progress made in raising fuel efficiency in Cornish pumping engines via detailed observation and reporting of the performance of different designs. Systematic data collection was used as a substitute for theoretical understanding. An important implication was that this localized technological learning did not diffuse to other locations and branches of industry.

It is important, however, not to exaggerate what was achieved in the First Industrial Revolution. A striking feature of the estimates in Table 5 is the weakness of TFP growth in the period 1873–1913. When growth accounting is conducted using hours worked and identifying a separate contribution from labour quality, TFP growth averaged 0.1 per cent per year. It is not correct to see the slowdown in TFP growth as a blip at the start of the twentieth century as is sometimes claimed (Crafts and Mills, 2020). As with the example of steam engines discussed above, the slowdown in TFP growth after 1873 is indicative of the limitations of the method of invention characteristic of the First Industrial Revolution.

The Second Industrial Revolution is a term conventionally applied to the late nineteenth and early twentieth centuries, say, 1870–1914. Again, it is useful to recognize that this is also an episode of a major change in the technology of developing new technology. Again, this entailed a step change in λ, σ, and q. The Second Industrial Revolution might be defined as the invention of another (superior) method of invention, in this case based on applied science and the innovation of the industrial research and development (R&D) laboratory in contrast to the First Industrial Revolution which had little or no scientific base.[9] Thomas Edison established his first laboratory in Menlo Park in 1876. The rise of electricity as a GPT was an important aspect of technological progress resulting from the Second Industrial Revolution.[10]

By 1918, 665 R&D laboratories had been established in American manufacturing (Mowery and Rosenberg, 1989), and by 1930 about half of all patents granted in the United States went to firms and half to independent inventors; the latter had accounted for about 95 per cent of patents in 1880 (Nicholas, 2010). Whereas only 12 per cent of 'great inventor' patents were granted to people with science or engineering training in pre-1845 birth cohorts in the United States, for the 1866–85 cohort this had risen to 60 per cent (Khan and Sokoloff, 2006). As with the First Industrial Revolution, TFP growth went to a new level, averaging 1.1 per cent per year during 1899–1929 (Bakker *et al.*, 2019).[11]

The Third Industrial Revolution is a term often used to refer to the period from the 1960s to the 2000s, when computer science came of age. It encompassed rapid development of computer hardware and software from the mainframe, through the PC, to the Internet (Schwab, 2017). A key characteristic of ICT is that it is both a knowledge technology and a GPT (Mokyr, 2002). As an IMI, ICT not only significantly reduced the access costs of knowledge, but also provided a new technology for innovation reflected in a big increase in the share of patent citations going to software, together with significantly more patents per R&D dollar as software intensity increased (Branstetter *et al.*, 2019).

Nordhaus (2007) documents the massive fall in computing costs over the second half of the twentieth century. Total costs of computation in 2006 dollars per million units of computer power fell from 25.7 in 1940–9, to 0.000592 in 1970–9, and 0.000000000137 in 2000–6. Xavier Sala-i-Martin (1997) wrote a paper based on 4 million regressions which would have taken his computer about 33 hours.[12] This contrasts with 40 hours

[9] Or in Mokyr's words, 'It created a chemical industry with no chemistry, an iron industry without metallurgy, power machinery without thermodynamics' (Mokyr, 1999, p.219).

[10] Gordon (2016) lists several other 'great inventions' associated with the period of the Second Industrial Revolution, including the internal combustion engine and chemical engineering.

[11] This estimate is arrived at after making a big deduction from crude TFP growth, which averaged 1.7 per cent per year, for the contribution of growth in labour quality. An earlier much cited estimate by Kendrick (1961) puts TFP growth at 1.4 per cent per year during 1899–1929. The national innovation system in the UK was much less successful in exploiting the potential of the Second Industrial Revolution.

