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Technological change: History, theory and measurement. A brief account

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Technological Change: History, Theory and Measurement A Brief Account

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Abstract

Technological change, an overwhelming fact in recent socioeconomic history, involves, as Joseph A. Schumpeter famously put it, "creative destruction" on a large scale: it gives rise to new goods, production methods, firms, organisations, and jobs, while rendering some received ones obsolete. Its impact extends beyond the economy and affects society, culture, politics, and the mind-set of people. While it allows solving certain problems, it causes new ones, inducing further technological change. Against this background, the paper attempts to provide a detailed, yet concise exploration of the historical evolution and measurement of technological change in economics. It touches upon various questions that have been raised since Adam Smith and by economic and social theorists after him until today living through several waves of new technologies. These questions include: (1) Which concepts and theories did the leading authors elaborate to describe and analyse the various forms of technological progress they observed? (2) Did they think that different forms of technological progress requested the elaboration of different concepts and theories – horses for courses, so to speak? (3) How do different forms of technological progress affect and are shaped by various strata and classes of society? Issues such as these have become particularly crucial in the context of the digitisation of the economy and the widespread use of AI. Finally, the paper explores the impact of emerging technologies on the established theoretical frameworks and empirical measurements of technological change, points to new measurements linked to the rise of these technologies, and evaluates their pros and cons vis-à-vis traditional approaches.

Keywords: technological change, classical economics, neoclassical economics, growth accounting, endogenous growth, evolutionary economics, sociotechnical studies, GPTs, digitalisation, AI

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Executive summary

This report, authored by Heinz D. Kurz, Rita Strohmaier, and Mark Knell, provides a comprehensive historical and analytical account of technological change and its significant impact on economic and social structures. Central to the analysis is the principle of "creative destruction," which illustrates how innovation not only resolves existing challenges but also disrupts established systems, transforming industries, labour markets, and institutional arrangements. A thorough understanding of the nature, pace, and consequences of technological change is essential for developing effective and forward-looking public policy.

Purpose and Scope: The report traces the evolution of economic thought on technological change, from classical thinkers such as Adam Smith and Karl Marx to contemporary economists. It emphasises the necessity of employing diverse analytical frameworks to account for various forms of technological progress, particularly distinguishing between radical innovations that fundamentally alter industries and incremental innovations that enhance existing processes.

Summary of Findings: Technological change has historically served as a central force in economic transformation. The analysis reveals how innovations have consistently improved labour productivity while reshaping patterns of income distribution and social organisation. Contributions from classical economists established a foundation for recognising technology's critical role in production; however, the complexities of modern advancements require a more sophisticated understanding of their extensive effects.

The study highlights the concept of pervasive technological change, which fuels long-term economic cycles and has historically coincided with industrial revolutions. Key innovations, such as the steam engine and electricity, necessitated significant structural adjustments across labour markets, capital investments, regulatory systems, and educational frameworks, demonstrating the systemic nature of technological revolutions.

Furthermore, the paper explores how emerging technologies challenge traditional economic theories and existing measurement tools. It argues for the development of a renewed empirical foundation capable of capturing the complexities of contemporary technological advancements. Schumpeter's theory of long economic waves, driven by radical innovation, is revisited to underscore the cyclical, disruptive, and transformative characteristics of technological progress.

Policy Implications: Policymakers should support the advancements of economic analyses to better reflect the varied effects of technological change, particularly concerning labour dynamics, productivity, and inequality. Proactive management of disruptions caused by major technological innovations is essential; this includes strengthening social safety nets, updating skills training programmes, and promoting labour markets adaptability. Additionally, governments should invest in developing new statistical measures and indicators to effectively capture the societal and economic causes and impacts of emerging technologies. It is also crucial for policymakers to distinguish between incremental and radical innovations, creating differentiated strategies that address the distinct challenges and opportunities posed by each. Finally, public policy should ensure that the benefits of technological change are widely shared, facilitating equitable access to education, innovation funding, and digital infrastructure..

1 Introduction

Innovations, the "realisation of new combinations", Joseph A. Schumpeter insisted, are "the overwhelming fact in the economic history of the capitalist society" ([1912]: 159). He and major social scientists such as Adam Smith and Karl Marx also pointed out that technological and organisational change do not only revolutionise the economic world in which we live, they also affect in fundamental ways society, politics, culture, the distribution of power amongst various strata and classes of society, the way we think and feel, and so on.

Starting with the classical political economists, including Marx, economic thinking has revolved around three pivotal questions concerning technological change:

(1) To understand the causative factors, driving forces, and pace of technological and organizational transformations.

(2) To classify different forms of technological progress and investigate when and why certain forms dominated, what caused their historical sequencing and path dependency.

(3) To assess and possibly anticipate the diverse effects of technological change on employment, income and wealth distribution, power relationships, economic growth, foreign trade, and so on.

While variously seen as a lever of riches, wealth and well-being, ever since the inception of systematic economic analysis in the antechamber of the First Industrial Revolution, the understanding gradually took shape that technological change is capable of solving pressing problems of humankind, but at the same time is often the source of entirely new problems. The basic idea underlying this understanding is the doctrine of the unintended consequences of human action, advocated inter alia by members of the Scottish Enlightenment and especially Adam Smith, who championed the rise of political economy as a new field of scientific inquiry. A main problem humankind is facing at present, global warming and climate change, is but the most significant and arguably most dangerous case of such unintended consequences.

The questions that were and are being asked since Smith and social theorists after him up until today, living through several waves of new technologies, are the effects these waves had on the socioeconomic system, broadly understood, and reverberations from there back to the origins of technological change, the economic system. More specifically, these include the following:

(1) Which concepts and theories did the leading authors elaborate in order to describe and analyse the various forms of technological progress they observed?

(2) Did they think that different forms of technological progress requested the elaboration of different concepts and theories – "horses for courses", so to speak? This problem has significantly gained in importance vis-à-vis the digitisation of economy and society and the growing employment of AI.

(3) How do different forms of technological progress affect different strata and classes of society? Are there both winners and losers, how large are losses and gains in terms of employment, wages, profits, social reputation and so on? Which metrics are available to measure such changes and are new metrics to be developed in order to cope with new, qualitatively different types of change?

(4) What can be done to fight undesired consequeneces and promote desired ones?

These and related questions will be dealt with in this contribution against the background of the existing literature pertinent to the theme under consideration. The approach chosen combines a historical-cum-analytical outlook, a strong concern with theoretical tools and devices and a rich account of empirical findings. While we assess the different forms of technological change, their causes and their effects and the instruments forged by scholars to deal with them, what interests us is what we can learn today from them, confronted with new forms in what is variously called the "Second Machine" or the "4th and 5th Industrial Revolution" (Kurz et al. 2022).

The transition from the First to the Second Machine Age, as described by Brynjolfsson and McAfee (2014), signifies a profound change. In the First Machine Age durable instruments of production depreciated with age. However, in the Second Machine Age, learning machines that enhance efficiency over time appreciate in value, unless overtaken in a leapfrogging manner by newly invented machines. This transition alters the diffusion pattern of technical devices, moving from a sigmoid trajectory to an arguably exponential one, unless surpassed by entirely novel inventions. This dynamic shift illustrates in an exemplary way the transformative nature of technological change and its far-reaching implications across various domains of socioeconomic life.

The remainder of the paper is as follows: The first part traces technological change through the lenses of classical economists, Karl Marx, early marginalists, Robert Solow's growth accounting, and new (endogenous) growth theory. It thereby focuses on the main ideas and strands of thought that have been transcending into economic analysis up until today. The second part examines pervasive technological change, encompassing its core analytical frameworks – from evolutionary-economic concepts over sociotechnical systems to general purpose technologies (GPT) – and illustrates empirical approaches that have made use of these concepts. The third part finally analyses the impact of new technologies on theoretical frameworks and measurement devices. Identifying the Digital Revolution as the Fifth Technological Revolution, we explore successive industrial revolutions, the "second deep transition", and the trajectory towards the quantum age. The paper concludes by highlighting the influence of new technologies on economic thought and the emergence of novel measurements in the digital revolution.

2 A summary of some major analyses of technological change

This part is dedicated to a short history of major attempts to come to grips with various forms of technological progress and their effects on labour productivity, the composition of skills, income distribution, economic growth and development. The part informs about major differences between different forms of technological progress and how later forms grew out of earlier ones. In addition, it informs about parallel attempts by economists to grasp these differences analytically and identify both the genuine significance of each form and at the same time how it relates to preceding and following forms. Digitisation may then be understood as a particular phase in a long chain of technological change, where each phase reflects its path-dependent nature. Fascinated by the new idea and perceived reality of socio-economic "progress", economists were keen to express the rate of change or rate of progress in terms of some compact measure. The problem of measurement was high on the agenda ever since, especially because technological progress involved not only quantitative, but also qualitative change. How to cope with this fact? Was there such a thing as an "ultimate measure" of all forms and types of technological change, which allowed one to measure these in a meaningful way in terms of a well-defined device across time and space, all their heterogeneity notwithstanding? Or did this involve chasing a will-o-the-wisp? Were different forms and types of technological change invariably irreducible to some common norm and therefore incommensurable and had to be treated differently?

2.1 In the antechamber of the First Industrial Revolution

In early pre-First Industrial Revolution contributions to economic development, that is, in the mercantile period, the focus is on the role of "demonstration effects" of foreign trade in consumption and production on labour productivity and slowly changing consumption patterns and lifestyles. With the rate of technological change being small, trade is seen as a device to move towards what may be called the "world frontier of technological knowledge" by adopting existing technologies experienced abroad and adapting them to domestic needs, wants and capabilities. The authors under consideration, including William Petty, François Quesnay, David Hume and Adam

Smith saw themselves as the founders of a new science, political economy, that was both empirical and theoretical, concerned with providing a quantitative analysis of the productive capacity of a nation and the means and ways to increase it.

2.2 The classical economists

A significantly more profound analysis of technological change is provided by the Classical economists, especially Adam Smith (1776) and David Ricardo (1821), and of Charles Babbage (1835), the so-called "father of the computer", who as early as the 1830s already pointed in the direction of a Second Machine Age, that is, machines that are capable of learning and self-optimising (see Kurz 2022).

The authors under consideration laid the ground for a modern understanding of technological change and also discussed in some depth the problem of how to measure it. Their concern was no longer with approaching a given technological frontier but with *moving the existing frontier outwards*. Technological progress was seen to increase the productive powers of society, and the main indicator to measure and express this progress was in terms of the rate of growth of *labour productivity*. An increase in labour productivity led to an increase in *real income per capita*, and the economic performance of a nation and how it compared with other nations was henceforth measured in terms of differential rates of growth of labour productivity. It was also clear to the classical economists that the "productive powers" of society depended crucially on the "quantity of science" at its disposal, as Adam Smith stressed verbatim. Hence, attempts were made already at an early time to move science and technology as productive forces into the centre of economic inquiry.

Since commodities were produced by means of (direct) labour and other commodities used as inputs, these authors suggested to reduce these other commodities also to labour and commodities used up in their production, and so on and so forth. By this *Method of Reduction* they arrived at the sum total of labour, which, for a given technological knowledge, was directly or indirectly needed in the production of a commodity.

The characteristic feature of technological progress was seen to consist in reducing this amount, that is, it was seen to be *labour-saving*. Since the direct and indirect amount of labour mentioned gives the total (labour) cost of production of a commodity, it was expected to approximate its price in the market: the *labour theory of value* was introduced to explain *relative prices*. Technical progress in the production of commodity *j* implied that in competitive conditions its price would eventually decrease relative to the prices of all other commodities. To the extent to which commodity *j* entered as an input into other commodities, also their prices, measured in labour terms, would tend to decrease somewhat because of the decrease in a cost element. Hence the classical authors put forward a sophisticated theory of how the system of relative prices would change vis-à-vis cases of technological change affecting the various industries of the economy differently.

But they also saw that technological change associated with new means of production does not typically leave the dimension of the system of production unaffected: new methods of production and new consumables enter the system and some received methods and consumables exit from it, with the number of entries typically exceeding the number of exits. Technological progress therefore had an important qualitative-cum-quantitative dimension, which poses difficult measurement problems. How does the system of social accounting elaborated in a "world of corn and wood" perform in a "world of coal and iron", not to speak (yet) of a "world of bits and bytes"? How would it have to be changed to provide us with reliable information about the economic process and its incessant changes? Early versions of the problem mentioned we encounter in the classical authors, for example, in terms of their search for an "ultimate measure of value".

The classical economists proposed a method of measuring technological progress, which is still widely used in economics today: they proposed to measure technological progress in terms of the *rate of growth of labour productivity*. Let us denote (net) labour productivity by y, which equals the ratio of net social product Y and the labour worked during a year L, then the rate of growth of technological progress, g_{TP}, is given by

$$g_{TP} = \frac{\mathrm{D}y}{y}.$$

The classical authors were fully aware of the problem of the heterogeneity and changing heterogeneity of labour as a consequence of technological improvements. They sought to render heterogeneous labours homogeneous by using the wages structure as a scale to express the different weights of different kinds of labour. If an hour of labour of type i is paid 15 Euros and an hour of labour of type j 30 Euros, then one hour of labour of type j is equivalent to two hours of labour of type i. The classical authors applied their scheme of rendering different types of labour commensurable with one another on the explicit presumption that the wage structure would not change much in the period of time considered. In this case, intertemporal and interspatial comparisons were taken to be possible. While this might have been an admissible assumption at their time, it is no longer one today with wages of skilled and unskilled labour growing at different rates. This requires rethinking the way of rendering heterogeneous labour homogeneous. The classical economists would at any rate have been surprised by, and opposed to, the contemporary procedure in many productivity studies to simply add hours of labour performed without considering the heterogeneity of labour and the different wage rates paid. This is like "adding apples and pears", which, first year students of economics are told, must not be done: prices (or wage rates) are to be used as aggregators.

The classical authors also began to distinguish between *different forms of technological progress* and the different effects these had regarding employment, economic growth, income distribution, the balance of power in society, the environment and so on. They distinguished between direct labour-saving and indirect labour-saving (that is the saving of labour embodied in capital gooods alias capital-saving) forms and land-saving forms of technological progress. They also contemplated cases in which the saving of some inputs was accompanied by an increase in the use of some other inputs. And they showed how these different forms affected the different strata and classes of society differently – landlords, capitalists and workers and different subgroups of them. Ricardo, for example, was very clear that the replacement of labour power by machine power might at least in the short and medium run cause serious problems to the working class in terms of (what later was called) "technological unemployment", declining real wages and worsening working conditions, and that therefore the "Luddite movement" and the demolition and destruction of machines by infuriated workers was understandable up to a point (but, as he insisted, counterproductive). And he also anticipated a problem we are confronted with again today: in the case of "full automation", which he saw as the terminal point of the process of mechanisation that had just started, the demand for labour would vanish and nobody who is not possessed of a capital would have a right to consume. This he pointed out as early as 1821. The spectre is back again and the question will be how to ward it off.

A major tool of the analysis elaborated in the classical period that has proven its usefulness is what is known as the relationship between the distributional variables – the wage rate(s), the general rate of profits and the rent rate(s) – corresponding to a given "system of production". It is also known as the "wage-profit curve" or "wage frontier" (J. R. Hicks) and is represented in the case of only labour and capital by an inverse relationship between the real wage rate (or the share of wages) and the general rate of profits, or *w–r relationship*, given the system of production actually in use,

$$w = w(r), \text{with} \frac{\partial w}{\partial r} < 0$$

Different forms of technological progress are reflected in different shifts of the relationship in *w*–*r* space. In Figure 1 the rate of profits is measured along the abscissa and the real wage rate along the ordinate. Different forms of technological progress may now be illustrated in a schematic way. Fig. 1a represents the case of pure (direct) labour-saving progress. It moves the intersection of the wage frontier with the ordinate upwards, whereas its intersection with the abscissa and thus the maximum rate of profits remain constant. An increase in the maximum wage rate reflects an increase in labour productivity. The growth of labour productivity equals the ratio of the increase in the maximum wage rate, $W_1 - W_0$, and its level prior to the change, W_0, that is $(W_1 - W_0)/W_0$. Fig. 1b represents the case of pure capital-saving progress and Fig. 1c the case of labour-saving and capital-using progress. The latter is characterised by an increase in labour productivity and a decrease in what is called “capital productivity”, that is, the inverse of the capital-output ratio. This case played an important role in the analyses of authors such as Ricardo and Marx. It has been confirmed empirically in recent studies; see Foley and Marquetti 1999). Fig. 1d depicts the case in which both labour and capital productivity increase: the wage frontier shifts outward and is accompanied by an increase of both the maximum wage rate and the maximum rate of profit.

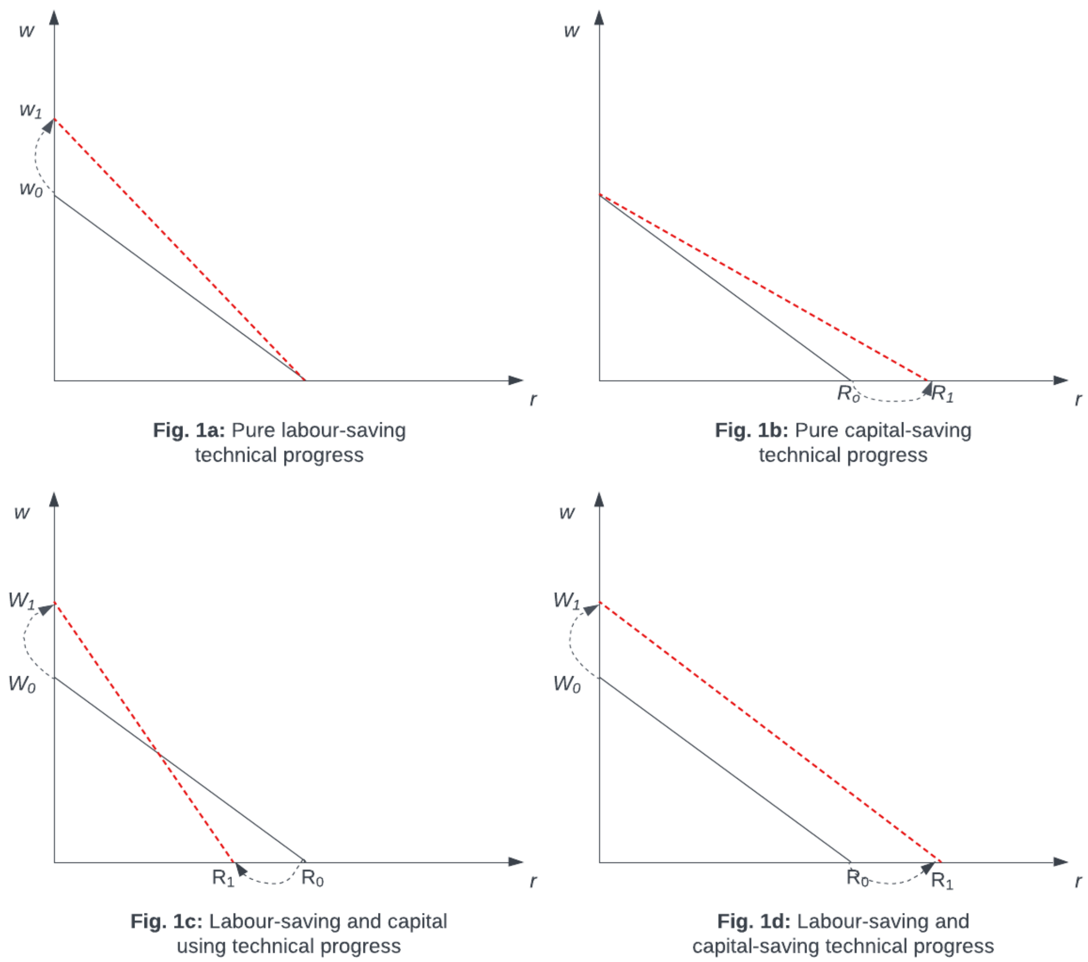

Figure 1: Wage-profit curves and forms of technical progress. Source: Own illustration.

For a reformulation of the classical theory of value and distribution, which provides the basis for a treatment of technological progress, see Sraffa (1960) and Kurz and Salvadori (1995). For a summary account of the classical authors' views on technological progress and economic dynamism, see Kurz (2010).

In empirical studies, using input-output tables for consecutive years, the movements of the *w–r* relationship over time have been documented for numerous countries (see, for example, Schefold 2013, Mariolis and Tsoulfidis 2016, Mariolis 2015, Strohmaier and Rainer 2016, Zambelli et al. 2017). Different patterns of technological change giving rise to different development and growth regimes have been distinguished and their properties discussed.[1] Figure 2 illustrates the wage frontiers of several countries in the year 2009 based on national input output tables. We could also plot the wage frontiers belonging to a single country across several years, using the national input-output database, tracing the impact of technological change on the position and curvature of the frontier.

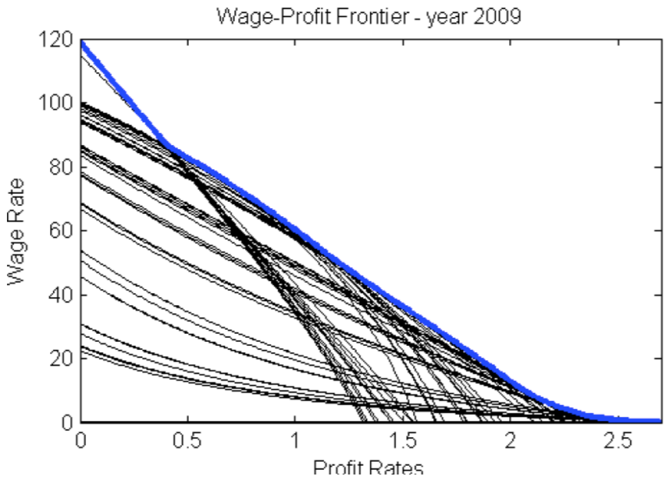

Figure 2: Wage frontiers derived from input-output tables. Source: Schefold (2013).

Charles Babbage and his group, which included the mathematician Ada Lovelace, the daughter of the poet Lord Byron (the programming language ADA is named after her), already glimpsed aspects of an entirely new age characterised by "intelligent machines"; see Babbage (1835). He stressed that machinery is invented and applied in order "to supersede the skill and power of the human arm". The question that is close at hand is, of course: Can it also supersede the power of the human brain – can the division of labour "be applied with equal success to mental as to mechanical operations"? If the answer is in the positive, and Babbage clearly was convinced that it is, what are the implications for humankind? Is there the danger of the majority of humans losing their employments and the rest becoming mere appendages to machines? Babbage therefore as early as the 1830s put forward a *principle of inclusion* of how to go about technological progress and its effects: "every person employed should derive advantage from the success of the whole". This implied that only innovations were acceptable from a social and inclusive point of view whose social benefits exceeded their social costs. He proposed inter alia the instalment of a scheme of profit-sharing which would allow workers to benefit from the prosperity of technologically innovating businesses without affecting their daily wages. Such a scheme, he was convinced, would get

[1] It deserves to be mentioned that in neoclassical analyses with their different analytical framework, wage frontiers and their shift due to technological progress also play an important role; see, for example the recent analysis of Korinek and Stiglitz (2021) of Artificial Intelligence and globalisation. See also Kurz (2020) for a treatment of the problem in terms of a classical multi-sector approach and unequal rates of profit of a monopolistic and a competitive sector, the former being subject to dynamically increasing returns to scale.

workers directly interested in the success of their firms and spur their diligence and inventiveness. Similar proposals heave repeatedly been put forward ever since and are high on the agenda vis-à-vis AI-based technological progress and its various impacts on different social classes. The co-existence of the deskilling of significant parts of the labour force and of the up skilling of other parts is a major concern, because it has the potential of further undermining social cohesion and destabilising the socio-political system.