[12] Sala-i-Martin states in the paper that his computer could run about 2,000 of his regressions per minute.

for Milton Friedman to run one regression in the late 1940s (Friedman and Schwartz, 1991).[13] This would suggest that the usual positive effects on the Schumpeter line and indeed the contribution to TFP growth of non-ICT sectors of the American economy increased from 0.14 per cent per year in 1974–95 to 0.89 per cent per year in 1995–2004 (Byrne *et al.*, 2013) as total TFP growth (including ICT sectors as well) rose from 0.50 per cent to 1.61 per cent per year. But, quite unlike the Second Industrial Revolution, this was not sustained.

Similarly, AI, notably through deep learning, may be the basis for a Fourth Industrial Revolution as a GPT which is also an IMI, and this may ultimately be its biggest contribution to productivity growth (Cockburn *et al.*, 2019). It can take data analysis to a new level and 'could become the world's most effective research assistant' (Mokyr, 2018, p. 23).[14] Royal Society (2019) highlights many research areas where AI may become a key tool. An obvious one is the discovery of new drugs. Recent breakthroughs include Halicin, the new antibiotic revealed by MIT in February 2020, and the solution of the 'protein-folding problem' by Deepmind in November 2020. It should be noted that if the impact of AI is to raise TFP growth across the economy through its role as a new technology for improving technology, this contribution to growth would not be attributed to AI by conventional growth accounting calculations of the type reported in Table 1 but would be recorded as higher 'other TFP growth'.

It has recently been suggested that the productivity of R&D is decreasing; in terms of Figure 2, the Schumpeter line is shifting down. If this is the case, it could reflect the picking of all the low-hanging fruit (Gordon, 2016) or an increasing burden of knowledge (Jones, 2009). Bloom *et al.* (2020) provide some evidence for the hypothesis that ideas have been getting harder to find; at the macro level they suggest that it is consistent with the fact that US TFP growth has slowed down markedly relative to R&D expenditure since the 1930s.[15] This conclusion is controversial but, if this is a correct interpretation of recent economic history, AI may be an antidote (Agrawal *et al.*, 2019): it may mean that ideas become easier to find—as they did during the First Industrial Revolution.

V. Conclusions

It typically takes time before a GPT has a substantial impact on productivity. The technology improves, complementary investments and innovations are made, businesses are re-organized, and learning accrues. The examples of steam, electricity, and ICT

[13] Backhouse and Cherrier (2017) review a wide array of implications of massively greater computing power for economists' research and conclude that it transformed economics in the course of the last 30 or 40 years.

[14] Textual analysis using machine learning has already become a major research tool in economics (Gentzkow *et al.*, 2019). This is exemplified by a recent paper inferring levels of happiness in the population over the last 200 or so years from text in digitized books (Hills *et al.*, 2019). The automated analysis was technologically infeasible 10 years ago and if performed manually would have taken at least 80 billion person hours.

[15] *Inter alia*, it is quite possible that the slowdown in TFP growth reflects a lack of economic dynamism (Dekker *et al.*, 2017) perhaps linked to weaker competition in the American economy (Philippon, 2019). See Crafts (2018) for a review of the evidence.

illustrate that time-lags are to be expected. It is quite plausible that this will also be the experience with AI as it progresses. If AI fulfils its promise, it will alleviate the current productivity slowdown. Nevertheless, many other things matter for productivity performance as well as the arrival of a new GPT. Optimism over AI is no reason to neglect supply-side policy reforms, for example, to address the trend to weaker competition in the American economy.

If AI does raise productivity substantially in due course, the dark side may be the disappearance of many jobs with significant downward pressure on real wages and labour's share of national income. The First Industrial Revolution is sometimes viewed as a worrying example of such an experience, as mechanization transformed industry. Such a pessimistic interpretation is, however, misplaced. This period was one of slow productivity growth and no big shift in income distribution; while there was displacement of workers by machines, at the same time new tasks proliferated. The key policy implication is that policies to reduce adjustment costs and facilitate redeployment of workers will be important to underpin reinstatement effects that can offset the initial displacement effects.

A useful way to conceptualize an industrial revolution is to see it as the invention of a new method of invention which has the potential to raise the rate of productivity growth. Looked at in this way, AI may be the basis for a Fourth Industrial Revolution, and a major channel for its impact as a GPT may be through raising the productivity of R&D. This would be especially welcome if, as some economists believe, ideas have been harder to find in recent times.

Appendix

Modern growth economics based on the idea of endogenous innovation makes TFP growth endogenous. The key ideas are captured in Figure 2, which is based on Carlin and Soskice (2006), in which x is the rate of (labour-augmenting) technological progress and $\hat{k}$ is the capital to effective labour ratio.

The downward-sloping (Solow) line represents the well-known inverse steady-state relationship between technological progress and the capital-intensity of the economy for a given savings rate in the neoclassical growth model.

The intuition for this is as follows. Steady-state growth means that the rate of growth of the capital stock is equal to the rate of growth of the labour force plus the rate of growth of labour-augmenting technological progress ($\Delta K/K = \Delta L/L + x$) and $\Delta K/K = sY/K$. So, capital stock growth is inversely related to the average product of capital. In the neoclassical model, it is assumed that marginal and average product of capital fall as the capital to labour ratio increases, so the rate of growth of the capital stock is inversely related to the capital to labour ratio. In equilibrium, faster technological change requires faster capital stock growth and for a given value of s this requires a lower capital to labour ratio. Hence the slope of the Solow line.

The upward-sloping (Schumpeter) line reflects the endogeneity of technological progress based on the assumption that a larger market increases innovative effort because it is potentially more profitable since success will be rewarded by greater sales. With more capital per unit of effective labour there will be higher income per person so the Schumpeter line is upward-sloping.

The equilibrium rate of technological progress is established by the intersection of these two lines and, in turn, this determines the rate of economic growth.

Figure 2 implies that the rate of innovation increases when either the Solow and/or the Schumpeter line shifts upward. In the former case, this will be the result of an increased rate of investment which in this model does have growth rate effects. In the latter case, this will be the result of an increase in innovative effort, together with the productivity and impact of that effort, for any given market size. This will in general reflect institutions and policies but, crucially for the argument of this paper, also the method of invention.

References

Acemoglu, D., and Restrepo, P. (2019), 'Artificial Intelligence, Automation and Work', in A. Agrawal, J. Gans, and A. Goldfarb (eds), *The Economics of Artificial Intelligence: An Agenda*, Chicago, IL, University of Chicago Press, 197–236.

Agrawal, A., McHale, J., and Oettl, A. (2019), 'Finding Needles in Haystacks: Artificial Intelligence and Recombinant Growth', in A. Agrawal, J. Gans, and A. Goldfarb (eds), *The Economics of Artificial Intelligence: An Agenda*, Chicago, IL, University of Chicago Press, 149–74.

Allen, R. C. (2007), 'Pessimism Preserved: Real Wages in the British Industrial Revolution', Oxford University Department of Economics, Working Paper No. 314.

— (2009), 'Engels' Pause: Technical Change, Capital Accumulation, and Inequality in the British Industrial Revolution', *Explorations in Economic History*, **46**, 418–35.

— (2018), 'The Hand-loom Weaver and the Power Loom: A Schumpeterian Perspective', *European Review of Economic History*, **22**, 381–402.

— (2019), 'Class Structure and Inequality during the Industrial Revolution: Lessons from England's Social Tables, 1688–1867', *Economic History Review*, **72**, 88–125.

Backhouse, R., and Cherrier, B. (2017), '"It's Computers Stupid!" The Spread of Computers and the Changing Roles of Theoretical and Applied Economics', *History of Political Economy*, **49**, S103–S126.

Bakker, G., Crafts, N., and Woltjer, P. (2019), 'The Sources of Growth in a Technologically Progressive Economy: The United States, 1899–1941', *The Economic Journal*, **129**, 2267–94.

Bloom, N., Jones, C. I., Van Reenen, J., and Webb, M. (2020), 'Are Ideas Getting Harder to Find?', *American Economic Review*, **110**, 1104–44.

Branstetter, L. G., Drev, M., and Kwon, N. (2019), 'Get with the Program: Software-driven Innovation in Traditional Manufacturing', *Management Science*, **65**, 541–58.