Whilst it would be wrong to exclaim that "there is nothing new under the sun," it may come as a surprise that certain spectres that haunt us today do have precursors that haunted our ancestors. The problems then and today are clearly different, but share some similarities, and so are the remedies proposed then and now.

2.3 Karl Marx on technological change and the fate of capitalism

Karl Marx ([1867] 1954, [1890] 1959) largely built upon what he had inherited from the classical authors and was keen to classify the socioeconomic history in distinct phases, such as "Cooperation and the division of labour" (the transition from handicraft production to manufacturing), or to "Machinery and large industry" (the transition from manufacturing to the production of machines by means of machines, also called machinofacture). As Marx made clear, in the short and medium run these transitions were a blessing to some people, but for some time a burden to many others and caused serious social conflicts and tensions.

Marx's main aim was to identify and reveal the "law of motion" of modern society. To achieve this challenging task, he elaborated what he called an "economic interpretation of history". In a first step this consisted in a careful specification of the "mode of production" of the society under consideration – in our case in particular the properties of the capitalist mode of production and the relations of production that correspond to it. In a second step he sought to derive from these properties and relations the forces, economic and other, that would shape the society's further development. An important part of this task was to find out whether the capitalist mode of production was the hotbed of a particular form of technological progress that shaped its development and eventually fate. Marx was convinced that capitalism generates from within a particular form of technological change that is labour-saving and at the same time capital-using: it reduces the amount of labour needed directly and indirectly in the production of the majority of commodities by simultaneously increasing the amount of capital employed per unit of output. In terms of the concept he used, this form is reflected in a growing "organic composition of capital", or, expressed in terms of conventional economic analysis, by a growing capital-output ratio, $v = K/Y$ (K = capital stock; Y = social product). Assuming that wages are paid post factum, that is, at the end of the production period, the general rate of profits, r, is given by

$$r = \frac{P}{K} = \frac{P/Y}{K/Y} = \frac{\pi}{v}$$

where P denominates profits and π is the share of profits in national income. With v rising without upper boundary and π constrained from above by unity, the rate of profit is bound to fall from a certain point onwards. This is, in a nutshell, Marx's "law of the tendency of the rate of profit to fall". A falling tendency of the rate of profit, Marx was convinced, showed that capitalism was a transient mode of production and not an eternal one, as some of its advocates argued. Eventually it had to give way to socialism, which, Marx thought, would fundamentally change the relations of production amongst the different strata of society by abolishing "exploitation" and establishing a "classless" society.

Marx's economic interpretation of history apparently hinges crucially on whether or not his attempted derivation of the form of technological progress dominating capitalism from the characteristic features of the capitalist mode of production stands up to close scrutiny. While historically there have been phases in which the general rate of profit fell in certain capitalist economies, there is no evidence that this fall is a persistent phenomenon, as Marx assumed. There have been numerous studies that investigated the empirical validity, or otherwise, of Marx's "law". Moreover, the impact of different waves of technological progress on income distribution and the rate of return on capital (and its dispersion within and between different sectors of the economy) have been studied quite independently of Marx's doctrine in numerous works dealing with advanced and developing capitalist economies. See, in both cases, in particular Shaikh (2016), Schefold (2016), and Mariolis and Tsoulfidis (2016).

Box: Causes, forms and effects of technological progress

The classical political economists, including Marx, were concerned with the following problems:

- What causes technological (and organisational) change, what are the driving forces behind it, and what determines its pace?
- What forms or types of technological can be distinguished and which forms dominate when and why?
- Which effects do the different forms of technological change have regarding employment, income and wealth distribution, economic growth and development and foreign trade.

As regards the first problem, these authors emphasized systemic factors such as the intensity of competition and rivalry in the capitalist economy and institutional and historical influences on the culture of innovation and growth (Mokyr 2017). This is in stark contrast to early neoclassical economists like William Stanley Jevons, Carl Menger and Léon Walras who focused on an stationary economy. Compared to the allocation of scarce resources under given conditions, the transcendance of such conditions through innovations and economic dynamism played a much smaller role. Their main focus was what Joseph A. Schumpeter called the "circular flow" of the economy, that is, a system that reproduces itself without much technological and structural change.[2] Rediscovering the problem of economic growth in the mid 20th century, neoclassical economists first treated technological change as an exogenous factor increasing labour productivity without causing any costs or damage (see Section 2.2 below). Hence, for what Schumpeter considered the most important factor responsible for the remarkable restlessness of the capitalist economy, these authors had not explanation at all. The restlessness was reflected in a *given rate of technological progress*. It was only in the second half of the 20th century that mainstream (neoclassical) economics felt the need to widen the view and take technological progress (more) seriously (see Section 2.5 below).

As regards the second problem, the classical authors deserve to be credited with having distinguished between different forms of technological progress. The arguably most important author in this regard was David Ricardo, who discussed land saving, direct labour saving, indirect labour (or capital) saving forms of technological progress and in the famous Chapter 32 of his *Principles* discussed a form of technological progress that replaces circulating capital (i.e. wages) by fixed capital (i.e. improved machines). It matters in which sectors of the economy technological progress takes place: while progress in industries producing "luxuries" affects only a small subsystem of the economy, progress in industries producing "necessaries" generate ubiquitous effects and alter the mathematical properties of the economic system.

These considerations directly inform the third problem, as different forms of technological progress also imply different effects for the economy and society. Historical concerns about "technological

[2] This fact is also a reason why Schumpeter, who was initially very fond of Walras's general equilibrium theory, later began to question its explanatory potential. Compared to Marx, it was hardly able to explain what is causing capitalist economies to be so dynamic and so incessantly propelled forward: "creative destruction". Technological progress, he saw very clearly, was also not a boon to everybody all the time but may at least temporarily be a serious bad to certain strata of society.

unemployment" during the First Industrial Revolution, impacting certain societal strata, particularly workers, still resonate today with fears surrounding the potential job displacement by Artificial Intelligence and Smart Machines. Furthermore, there is a growing expectation that these technological shifts might exacerbate inequality in income and wealth, leading to societal segregation (Kurz 2022).

2.4 Joseph Schumpeter on innovation and long waves of economic development

Joseph Schumpeter ([1912]1934, 1939, 1942) was deeply impressed by Marx's investigation of the economic dynamism of capitalism and saw his work to be much superior to that of the neoclassical economists in this regard, including Léon Walras. While he credited Walras with having elaborated a thorough analysis of the "circular flow" of the economy, that is, a stationary state characterized by the absence of any technological and organisational improvements, he had failed to develop a theory of economic dynamics. But since its dynamism is the outstanding feature of capitalism, the Walrasian theory has little to offer to understand better this mode of production. While he praised Marx for his achievements, he was keen to turn upside down crucial elements and propositions of Marx's doctrine, especially the view that profits reflect the "exploitation of workers" and that socialism is a superior mode of production which will eventually replace capitalism.

In nuce, Schumpeter argued as follows. Basically all economic theory up until then had focused attention on three social classes of actors – workers, landlords and capitalists – and had missed *entrepreneurs* or "agents of change". It therefore missed the source of the restlessness and dynamism of capitalism and its innate drive to innovation and change. This neglect had further consequences that undermined the explanatory power of theory. First, by lacking a proper view of the salient features of successful entrepreneurship, it did not really understand the roots of technological change. It also did not understand that fettering entrepreneurship would suffocate the working of the "capitalist machine". Capitalism, if unfettered, would be superior to all competing socioeconomic orders, because it was organised precisely for the purpose to generate and absorb novelty in a process of "creative destruction". Entrepreneurs, Schumpeter insisted, were not the enemy of workers: their innovations rather led to an increase in the quality of products and a growing labour productivity, which, in the medium and long run, would result in rising real wages and improving working conditions. Profits were paid out of a rising labour productivity. In Schumpeter's view, profits were a child of innovations, not of exploitation.

Innovators in the early phases of capitalist development are typically people that have ideas but no liquid funds to realize them. Therefore a banking trade, willing to finance innovative projects by providing start-up firms with credit, is badly needed. These projects are often very risky, and bankers must be willing to bear the risk, but in case of success they are also extremely profitable. A well-functioning banking system with bankers that are able to judge the creditworthiness of entrepreneurs are therefore of paramount importance for economic dynamism and growth. Schumpeter rejects the marginalist idea that innovations are predominantly financed out of savings and insists that they are financed to a large extent by means of credit. The increase of liquid means via credit expansion in an economic system with full employment will lead to rising prices and a redistribution of productive resources away from static firms to dynamic ones.

The diffusion of the new and gradual replacement of the old is, however, not smooth but unfolds in economic cycles of various kinds and is reflected in crises (see Kurz et al. 2018). The severity of crises and the amplitudes of cycles depend not least on the types and magnitudes of technological change, its "disruptive" character. Most important according to Schumpeter are long waves of economic development, "Kondratievs", which last for about 50-60 years. He opined that Marx's "law" of the tendency of the rate of profit to fall refers only to the downward part of a Kondratiev and misses the upward part. Schumpeter (1939) subdivided the history of economic development since the second half of the 18th century in altogether four Kontratievs, with the fourth still under way when he was still alive. Each Kondratiev, he was convinced, was triggered by a fundamental technological breakthrough in particular industries of the economy and then spread out across the entire socioeconomic system. He explained the world economic crisis in the 1920s and 1930s in terms of an unfortunate coincidence of the troughs of three types of economic cycles, the Kondratiev, the Juglar (a business cycle) and the Kitchin (an inventory cycle). He insisted on the path-dependency of technological change and took pains to study in some detail the characteristic features of its various waves.

Schumpeter still has a tremendous impact on the theory and empirics of technological change. It suffices to refer to the recent book by Aghion et al. (2021), who inter alia counterpose the neoclassical concept of "total factor productivity" (see the following subsection), a "black box" whose explanatory power is very limited, with Schumpeter's much richer view of the phenomena at hand. The metaphor of "creative destruction" captures what is at stake much better than the Solovian "manna from heaven": it emphasizes the heterogeneity, and possibly irreducible heterogeneity, of different forms of technological progress.

In fact, developments in the explanandum and the explanans since quite some time show impressively that there is no unanimously accepted analytical device and metric that would allow for unambiguous intertemporal and interspatial comparisons of various forms of technological change and their effects. The looking glass rather shows a kaleidoscopic landscape and no homogeneous and single-valued perspective. (More on this will be presented in Parts 3 and 4).

2.5 Early marginalist contributions

Technological and the corresponding structural change have almost entirely been lost sight of at the time of the so-called "marginalist revolution", which saw the introduction of the twin concepts of "marginal utility" and "marginal productivity" in economics. The attention then focused on the *static* problem of the *optimal allocation* of given amounts of productive resources, or endowments, given technical alternatives and given preferences of agents. The concern was first and foremost with reaching a point *on* the given and fixed production possibility frontier rather than with shifting that frontier *outwards* by means of technological and organisational progress. In major marginalist authors such as William Stanley Jevons (1874), Carl Menger (1871) or Léon Walras (1954), technological progress played a limited and frequently even negligible role. The static viewpoint adopted effectively crowded out a dynamic one.

However, there were exceptions to the rule that deserve to be mentioned. Schumpeter is the most important case in point. But there are others. Wicksell is one of them. But while towards the end of the 19th century he analysed somewhat the role of technological change in order to get hold of the dynamic properties of the economic system, his main concern was nevertheless with solidifying the production theoretic basis of marginalist theory. He asked in particular whether the information contained in a given set of methods of production available to produce a particular commodity could perhaps be used to build up a *production function* for the commodity that contained only efficient input-output constellations. In this case, with an infinite number of such methods of production at one's disposal, it was taken for granted that a production function could be constructed

$$y_j = f_j(a_1, a_2, \ldots, a_n)$$

where y_j designates output and a_i the amount of input i needed in the production of that output. The highly restrictive assumptions that need to be met for this to be possible, a construction, which, in addition, is possessed of certain properties the economists favoured because of their easy analytical tractability, were far from clear at first. Scholars like Wicksell (1893) and Wicksteed (1894) began to study these conditions. They pointed out that it would be good to have linear homogeneous functions that were twice differentiable, with the first derivative positive and the second declining.[3] In this case, if the proprietors of the services of the factors of production involved are paid the services' marginal products, the Euler Theorem tells us that the product would be just exhausted, neither more nor less. Functions with such properties then became the preferred workhorse used by neoclassical authors dealing with technological progress and economic growth. A type of production function that became particularly prominent is the Cobb-Douglas function. Wicksell already put forward its functional form more than twenty years prior to its alleged discoverers Cobb and Douglas. In a neoclassical framework, technological progress implied, as Schumpeter emphasised, the "putting up of a new production function".

The next question was whether a *production function for the economy as a whole* could be elaborated by aggregating methods of production across all industries of the economy. However, it became quickly clear that starting from any given situation at the micro level, no macro production function could be derived in terms of a consistent aggregation of the micro-units. Yet this did not prevent neoclassical authors to use such functions, and especially the Cobb-Douglas function,

$$Y = AK^{\alpha}L^{1-\alpha}$$

with A as a shift factor expressing the productivity of the system, K as the capital stock employed, L as the work force employed and $\alpha = (\partial Y/\partial K)/(Y/K)$ as the partial elasticity of production with regard to capital. If marginal productivity theory of distribution happens to apply then, $\partial Y/\partial K = r$, and α can be interpreted as the share of profits in national income.

These steps set the stage for neoclassical *growth accounting*, which was championed by Robert Solow in a number of contributions in the 1950s and 1960s and triggered an avalanche of similar studies across the world. See Solow (1956, 1957). For a summary account of growth accounting studies, see Barro and Sala-i-Martin (2004: chaps 10-12).

2.6 Robert Solow's growth accounting and after

Solow (1957) started from the premise that the rate of growth of the social product of an economy can be explained in terms of the rates of growth of the factors of production cooperating in its generation, that is, capital and labour. (Solow boldly subsumed land under capital, whereas other neoclassical authors such as James E. Meade did not.) Differentiating the Cobb-Douglas function above with regard to time and expressing the result in terms of proportional growth rates and confronting the result with time series of output and capital and labour inputs resulted in a huge surprise: the growth rates of output predicted by the model was significantly smaller than the empirically estimated growth rates. Depending on countries and time periods chosen, the differences amounted variously to 30 or 40 per cent and in some cases even much more. (See Barro and Sala-i-Martin 2004: chaps 10-12.) This was a sobering result. Looking for the cause of the disappointment, it was quickly maintained that the Solow model missed out the important role of technological progress.

The conclusion was swiftly drawn by Solow that the "unexplained rest" or "Solow residual" was entirely due to technological progress and to nothing else. For example, if the production function would exhibit increasing or decreasing rather than constant returns to scale, the residual would be smaller or larger. But how could one discriminate in the given framework between the effect of technological progress and, for example, that of increasing returns (which were soon to become a major theme in growth economics)? The given explanation was, of course, no explanation at all; it was rather, as Abramovitz (1956) put it, a "measure of our ignorance". A huge literature on growth accounting burgeoned (see again the summary account in Barro and Sala-i-Martin 2004), which

[3] Starting from a set of methods of production it can be shown when a production function exists, and when not, and what its properties are (see Kurz and Salvadori 1995: chap. 2). In each production function is "embodied", so to speak, a $w-r$ frontier as the outer envelope of all $w-r$ relationships of those methods of production that contribute to the efficient set. The $w-r$ frontier plays an important part also in neoclassical analyses of technological change.

tried to reduce the unexplained rest and eventually make it vanish by bringing in new factors of production, such as schooling and education, research and development expenditures and so on and so forth. In more recent times, and not necessarily tied to the growth accounting literature, cultural differences got in the focus of attention and in the tradition especially of Max Weber the question was raised whether different religions and ethics played a role and engendered different "cultures" of innovation and economic growth (see Mokyr 2017).

New measures of technological change were suggested, the most widespread of which is the concept of *total factor productivity*. It is used in numerous contemporary empirical studies but carries with it all the blemishes affecting the concept of a macroeconomic production function and the treatment of technological progress as a residual. The growth accounting literature turned out to be highly problematic, because it failed to cogently explain technological progress as generated from within the economic system by the purposeful activities of agents and because it employed concepts, especially the production function, which was severely under attack. Technological progress was portrayed as a purely external factor, mysteriously shifting the macro production function. For a critical examination of the use of the concept, see Felipe and McCombie (2013), who maintain that no convincing explanation at all is given in terms of it.

Before we continue, the attention ought to be drawn to studies of the diffusion of new methods of production in the economic system. A major author in this regard was Dale W. Jorgenson, who from an early time onwards investigated diffusion patterns of new techniques in various industries and confirmed that they typically exhibit a sigmoid or S-type form. In Jorgenson (2001) he studied information technology in the US economy. Sigmoid diffusion patterns of new technical devices were also assumed, for example, in dynamic input-output studies dealing with the introduction and diffusion of early forms of automation in manufacturing and offices; see, e.g., Kalmbach and Kurz 1990).

2.7 Endogenous theories of technological progress and economic growth

In the neoclassical literature up until recently, and very different from the approach of the classical authors and later theories (see Section 2.4), technological progress was essentially given from the outside of the economic system, which means it was largely treated as an exogenous factor – as "manna from heaven" – rather than an endogenous one generated from within the system. It was only in the 1980s that things began to change, and technological change began to be modelled as the outcome of actions of economic agents. The literature under discussion is known as "new" or "endogenous growth theory", with Romer (1986, 1994; 1990), Lucas (1988), Aghion and Howitt (1992, 1998) and Acemoglu (2009) as main representatives. The characteristic feature of this literature is a new take on technological progress within a neoclassical analytical framework. It is worth mentioning that there are also Schumpeterian elements brought up in what is known as neo-Schumpeterian theory. And there are also numerous non-neoclassical approaches with endogenous technological progress. For a lack of space, we refrain from discussing them in any depth. However, in the following chapters we will touch upon some of them, especially agent-based models (see Section 4.4).

In these theories, that growth is conceptualised as essentially *intensive* rather than merely extensive, that is, the focus is on why rising levels of income per capita. Another property is that the rate of return on capital is prevented from falling, which is brought about by means of various devices. The first generation of such models defined the confines within which subsequent contributions were carried out. We focus attention on the first generation and especially on the treatment of the problem of technological progress. For a more detailed treatment of these models, see Acemoglu (2009), Aghion and Howitt (1998), Barro and Sala-i-Martin (2004), Jones (1998), and Kurz and Salvadori (1998, 1999).

One class of models preserve the usually postulated dualism of accumulable and non-accumulable factors of production but restrict the impact of an accumulation of the former on their returns by a modification of the macroeconomic production function. Jones and Manuelli (1990), for example, allow for both labour and capital and even assume a convex technology, as the Solow model does. However, a convex technology requires only that the marginal product of capital is a decreasing function of its stock, not that it vanishes as the amount of capital per worker tends towards infinity. As capital accumulates and the capital-labour ratio rises, the marginal product of capital will fall, approaching asymptotically its given lower boundary. With a given propensity to save (and invest) and assuming that capital never wears out, the steady-state growth rate is endogenously determined. Assuming, on the contrary, intertemporal utility maximization, the rate of growth is positive provided the lower boundary is larger than the rate of time preference.

Then there is a large class of models contemplating various factors counteracting any diminishing tendency of returns to capital. Here we shall be concerned only with the following two sub-classes: human capital formation and knowledge accumulation. In both kinds of models, *positive external effects* play an important part; they offset any fall in the marginal product of capital.

Models of the first sub-class attempt to formalize the role of human capital formation in the process of growth. Elaborating on some ideas of Uzawa (1965), Lucas (1988) assumed that agents have a choice between two ways of spending their (non-leisure) time: to contribute to current production or to accumulate human capital. With the accumulation of human capital there is said to be associated an externality: the more human capital society as a whole has accumulated, the more productive each single member will be. This is reflected in the following macroeconomic production function

$$Y = AK^{\alpha}(uhN)^{1-\alpha}h^{*\gamma},$$

where the labour input consists of the number of workers, N, times the fraction of time spent working, u, times h which gives the labour input in efficiency units. Then there is the term h^{*}. This is designed to represent the externality. The single agent takes h^{*} as a parameter in his or her optimizing by choice of c and u. However, for society as a whole the accumulation of human capital increases output both directly and indirectly, i.e., through the externality.

Lucas's conceptualizes the process by means of which human capital is built up by

$$\dot{h} = vh(1-h)$$

where v is a positive constant.

It can be shown that if there is no externality, that is, if γ equals zero, and returns to scale are constant and the Non-substitution Theorem holds, endogenous growth in Lucas's model is obtained in essentially the same way as in the models of Rebelo (1991) and King and Rebelo (1990): the rate of profit is determined by technology and profit maximization alone; and for the predetermined level of the rate of profit, the saving-investment mechanism determines the rate of growth. Yet, as Lucas himself pointed out, the endogenous growth is positive *independently* of the fact that γ here is the above-mentioned externality, i.e., independently of the fact that γ is positive. *While complicating the picture, increasing returns do not add substance to it: growth is endogenous even with constant returns to scale.* In case returns are not constant, the Non-substitution Theorem does not apply, implying that neither the competitive technique nor the associated rate of profit are determined by technical alternatives and profit maximization alone. However, these two factors still ascertain, in steady states, a relationship between the rate of profit and the rate of growth. This relationship and the relationship between the same rates pertaining to the saving-investment mechanism determines both variables.

Models belonging to the second sub-class conceive technological change as generated from within the economic system, i.e. endogenously. The proximate starting point of this kind of models in modern times was Arrow's (1962) paper on "learning by doing". Romer (1986) focuses on the role of a single state variable called "knowledge" or "information" and assumes that the information contained in inventions and discoveries has the property of being available to everybody at the same time. Information is therefore regarded as a *non-rival good*. Yet, it is not ipso facto also totally *non-excludable*, that is, it can be monopolized at least for some time. It is around the two different aspects of publicness – non-rivalry and non-excludability – that the argument revolves. Discoveries are made in *R&D* departments of firms. This requires that resources be withheld from producing current output. Therefore, as Romer (1986: 1015) put it, "there is a trade-off between consumption today and knowledge that can be used to produce more consumption tomorrow". He formalizes this idea in terms of a "research technology" that produces "knowledge" from forgone consumption. Knowledge is assumed to be *cardinally* measurable and not to depreciate: it is like *perennial capital*.

Since the publication of the papers mentioned, an enormous literature has built up in which the several aspects dealt with have been studied and new aspects added. It must suffice to provide some examples. Romer (1990) tried to enrich the model by introducing a "product-diversity" specification of physical capital: in a research sector "new designs" for intermediate products are being invented, which are then used in another sector by monopolistic firms to produce these intermediate products. The sector producing the final product employs the latter and is taken to be the more productive, the greater is the product diversity of its capital inputs. Aghion and Howitt (1992) and Grossman and Helpman (1991) incorporate (Petralia 2020; Calvino et al. 2023) imperfect markets and *R&D* in the model. They seek to formalize what Joseph A. Schumpeter famously called "creative destruction" (see also Kurz 2017). A different route was taken by Martin L. Weitzman (1998) who took his inspiration from agricultural research stations, in which new "hybrid ideas" are generated by cross-breeding known ideas. The economic historian Joel Mokyr (1990) used arguments partly forged in the recent growth literature to interpret economic history and especially the origins and consequences of the First Industrial Revolution for the growth performance of industrialising countries; see also more recently Mokyr (2017).

The interesting thing to note is that notwithstanding the models' occasionally great complexity, in the steady state they all replicate in one form or another a characteristic feature of *linear* growth models. As Romer (1990: 84) put it: "Linearity in [the number of intermediate products] is what makes unbounded growth possible, and in this sense, unbounded growth is more like an assumption than a result of the model." And Weitzman (1998: 345) concluded that in his model "everything comes full circle to steady-state growth rates being linearly proportional to aggregate savings', just as in the models of Harrod and Domar long ago."