Broadberry, S., Campbell, B., Klein, A., Overton, M., and van Leeuwen, B. (2015), *British Economic Growth, 1270–1870*, Cambridge, Cambridge University Press.

Brynjolfsson, E., Rock, D., and Syverson, C. (2019), 'Artificial Intelligence and the Modern Productivity Paradox: A Clash of Expectations and Statistics', in A. Agrawal, J. Gans, and A. Goldfarb (eds), *The Economics of Artificial Intelligence: An Agenda*, Chicago, IL, University of Chicago Press, 23–57.

Byrne, D. M., Oliner, S. D., and Sichel, D. E. (2013), 'Is the Information Technology Revolution Over?', *International Productivity Monitor*, **25**, 20–36.

Carlin, W., and Soskice, D. (2006), *Macroeconomics: Imperfections, Institutions and Policies*, Oxford, Oxford University Press.

Cockburn, I. M., Henderson, R., and Stern, S. (2019), 'The Impact of Artificial Intelligence on Innovation: An Exploratory Analysis', in A. Agrawal, J. Gans and A. Goldfarb (eds.), *The Economics of Artificial Intelligence: An Agenda*, Chicago, IL, University of Chicago Press, 115–46.

Crafts, N. (2004), 'Steam as a General-purpose Technology: A Growth Accounting Perspective', *The Economic Journal*, **114**, 338–51.

Crafts, N. (2018), 'The Productivity Slowdown: Is It the "New Normal?"', *Oxford Review of Economic Policy*, **34**(3), 443–60.
— (2020), 'Slow Real Wage Growth during the Industrial Revolution: Productivity Paradox or Pro-Rich Growth?', *Oxford Economic Papers*, forthcoming.
— (2021), 'The Sources of British Economic Growth since the Industrial Revolution: Not the Same Old Story', *Journal of Economic Surveys* (2020), forthcoming.
— Mills, T. C. (2020), 'Sooner than You Think: the Pre-1914 UK Productivity Slowdown was Victorian not Edwardian', *European Review of Economic History*, **24**, 736–48.
— Woltjer, P. J. (2021), 'Growth Accounting in Economic History: Findings, Lessons, and New Directions', *Journal of Economic Surveys*, forthcoming.
David, P. A. (1991), 'Computer and Dynamo: the Modern Productivity Paradox in a Not-Too-Distant Mirror', in OECD, *Technology and Productivity: The Challenge for Economic Policy*, 315–47, Paris, OECD.
Dekker, R., Haltiwanger, J., Jarmin, R. S., and Miranda, J. (2017), 'Declining Dynamism, Allocative Efficiency, and the Productivity Slowdown', Federal Reserve Board Finance and Economics Discussion Paper No. 2017–019.
Dowey, J. (2017), 'Mind Over Matter: Access to Knowledge and the British Industrial Revolution', unpublished PhD thesis, London School of Economics.
Feinstein, C. H. (1988), 'National Statistics, 1760–1920', in C. H. Feinstein and S. Pollard (eds), *Studies in Capital Formation in the United Kingdom, 1750–1920*, Oxford, Clarendon Press, 259–471.
Frey, C. B. (2019), *The Technology Trap: Capital, Labor and Power in the Age of Automation*, Princeton, NJ, Princeton University Press.
Friedman, M., and Schwartz, A. J. (1991), 'Alternative Approaches to Analyzing Economic Data', *American Economic Review*, **81**, 39–49.
Gentzkow, M., Kelly, B., and Taddy, M. (2019), 'Text as Data', *Journal of Economic Literature*, **57**, 535–74.
Gordon, R. J. (2016), *The Rise and Fall of American Growth*, Princeton, NJ, Princeton University Press.
Handfield-Jones, S. J., and Phelps-Brown, E. H. (1952), 'The Climacteric of the 1890s: a Study in the Expanding Economy', *Oxford Economic Papers*, **4**, 266–307.
Hills, T., Proto, E., Seresinhe, C., and Sgroi, D. (2019), 'Analysis of National Subjective Well-being using Millions of Digitized Books', *Nature Human Behaviour*, 15 October.
Jones, B. (2009), 'The Burden of Knowledge and the "Death of the Renaissance Man": Is Innovation Getting Harder?', *Review of Economic Studies*, **76**, 283–317.
Kanefsky, J. (1979), 'The Diffusion of Power Technology in British Industry', unpublished PhD dissertation, University of Exeter.
Kelly, M., and O'Grada, C. (2020), 'Connecting the Scientific and Industrial Revolutions: The Role of Practical Mathematics', UCD Centre for Economic Research Working Paper No. 20/17.
Kendrick, J. W. (1961), *Productivity Trends in the United States*. Princeton, NJ, Princeton University Press.
Khan, B. Z., and Sokoloff, K. L. (2006), 'Institutions and Technological Innovation during Early Economic Growth: Evidence from the Great Inventors of the United States, 1790–1830', in T. Eicher and C. Garcia-Penalosa (eds), *Institutions and Economic Growth*, Cambridge, MA, MIT Press, 123–58.
Lipsey, R. G., Bekar, C. T., and Carlaw, K. I. (1998), 'The Consequences of Changes in GPTs', in E. Helpman (ed.), *General Purpose Technologies and Economic Growth*, Cambridge, MA, MIT Press, 193–218.
— Carlaw, K. I., and Bekar, C. T. (2005), *Economic Transformations: General Purpose Technologies and Long-Term Economic Growth*, Oxford, Oxford University Press.
Mokyr, J. (1999), 'The Second Industrial Revolution, 1870–1914', in V. Castronovo (ed.), *Storia dell' Economia Mondiale*, vol. 3, Rome, Laterza, 219–45.
— (2002), *The Gifts of Athena: Historical Origins of the Knowledge Economy*, Princeton, NJ, Princeton University Press.