These findings ought to be remembered when turning to most recent technological developments: an accelerating growth in technological and economic knowledge due to AI, Smart Machines and so on must not be mistaken to mean a proportional corresponding acceleration in the rate of exploiting the opportunities the new knowledge offers. As Weitzman's model shows, while the growth rate of new opportunities may speed up, not all of them can actually be adopted. Because of the growing autonomy of machines, we can expect to see an increase in the rate of adoption of novelty, but not pari passu with the rate of their creation.

2.8 In a nutshell: the evolution of technological change in economic thought

Authors in the mercantile period in which long-distance trade and the colonisation of newly discovered continents and countries played an important role, the "demonstration effect" with regard to new, hitherto unknown methods of production (and consumption patterns) invited imitation processes and moved domestic technological knowledge towards the frontier of knowledge worldwide. In the classical authors from Adam Smith to David Ricardo and Charles Babbage the perspective changed considerably. The focus was henceforth on the domestic inventions of new methods of production and organisation and their labour-saving properties. However, technological progress was not only seen as a boon, but also as a bane: it reduced the toil and trouble to be mustered per unit of output, but it also unleashed the spectre of technological unemployment. It was understood that different forms of technological change affect the lives and wellbeing of different strata of society differently, and those who suffer from technological change, or expect to do so, will try to fight it – landlords who feared that land-saving innovations would diminish the rents of land and workers who experienced unemployment and falling real wages. David Ricardo distinguished between different forms of technological progress and argued that certain types of machinery were detrimental to the interests of workers. He even contemplated the case of a fully automated system of production. He was the first to clearly establish an inverse relationship between the general rate of profits in the economy and the share of wages in national income – viz. his "fundamental law of distribution". Charles Babbage began to investigate the fascinating question whether the division of labour can be generalised from mechanical to mental operations and whether eventually machine power can also in this respect replace labour power. Marx developed the classical approach to technological progress and its labour-saving tendency into a theory of the self-transformation of the socioeconomic system that reflects fundamental changes in the mode of production. Classical concepts were and still are being used in modern times and employed to distinguish between different kinds of technological change and the accompanying growth in labour productivity. The tool used is the relationship between the real wage rate (w) and the rate of profit (r), that is bound to move in w-r space as innovations shake up and change the system. Adam Smith's conceptualization of the division of labour as a process that exhibits dynamically increasing returns to scale was early on seen to be very important, but also very difficult to deal with analytically, not least because it raises the tricky issue to decide how much of an increase in output is due to scale economies and how much to technological progress.

Early marginalist authors generalised the idea of the substitutability of factors of production for one another. This led to the elaboration of a tool that became very prominent in the economics of technological change: the production function whose technical parameters express inter alia the ease or difficulty with which factors of production can be substituted for one another. There was also the idea that it was possible to aggregate across micro units of production and build up a production function for the economy as a whole, or aggregate production function (although no process of consistent aggregation was ever carried out). Technological change was then conceived as the quantitative change in total output brought about for given amounts of labour, capital and land. It was seen as a kind of "manna from heaven". As regards the functional form of the production function adopted, economists for a long time and even today are particularly fond of the so-called Cobb-Douglas function, because its linear-homogeneous variant invites one to interpret the partial elasticities of production as factor income shares. Since these elasticities are given and constant, they were seen to mimic a stylised fact of economic history up until a few decades ago: relatively constant shares of profits (and wages). In more recent times this is no longer the case: the share of wages has declined and the share of profits increased. Some neoclassical authors have therefore replaced the Cobb-Douglas function by more general functions.

The growth accounting literature that began to boom in the 1950s with contributions by Robert Solow ironically started by testing explanations of economic growth in which technological change played no role whatsoever, but only the growth of factors of production actually employed, labour and capital, did. This left a substantial part of actual economic growth experienced in numerous countries unexplained. In response to this sobering finding, many authors were inclined to attribute the "unexplained rest" to the beneficial working of technological change. Technically speaking, this led to the addition of a time factor in production functions, which over time shifted the function upwards. It has the effect of preventing the marginal productivity of capital from falling (or at least from falling swiftly and without lower boundary as capital intensity increases), and therefore of stabilising the propensity to accumulate capital. The attribution of the unexplained rest of actual growth to technical progress without further ado was however quickly seen to be unsatisfactory. A huge research industry began to burgeon in which additional factors were introduced next to labour and capital that were taken to promote productivity (schooling, health, etc). Important representatives of such extensions of the approach, which aimed at reducing the unexplained rest, were Edward Denison and John Kendrick (Nelson 1981). However, also these attempts shared the same feature as their precursors: they did not explain the increase in the productiveness of a socioeconomic system by tracing it back to individual, purposeful actions. In short, they lacked "micro-foundations", that is, did not meet a requirement typically imposed in neoclassical contributions. (Things are different, for example, in Keynesian economics, which is to a considerable extent concerned with providing macro-foundations of microeconomic behaviour.)

While in early neoclassical growth accounting, technological progress was essentially seen as an exogenous force that increases the productivity of some other forces whose quantitative change over time could be measured, since the 1980s the focus of attention switched to explaining technological progress in terms of profit-seeking activities of agents, that is, of rendering it *endogenous*. This was done along different lines of thought, each one of which had been discussed in the literature since quite some time. What was new was the attempt to formalise the respective core ideas in models of constrained optimisation. For example, an echo of Adam Smith's observation that a deepening of the social division of labour will result in the emergence of what today is called an *R&D* sector is to be found in contributions by Romer and Weitzman. They also entertain versions of the idea that new, economically useful knowledge results from the combination of reconfigured particles of already known knowledge. The idea that schooling and educating people has a positive impact on labour productivity, because it involves the accumulation of human capital, is an old idea entertained, for example, by Smith and especially Friedrich List. In many ways the horizon regarding the factors affecting technological change and economic growth and development has increased quite a bit and has brought back the richness of the studies of major social scientists, such as Smith, John Stuart Mill (1848), Karl Marx and Joseph Schumpeter, to name but a few. The complexity of the field has risen greatly; it comprises the interrelationship of economic, social, cultural, political and historical factors (see also Haas et al. (2016) for a summary account on technological change and innovation).

Scholars do not only ask what is the productivity of the *R&D* sector or of the schooling and higher education system of a country, but also how effective is the translation of their achievements in the manufacturing and other sectors in the form of new methods of production and organisation and new and better products, and what is the role of the public administration in all this: does it promote the process of modernisation or does it slow it down? Which role is to be attributed of all this to the quality of the political system, to corruption in economy and society, to the tax system, to fairness and trust? And which impact can be imputed to the different factors at work, what is their aggregate effect in regard to technological change and productivity growth? What do we know about the interaction of the factors? Which new conceptual and statistical tools and devices have to be forged in order to get a clearer picture of what is happening? Do the received economic concepts and measurement devices, some of which were elaborated decades if not centuries ago, need a fundamental overhaul in order to get attuned to an age of bits and bytes, platforms and Artificial Intelligence? The "Second Machine Age" (Brynjolfsson and McAfee 2014) confronts humankind with considerable challenges.

Table 1: In a nutshell: schools of thought and their empirical application.

Schools of thought	**Data and methodology**	**Strengths**	**Problems and weaknesses**	**Reference**
Classical approach and modern versions of it	Focus on the system of production as a whole and the impact of technological progress on labour productivity and vertically integrated labour coefficients Focus on intertemporal and interspatial comparisons Input-output data, Econometrics	General analysis taking into account sectoral interdependencies Taking labour heterogeneity seriously Tracing shifts in the wage frontier	Qualitative change. Is there an "invariable measure" (Ricardo) of value, different forms of technological change etc.? The answer is no. Recourse to index numbers	Ricardo (1821) Sraffa (1960) Schefold (1976) Pasinetti (1977) Kurz and Salvadori (1995)
Early neoclassical studies	Macroeconomic approach "Aggregate" production function Growth accounting Diffusion processes showing sigmoid shapes Econometrics	It is relatively simple and conveys the impression of moving on solid ground	Does not explain technological change, but treats it like "manna from heaven" Based on problematic aggregate production functions Increasing returns to scale vs. technological progress	Solow (1956, 1957) Felipe and McCombie (2013) Jorgenson (2001)
"New" growth theories	Seek to provide "micro-foundations" of technological change within an optimizing framework Econometrics	Return to the broad view of technological change of the classical authors and widen somewhat the perspective Provide a version of Adam Smith's concept of cumulative and circular causation	Focus on "knowledge" and treat it as an accumulable and cardinal factor of production; preserve the aggregate framework vis-à-vis a growing heterogeneity Focus on numerous factors that explain technological change; offer a "kaleidoscopic" point of view	Romer (1986, 1990) Lucas (1988) Grossman and Helpman (1991) Barro and Sala-i-Martin (2004)
Schumpeter and Schumpeter-ian approaches	Conceive of technological change as a process of "creative destruction" A blend of different kinds of methodologies and data bases Quantitative and qualitative studies	Focus on "entrepreneurship" and "agents of change" Stress the importance of credit and the banking system for economic development Seek to understand the creative-cum-destructive part of technological change Stress the necessarily cyclical character of the absorption of new methods of production	Technological change necessitates the elaboration of various measures, which are bound to change over time: "horses for courses", no unique and invariant metric Concern with long waves of economic development ("Kondratievs").	Schumpeter (1912, 1934, 1939) Kurz (2012) Kurz et al. (2018) Aghion et al. (2021)

3 Pervasive technological change

Ever since, economic history has been intrinsically interwoven with technological transformation. The question to what extent the former is shaped or even determined by the latter, has been at the core of a long-standing debate among economic historians, theorists and applied economists. This discussion is often linked to the regular occurrence of long waves in economic development (see Section 4.1), a phenomenon that had already been pointed out by Jevons and then van Gelderen (1913) and became later synonymous with the term of Kondratiev-cycles (see Ayres 1990). Schumpeter (1934) identified 'swarms' or clusters of innovations as causal for the cyclical pattern of economic growth, boosting productivity especially in those sectors most affected by technological change, and Mensch (1975) saw that clusters of basic innovations arrive during the downswing or at the bottom of each Kondratiev-cycle (see also Ayres 1990 and Coccia 2018). The more pervasive thereby the underlying innovations – affecting the production recipe of a wide range of sectors – the bigger the impact on economic and social development, and the longer it takes the socioeconomic system to readjust to a new technological paradigm.

The relation between pervasive technological change and long waves of development is empirically grounded in the emergence of industrial revolutions: the First Industrial Revolution is inevitably linked to the invention and diffusion of the steam engine and the slide rest, and the Second Industrial Revolution to the emergence of electricity and the automobile. Each of these technologies triggered painful structural adjustments with regard to different aspects of the socioeconomic system, such as the workplace, infrastructure, education, among many others. Understanding the underlying alignment processes is therefore the ultimate *raison d'être* and motivation why to study pervasive technological change as a genuine phenomenon that involves distinct causes, features and consequences different from incremental innovations.

The interest in this phenomenon was spurred by the emergence of new information and communication technologies (ICT) that started out with the invention of the Intel Microprocessor in 1971 and has since then evolved into the digital revolution (Perez 2010). Particular attention in this regard has been paid to phases of temporal or persistent economic slumps, and especially to the role of ICT in solving the productivity puzzle (or Solow's Paradox), whereby "you can see the computer age everywhere but in the productivity statistics" (Solow 1987) or in explaining tendencies of stagnation (Summers 2014; Gordon 2016). These research questions have experienced an additional boost in the context of the "Fourth Industrial Revolution", whose technological core is assumed to be a melting pot of different technological breakthroughs mainly from the physical, the digital and the biological sphere (Schwab, 2015) and which should hit the global economy not far into the future (see Section 4.3).

While Schumpeter did not elaborate much on the nature and characteristics of the temporal clustering of innovations, various economists have since then argued that innovations within this set are usually highly interrelated – they depend on each other for their efficient employment in the production system (see, e.g. Dosi 1982; Freeman et al. 1982; Perez 1985; Mokyr 1990; Lipsey et al. 2005). In fact, it is this "complementarity" between one or several generic technologies and their follow-up innovations that, on the hand, warrants the long gestation period of a new technological paradigm and, on the other, enables its pervasive diffusion and socioeconomic impact (see, e.g., Jovanovic and Rousseau 2005, Bekar et al. 2018, Teece 2018).

3.1 The notion of pervasiveness

A technology can be defined as pervasive, if its trajectory persistently affects and responds to its technological and socio-economic environment. The class of innovations that (explicitly or implicitly) feature pervasiveness as a decisive characteristic are typically known as "generic", "enabling" or "general purpose technologies". Generic technology refers to a technology "the exploitation of which will yield benefits for a wide range of sectors of the economy and/or society" (Keenan 2003, quoted in Maine and Garnsey 2006). "All-pervasive" generic technologies are also at the heart of technological and techno-economic paradigms (Dosi 1982, Perez 1985) and facilitate the foothold of a technological breakthrough in the economy. They are not necessarily the technological revolution itself but play a crucial role in its further development – similar to the concept of enabling technologies (Lipsey and Bekar 1995), which are also characterised by their wide range of application and their complementarities. Due to these features, they cause deep structural adjustments in the socioeconomic system. As will be discussed below, an approach that has drawn much attention in the last ten years is the concept of general purpose technologies (GPTs), introduced and originally studied in a microeconomic framework by Bresnahan and Trajtenberg (1995). In contrast to generic technologies, that are the pervasive counterpart of the "double nature of technological revolutions" (Pérez 2002, p. 9), enabling wide-spread productivity surges in the presence of technological breakthroughs, GPTs per se entail the explosive dynamism of brand-new innovations – they *are* themselves "engines of growth" (Bresnahan and Trajtenberg 1995).

Different types of complementarities arise from the feature of pervasiveness. These are especially well defined in the GPT framework. According to Bresnahan (2010), "a GPT (1) is widely used, (2) is capable of ongoing technical improvement, and (3) enables innovation in application sectors." Thus, despite its pervasive applicability, each sector has to a certain degree to customize the technology to its own production process, and this continuously, as the GPT improves over its lifetime. The productivity gains associated with technological progress are covered under the term "*innovational* complementarities". Teece (1986, 1988) and Lipsey et al. (2005) focus especially on complementarities occurring on the microfunctional/technological level. Bekar et al. (2018) have further refined the concept, distinguishing different types of *technological* complementarities: (1) complementarities with a cluster of technologies that facilitate the GPT; (2) complementarities with a cluster of technologies that are enabled by the GPT; (3) complementarities with a cluster of technologies that themselves affect economy, society, policy and institutions. In addition to innovational and technological complementarities, the evolution of a GPT also involves, as Teece (2018) suggests, several other types of complementarities: *production* (Hicksian) complementarities, where demand in one input increases due to a decrease in the price of another (in this case, the GPT), driven by the steep cost degression typically associated with new technologies; *consumption* (Edgeworth) complementarities, where the increased demand for the GPT leads to higher demand for related goods or services; *asset price* (Hirshleifer) complementarities, which create new financial arbitrage opportunities arising from the emergence of the GPT; and *input oligopoly* complementarities, where the collusion between two firms (e.g. microprocessors and mainboards), results in higher collective profits, as the monopoly power over each input commodity generates greater returns than if the firms operated individually. In short, pervasiveness is dependent on the extent to which innovational, technological and other socioeconomic complementarities arise and interact.

The analytical concepts presented in the remainder of this chapter have also given rise to empirical studies on pervasive technological change. In general, the various approaches employ distinct empirical techniques and levels of analysis, including country, industry, firm and individual/worker levels. Each approach has its own advantages and disadvantages. These approaches range from historical accounts and case studies, including those grounded in cliometrics, to data-heavy quantitative-empirical models, such as econometric and input-output analysis. Depending on the theoretical background, the research has thereby focused on investigating the causes and framework conditions of pervasive technological change, the socioeconomic consequences associated with it, as well as the measurement of the microfunctional (i.e. technology-related) characteristics of generic technologies. In particular, the theoretical GPT concepts, assessing the key characteristics and stylized impact of this type of technology, have led to a series of papers that aim at empirically underpinning the analytical findings (Bekar et al. 2018). We therefore complement our guided tour into the conceptual frameworks to pervasive technological change with a short overview of the empirical techniques applied to each of them and illustrate them with representative examples.

Sections 3.2 and 3.3 outline important and novel contributions in the field of pervasive technological change, both from a theoretical and empirical perspective, with the assessment aiming at giving a broad overview of existing works and leverage points for future endeavours in this context.

3.2 Evolutionary-economic concepts

It was not until the mid-90s that pervasive technologies became a major issue in economics, largely due to the growing impact of ICT. Existing theories struggled to explain both the technology's evolving productivity patterns and its diffusion across the economy. The first strand of models, in the line of appreciative theorizing from an evolutionary-economic perspective – techno-economic paradigms, macro-vs. microinventions, as well as the structuralist-evolutionary model of technological change – are all substantiated by the empirical investigation of technological change and industrial revolutions. By stressing the ties between technology, economy and society, these approaches, all rooted in the "ex-post-rationalisation" of economic history (Lipsey et al. 1998), have contributed to a general understanding of how pervasive innovations evolve and impact the socioeconomic system.

Techno-economic and technological paradigms and trajectories

Developed partly in response to Schumpeter's "a-historical theory of entrepreneurship" (Perez 2015), the concept of techno-economic paradigms (TEPs, see, Perez 1985 and Freeman and Perez 1988) has become a core concept in the field of technological change. Western history from the 1770s up to now can be described as a succession of such paradigms or technological revolutions, each generating a "great surge" of development. Each revolution is driven by a techno-economic paradigm (TEP) that creates entirely new industries and organisational forms and guides the interplay between technology, the economic structure, management and social institutions. As each part advances along a genuine trajectory, the arrival of a new TEP initiates a structural crisis at the macro level, necessitating adjustments in capital equipment, work profiles, firm management, industrial organisation and institutional landscape. New inputs are required, that feature strong cost degression alongside the evolution of the new paradigm. Certain social mechanisms synchronize the subsystems again. Each technology lifecycle is characterized by certain phases: the installation period, marked by the emergence of a new technology; the frenzy phase, involving substantial investments in innovative activities that potentially create a financial bubble if the hyped expectations fail to materialise; and the deployment period, where the technology benefits economy and society more broadly (Perez 2013). The shift from one paradigm to another thus concerns various dimensions, most notably the labour market, leading to increasing unemployment due to rationalisation effects, technological replacement and economic stagnation (Perez 2010), and rising inequality in skills and wages between new and old industries and across regions and countries.

Similarly, a technological paradigm, introduced by Dosi (1982) in analogy to Kuhn's concept of paradigm shifts in sciences, signifies a ""model" and a "pattern" of solution of *selected* technological problems, based on *selected* principles from the natural science and on *selected* material technologies" (p.152). The term encapsulates the fact that among the myriad potential directions technological development could follow, only a limited subset is actualized (Verspagen 2007). This subset of basic innovations subsequently determines the fundamental course of techno-economic evolution over an entire era, continuously sparking and being enhanced by incremental innovations. Nevertheless, context-specific factors shape technology development along the way – leading to different "technological trajectories" depending, e.g., on societal aspects, economic needs and local circumstances (cf. the notion of technological style in the large technical systems literature). Both theories, the techno-economic (macro) paradigm and the technological (micro) paradigm, can be viewed as being complementary to each other, insofar as the trajectories of the latter must align with (and cumulatively shape) the former (Knell and Vannuccini 2022).

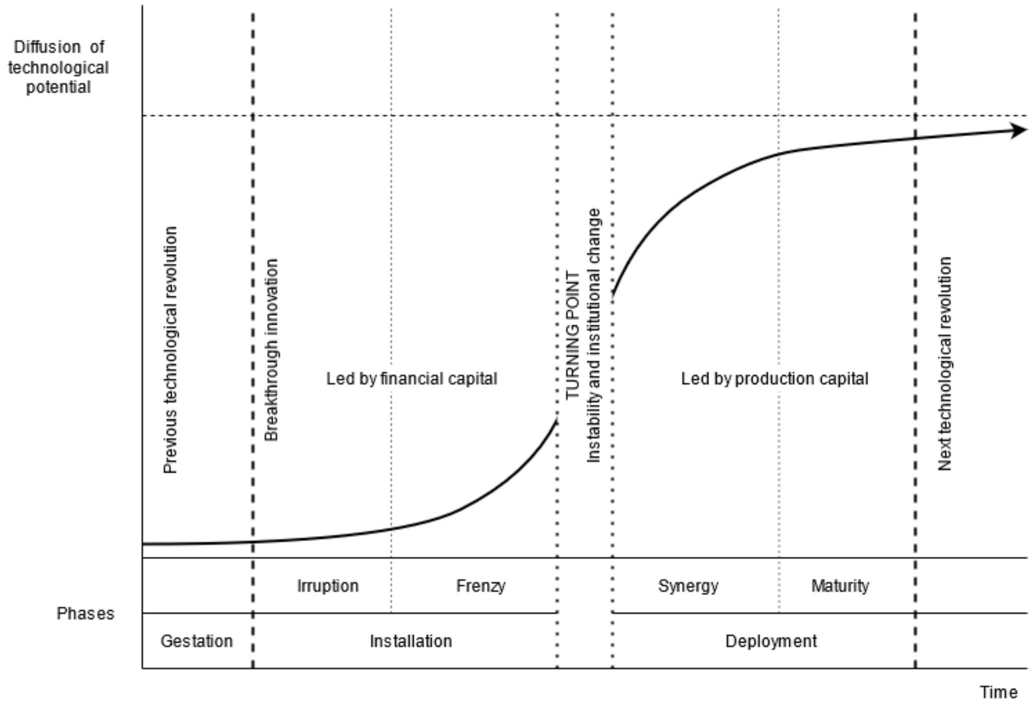

Figure 2: Phases of the techno-economic paradigm. Source: Knell and Vannuccini (2022), based on Perez (2002: 48).

Empirical application. The historical accounts of the emergence of new technologies by Chris Freeman and colleagues have significantly enriched our understanding of the relationship between pervasive technological change and long waves of economic development. For instance, Freeman and Perez (1988) provide a comprehensive overview of five distinct technological revolutions that initiated "great surges" of development, starting with Richard Arkwright's water-frame of 1771 (see also Section 4.3). Freeman and Louçã (2001: 97) propose three methodologies to trace long waves of economic development: (1) traditional statistical and econometric methods, (2) simulation of formal models and (3) historical narratives. Criticising the strong and unrealistic assumptions that often underlie the first two approaches (Knell and Vannuccini 2022), they establish the connection between technological revolutions and long waves based on "reasoned history". This macroeconomic perspective on technological change is pivotal for challenging the neoclassical economic paradigm, as affirmed by Freeman[4]. However, innovation research is still largely focusing on micro level studies.

The TEP notion has also been applied in the quantitative-empirical context. Most recently, Espinosa-Gracia and Sánchez-Chóliz (2023) employ the concept of long waves to analyze the joint persistence of economic crises and changes in social inequality since 1929. They identify four important subdomains – technology, the economy, science and institutions – that together shape income distribution. Using quarterly data of output growth rates, gross investment growth rates and industrial production indices for selected industrial countries, they show that income inequality cannot be attributed to economic productivity and technological change alone but is the result of

[4] "Most of the people working on innovation systems prefer to work at the micro-level. They are a bit frightened still of the strength of the neoclassical paradigm at the macroeconomic level. But I think that's where they have to work. You have to have an attack on the central core of macroeconomic theory. It is happening but not happening enough." (Chris Freeman in an interview with Naubahar Sharif, [10/24/2003], quoted in Fagerberg et al. 2011)

the "global social system". The non-linear and non-deterministic long-run growth trends they detected further support the long-wave theory.