Mokyr, J. (2009), *The Enlightened Economy: an Economic History of Britain 1700–1850*, New Haven, CT, Yale University Press.
— (2018), 'The Past and Future of Innovation: Some Lessons from Economic History', *Explorations in Economic History*, **69**, 13–26.
Mowery, D., and Rosenberg, N. (1989), *Technology and the Pursuit of Economic Growth*, Cambridge, Cambridge University Press.
Musson, A. E. (1963), 'British Industrial Growth during the 'Great Depression' (1873–96): Some Comments', *Economic History Review*, **15**, 529–33.
Nicholas, T. (2010), 'The Role of Independent Invention in US Technological Development, 1880–1930', *Journal of Economic History*, **70**, 57–82.
Nordhaus, W. D. (2007), 'Two Centuries of Productivity Growth in Computing', *Journal of Economic History*, **67**, 128–59.
Nuvolari, A., and Verspagen, B. (2009), 'Technical Choice, Innovation and British Steam Engineering, 1800–1850', *Economic History Review*, **62**, 685–710.
Philippon, T. (2019), *The Great Reversal: How America Gave Up on Free Markets*, Cambridge, MA, Belknap Press.
Royal Society (2019), *The AI Revolution in Scientific Research*.
Sala-i-Martin, X. (1997), 'I Just Ran Four Million Regressions', NBER Working Paper No. 6252.
Schwab, K. (2017), *The Fourth Industrial Revolution*, New York, Crown Business.
Shaw-Taylor, L. (2009), 'The Occupational Structure of England and Wales, 1750–1871: A Preliminary Report', Cambridge Group for the History of Population and Social Structure Occupations Project Paper No. 19.
Thomas, R., and Dimsdale, N. (2017), 'A Millennium of UK Data', Bank of England OBRA Dataset, http://www.bankofengland.co.uk/research/Pages/onebank/threecenturies.aspx
Whitehead, A. N. (1925), *Science and the Modern World*, London, Cambridge University Press.
Wood, G. H. (1910), 'The Statistics of Wages in the United Kingdom during the Nineteenth Century (Part XVIII): The Cotton Industry', *Journal of the Royal Statistical Society*, **73**, 411–34.