Other contributions refer to the TEP term at the micro level, without embracing the full concept: Based on the analysis of US patents and firm data, Cantwell and Santangelo (2000) discuss how innovative profits are increasingly generated through multinational corporations in the ICT-based paradigm. As regards qualitative case studies, Daniels (2005) discusses the potential of a green TEP for sustainable development in lower-income countries, while Pihkala et al. (2007) explore the impact of techno-economic shifts on regions, emphasizing the role of social capital for adjusting to a new paradigm.

Similarly, quantitative-empirical applications of the concept of technological trajectories and paradigms have focused on the micro level. They typically use patent citation analysis to trace the development path of a specific technology: Verspagen (2007) uses USPTO patent data in the field of fuel cells during the period from 1860 to 2002 to investigate if the main research paths (1) have been "selective" both in terms of a small set of technology fields and the particular organizations involved, and (2) attract cumulative innovations. The study further operationalizes the notion of persistence in the main paths versus the exploration of new directions. Fontana et al. (2009) use patent citation networks to investigate the main technological trajectories of the Ethernet. Their findings support the cumulativeness of innovations around some "milestone inventions", the discontinuities along trajectories, i.e. the exploration of new directions, and the strong interrelatedness of technologies within a large technical system. Castaldi et al. (2009) used detailed records of tank design from between 1915 and 1945 to investigate the convergence and similarity in the evolution of this technology across different countries. The results indicate a significant alignment along a main technological trajectory.

Macroinventions

Mokyr's (1990) distinction between micro- and macroinventions articulates the technological complementarity of innovations: The success of a basic innovation (and the related paradigm) depends on follow-up innovations that improve upon the initial design and adapt it to local circumstances. In this respect, microinventions refer to incremental changes that enhance existing techniques, reduce costs, material and energy use, improve form and function, and increase durability – in evolutionary terms, they reflect an improvement in the species. On the other hand, macroinventions represent per se a new species and cause radical technological change, as they emerge ab nihilo without clear antecedent (Mokyr 1990: 13).[5] They set the course for subsequent technological developments and the trajectories for microinventions. But the relation is mutual, as microinventions enhance the viability of macroinventions. Despite them being the result of serendipitous discoveries, the selection process of macroinventions hinges upon their technical and economic feasibility and their fit into the existing institutional setting. They tend to cluster, following a critical-mass logic where one agent after the other joins the wave of innovation. While the right social, economic and political framework conditions might foster the emergence of macroinventions, microinventions are easier to predict, responding to price and market signals and often being a by-product of learning-by-doing and learning-by-using (Mokyr 1990: 298).

Empirical application. The concept of macroinventions has frequently been applied to the case of the British Industrial Revolution; this is not surprising, as Mokyr himself has claimed that the revolution presents a clustering of macroinventions followed by an acceleration of microinventions. In a historical study, Crafts (1995) underscores the significance of macroinventions for economic development during this time, referring to them as "exogenous technological shocks". Using a basic

[5] The stochastic nature of macroinventions is challenged by Allen 2009, who suggests that macro-inventions often emerge due to economic inducements and are typically conceived by "outsiders" being more receptive to oschmezut-of-the box thinking.

structural model that decomposes industrial production into a trend and a cycle component, Mills and Crafts (1996) demonstrate that trend growth in British industrial output accelerated gradually over several decades between approximately 1780 and 1840 – coinciding with the rise of macroinventions such as the steam engine. The study also supports the concept of serendipity and the lagged impact of macroinventions. Recently, Nuvolari et al. (2021) constructed a new composite indicator based on historical reference indices for all patents granted in England between 1700 and 1850 to empirically test the distinction between macro- and microinventions. The findings lend support to Mokyr's idea of the stochastic emergence of macroinventions and the cumulativeness of microinventions. They also align with Allen's (2009) perspective that macroinventions are economically incentivized (as evidenced, e.g., by their labor-saving bias) and can be attributed to a specific group of actors.

Enabling technologies

The notion of enabling technologies (Lipsey and Bekar 1995) was developed simultaneously with the concept of general-purpose technologies (GPT). While the authors in their later works refer to GPTs when conceptualizing pervasive technological change, we discuss their approach in this Section to emphasize the independent development of the theory and its evolutionary-economic roots.

Acknowledging the impact of radical innovations, Lipsey et al. (2005) stress that not all technologies impose deep structural adjustments upon the economic system, because they are themselves influenced by socioeconomic aspects. Therefore, a systemic view is required in which the technology is embedded in a structure of different components that determine its creation, adaptation and diffusion. This Structuralist-Evolutionary (SE) approach includes six components (Lipsey et al. 2005: 58 et seq.): (1) technological knowledge, i.e. knowledge about and embodied in product, process and organizational technologies; (2) the facilitating structure, i.e. the structure of the economy (including firms, markets, physical, human, and financial capital, infrastructure, education, etc.); (3) public policy objectives (inscribed in legislation, laws, rules, regulations, procedures, and precedents); (4) policy structure, comprising all public sector institutions; (5) natural endowments; (6) socioeconomic performance, e.g. as measured by GDP or employment. These components are interrelated and evolve in concert.

Empirical application. Lipsey et al. (2005) have applied this SE-concept to model the socioeconomic impacts of general-purpose technologies. They conduct a survey on GPTs in Western history, starting around the Neolithic Agricultural Revolution and covering the major technological and organizational developments up to the mid-2000s, their origins as well as their effects on the SE-categories. Their list of transformational technologies includes, amongst others, writing, printing, and the three-masted sailing ship.

Combining index theory with an empirical network model, Strohmaier et al. (2019) operationalized the SE-framework to study countries' readiness to structural transformation as a function of the strength and direction of connectivity among the broad components identified within this framework. This connectivity is measured by means of composite indicators. Measures derived from this network tool inform about the capability of an economy to absorb technological shocks that affect one or more components of its underlying SE-structure. The model was applied to a selected set of Western and Asian countries over the period 2007 to 2016 to trace the recent effects of the digital revolution and Industry 4.0.

3.3 Theories of sociotechnical change

The interrelation between structural features and long-term dynamics are also investigated in other strands of the literature, such as Large Technical Systems, the Technological Innovation System, the Multi-Level Perspective, Strategic Niche Management and Transition Management. These approaches have a stronger social science background than the afore-mentioned evolutionary-economic concepts and are particularly applied in the context of transition studies, to investigate the complex interplay between social, cultural, economic, and political factors in shaping technology development and diffusion; see Köhler et al. (2019) for a detailed discussion.

Large technical systems

Large Technical Systems (LTS) are characterised by their size, complexity and impact on society (Hughes 1983; 1987; Mayntz and Hughes 1988). They typically involve numerous interconnected (technical and social) components, requiring extensive coordination between them to achieve specific goals. LTS emerge from smaller-scale, local, intra-organizational technical systems and undergo characteristic transformations as they grow. The first phase involves the invention, development and innovation of the technology, often characterised by high levels of uncertainty. In the second phase, the technology is transferred and adapted to different environments, leading to a "technological style" that varies, based on geographical, political, legal and historical conditions. The third phase is characterised by growth through competition and consolidation, where efficiency and capital intensification become dominant system goals. During this phase, engineer-entrepreneurs are replaced by manager-entrepreneurs and eventually financier-entrepreneurs. Critical system features include reverse salients, load factor, and momentum. Reverse salients are elements lagging behind or lying in the dark, constraining the development of the collective system, requiring problem identification and solutions by inventors, engineers, managers and investors. The load factor refers to the ratio of the average system output to its maximum output over a given period, momentum to the structural concept and dynamic inertia related to the evolution of a technological system. It reflects the system's ability to sustain and accelerate its expansion and persistence over time. LTS may modify, merge with, or supersede older LTS. Technological path dependence is central to understanding the evolution of an LTS, as investments and legacy technologies may lead to a lock-in into a particular technological trajectory.

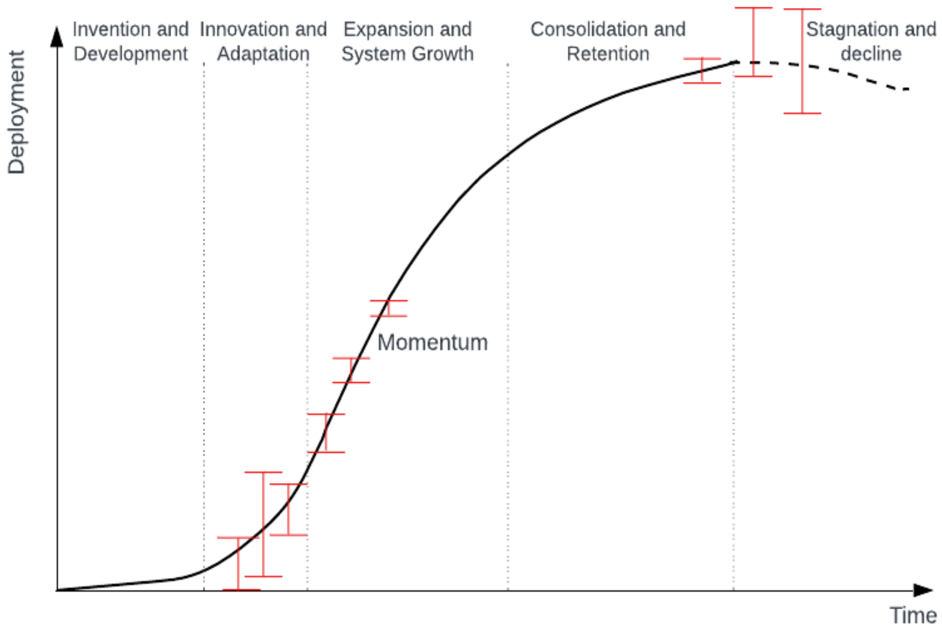

Figure 3: Stylised trajectory of an LTS. Source: Hughes (1987), Sovacool et al. (2018), own illustration. Note: The bandwidths represent the level of uncertainties that shape the trajectory in the respective phase (see Odenweller et al. (2022).

The LTS approach shaped the research strand of social construction of technology. Hughes emphasized the importance of distinguishing between technical phenomena – even if they are socially constructed – and purely non-technical, social phenomena, such as organisations, institutions and interactions, as otherwise the analysis would undermine the material-operational aspects of technological transformation. While the process of innovation itself and evolutionary theorizing have a less central role, the framework also shares many commonalities with the innovation system approaches, in particular, the strong focus on agency. This is covered by the notion of "system builders" – actors and entities that work together, often in a transdisciplinary manner, to solve a specific challenge or overcome a barrier.

Empirical application. The concept itself originated in the comprehensive historical accounts of early electrification by Thomas P. Hughes (see, e.g., 1983, 1987). Subsequent studies have honed in on specific features of large technical systems. For instance, Hanseth et al. (1996) applied the approach to examine the contents and process of standardization of information infrastructure in the EU, employing literature and document analysis. While their findings generally align with the theoretical framework, they caution against a one-size-fits-all approach to measuring technological change and specifically question the empirical validity of the notion of momentum, which suggests irreversibility in the technological trajectory after a certain point in time. If changes were genuinely not possible, an LTS would be unable to adapt to the inherent dynamics and would simply collapse.

(Technological) Innovation System

Innovation systems (IS) are in general defined over a set of organisations (as actors or agents) and institutions and the relationships among and between them (Markard and Truffer 2008). They can be delineated on a territorial basis (national and regional IS, see, e.g., Lundvall 1992; Edquist 1997), on industry structures spanning different geographic regions (sectoral IS, see, e.g., Malerba and Orsenigo 1995, Breschi 2000, Malerba 2002), or technology systems, crossing both territorial and sectoral boundaries (technological innovation system (TIS), see, e.g., Hekkert et al. 2007, Bergek et al. 2008).

The TIS approach combines elements from the (national) innovation system framework and industrial economics (Köhler et al. 2019). It can be understood as a network of different actors that interact with each other for the purpose of generating, diffusing and using a new technology, thereby offering a complementary perspective to the evolutionary-economic concepts of national, regional and sectoral systems of innovation. The national and regional innovation system literature usually focuses on weaknesses or failures – i.e., problems or deficits in the interaction between actors – and traces them back to the *components* of the system, such as infrastructure, institutions, networks, or lacking capacities and resources on the part of the actors (Klein Woolthuis et al. 2005; Wieczorek and Hekkert 2012). In contrast, the TIS approach typically revolves around the system's *functions* by investigating the key processes that shape an innovation: entrepreneurial activities, knowledge creation and diffusion, guidance of search (directionality), market formation, resource mobilization, and creation of legitimacy (see, e.g., Hekkert and Negro 2009; Praetorius et al. 2010). It therefore seeks to detect the "motors of change" – the catalysts of technological progress. A more recent literature stream combines both elements, components and processes of an innovation system, through a structural-functional analysis (see, e.g., Oliveira et al. 2020; Kriechbaum et al. 2018; Turner et al. 2016; Wesseling and van der Vooren 2017).

Empirical application. Similar to the LTS concept, the TIS concept is employed for in-depth analysis of specific technologies rather than whole transition processes (Markard and Truffer 2008). The empirical literature primarily comprises qualitative case studies of a technology or sector at the country level, often based on document analysis and semi-structured interviews. For instance, Binz et al. (2012) use the TIS approach as a conceptual basis for investigating leapfrogging in China, examining the case of onsite wastewater treatment. The TIS framework has also been applied in comparative, mixed-method studies: Bento and Fontes (2015), for example, explore the spatial diffusion of energy technologies, focusing on wind energy growth in Denmark (the core country) and Portugal (the follower country). While diffusion is approximated by logistic curves based on renewable energy and wind energy data, the system functions are assessed through document analysis.

The empirical application demands a clear delineation of the technological system under examination. This is often done arbitrarily, raising questions about the completeness of the analysis. Some studies attempt to address this issue by using technology distance indicators (based on patents and bibliometric data) to measure the distance of the TIS to other innovation systems.

Multi-Level-Perspective

The MLP approach (Rip and Kemp 1998; Geels 2002; Smith et al. 2010) is rooted in the sociology of innovation but also includes elements from evolutionary and institutional economics. It operates across three levels: 1) the socio-technical regime, a highly stable and inert rule structure at the meso level, associated with established products, technologies, practices, regulations, etc. It represents the selection environment (Markard and Truffer 2008) that a radical innovation is confronted with;[6] 2) the landscape, encompassing the external macroeconomic and macro-political sphere and normative and cultural patterns that influence technological trajectories; 3) niches, representing the micro-level; they play a pivotal role as “incubator rooms” for radical innovations, offering a protected space to develop in isolation from the prevailing regime. Changes in the landscape create a window of opportunity for these novelties to destabilize the existing sociotechnical regime, along various dimensions (e.g. markets, quality infrastructure, technologies). The tension between stability and change, on the one hand, and the single level/component and the entire system, on the other hand, lead to complex structural dynamics reminiscent of evolutionary frameworks.

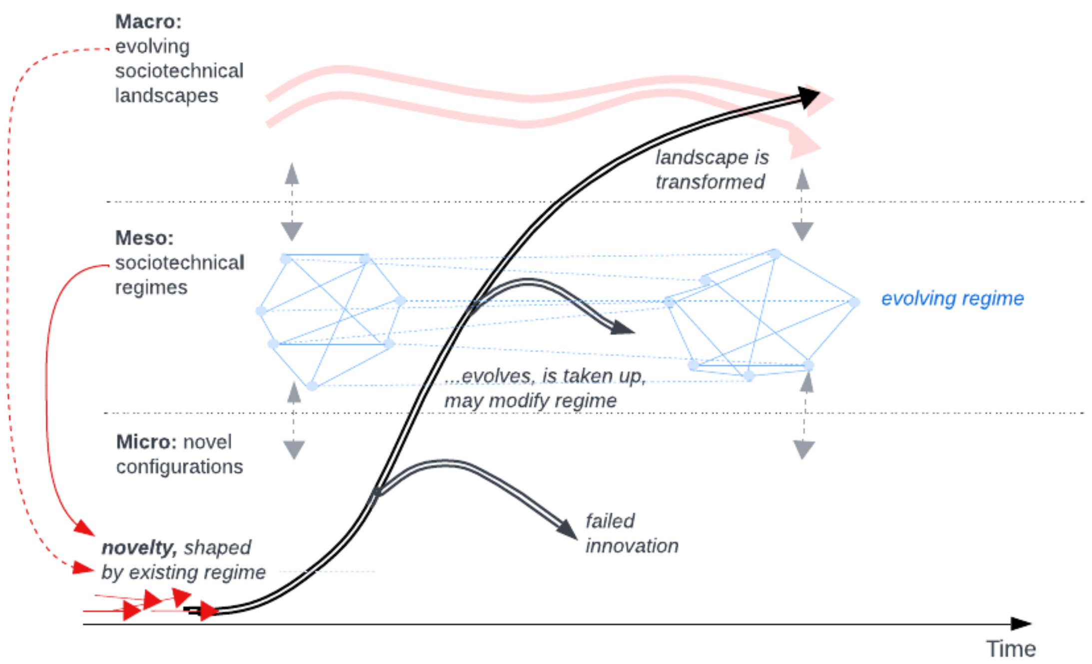

Figure 4: A multi-level perspective on technological transition. Source: Based on Geels (2002: 1262 ff.), own illustration.

[6] Geels (2004) also introduced the ‘sociotechnical system’, which integrates the sociotechnical regime and the material infrastructure into a coherent system that governs technology deployment.

Empirical application. The MLP approach has arguably generated the most extensive empirical literature within sociotechnical studies, often concentrating on niche-regime relations. For instance, Smink et al. (2015) delve into the institutional strategies adopted by incumbent firms in the Netherlands concerning sustainable energy innovations that challenge their interests (exemplified by LED light bulbs and biofuels). This case study is based on semi-structured interviews and document analysis. Applying a firm-level survey, Steen and Weaver (2017) investigate how incumbents in established energy sectors (oil/gas) in Norway diversify into other (niche) energy sectors such as hydropower. The MLP concept has also influenced policy-oriented studies: Spickermann et al. (2014), for example, use visioning, Delphi studies and focus group workshops to guide cities in Germany in how to develop a long-term future vision of urban mobility systems. Finally, the MLP-framework has been applied in quantitative-empirical research. Li and Strachan (2017) employ a dynamic, stochastic sociotechnical simulation model of technology diffusion, energy and emissions to model energy transitions for the UK under specific climate targets, considering landscape and actor inertia. Köhler et al. (2020) conduct qualitative case studies to inform simulation models of transition pathways for low-carbon mobility in the Netherlands, encompassing technological and behavioural change.

A common criticism revolves around the difficult empirical delineation of regimes (e.g. on the level of industrial sectors, technology fields, etc.) and the lack of insights on how regimes themselves change during the transition (see Markard and Truffer 2008).

Strategic Niche Management

Similarly to the MLP approach, Strategic Niche Management (SNM) (Rip and Kemp 1998; Geels and Raven 2006; Schot and Geels 2008) centers around niches as incubator rooms for nurturing new, and potentially transformative, technologies. These protected spaces (e.g. demonstration projects) allow dedicated actors – often new entrants – to jointly develop, refine and test emerging innovations and shield them from the dominant market, the inertia and the vested interests characterising the prevailing regime. In this context, three internal processes are pivotal: 1) visions and shaping expectations; 2) building social networks; 3) learning processes (Kemp et al. 1998). Through recursive loops of experiments and demonstration projects, these processes shape the overall innovation trajectory (Geels and Raven 2006; Schot and Geels 2008). The approach thus focuses on the supportive environment that makes novel technologies strive, build legitimacy and eventually challenge the existing sociotechnical regime.

Empirical application. Given the niche focus of the concept, studies in this realm typically operate at the micro level, honing in on specific transition aspects, often associated with sustainability. Seyfang and Haxeltine (2012), for instance, investigate the role of community-based initiatives (as a civil-society-based social innovation) in the transition to a low-carbon sustainable economy in the UK. This study involves document analysis, a survey, and participant observation. Also for the UK, Hargreaves et al. (2013) examines the role of intermediary actors in consolidating, growing and diffusing energy community projects, utlizing interviews and content analysis of case studies.

Transition Management

In comparison to the MLP and the SNM approach, the Transition Management (TM) framework (Rotmans et al. 2001; Rotmans and Loorbach 2009) is more practice-oriented. Accordingly, policy can shape transitions through four sequential steps: 1) strategic activities, focusing on vision setting and potential transition pathways; 2) tactical activities, developing more concrete roadmaps and agendas and supporting actors and networks, e.g. through regulatory measures and investment commitments; 3) operational activities, putting these strategies into action (e.g. feasibility studies and demonstration projects) with the aim to foster technological learning; 4) reflexive activities (evaluation and monitoring of projects), creating feedback loops between visions and implementation. As before, technological change is seen to be characterised by systemic complexity, but other evolutionary aspects, such as path-dependence, lock-in and co-evolution are featured less prominently.

Empirical application. Similar to the MLP and the SNM concept, the TM approach has been most frequently applied empirically in the context of sustainability, climate change and environmental issues, spanning industry/sector, regional, and country levels. Loorbach and Rotmans (2010), for instance, showcase recent advances in the TM approach by presenting four case studies at different levels of analysis, including the health care sector and sustainable waste and resource management. The study illuminates both the advantages and challenges associated with effectively managing transitions.

Sociotechnical studies are a rapidly growing field. Among the many emerging trends, three deserve particular attention:

(1) multi-system multi-technology interaction frameworks for exploring the sectoral complementarities and industrial transformative capacity of an emerging technology (see Bakhuis et al. 2024 for a comprehensive literature review). Adjacent sectors – sectors outside the technology's immediate value chain – can significantly enhance its development (Markard and Hoffmann 2016, Mäkitie et al. 2018), e.g. by providing key resources. They often also host valuable knowledge and capabilities that can be recombined to support the new technology. The emergence of a new technology can thus foster growth or revitalize other sectors (Fontes et al. 2021).

(2) the rise of integrative analyses, building upon feedback loops between qualitative and quantitative empirical research and combining different disciplines to enhance system analysis and predictive modeling (see, e.g., Wachsmuth et al. 2023)

(3) the integration of Knightian or "deep" uncertainty, where agents cannot make informed decisions on the probabilities of possible outcomes or the actual outcomes themselves (see Haas 2023).

3.4 General Purpose Technologies

Introduced by Bresnahan and Trajtenberg (1995), general purpose technologies (GPT) are characterised by three main criteria: (i) widespread usage, (ii) the potential for continuous technical improvement, and (iii) the ability to foster innovation in application sectors. The initial GPT concept focused on the coordination of innovation activities between up- and downstream sectors in a partial equilibrium model. The lack of technological information flowing between the GPT-providing and the using sectors prevent positive externalities from coming to full play.

First generation models

Not last in an attempt to explain the productivity slowdown in the U.S. in the 1980s, a "first generation" of GPT growth models (Cantner and Vannuccini 2012) were subsequently developed around the original notion of GPTs. Key contributions include, in addition to Bresnahan and Trajtenberg (1995), Helpman and Trajtenberg (1998a, 1998b), Aghion and Howitt (1998) and Petsas (2003). Models in this line view a GPT as a process innovation that triggers product innovations in other sectors. In Helpman and Trajtenberg (1998a), the necessary development of complementary components causes resource shifts from manufacturing to R&D and productivity slumps before subsequent growth. Helpman and Trajtenberg (1998b) focus on the diffusion process of a GPT across sectors, driven by complementary development, and on its impact on prices, on income distribution and GDP. Aghion and Howitt (1998) adapt their Schumpeterian growth model to investigate the diffusion of GPTs. A firm adopts a GPT by imitating other firms that have already implemented the technology successfully. The likelihood of imitation increases with the pool of successful adopters. This results in an S-shaped diffusion path of the new GPT. Social learning may thus cause a slump during the first phase of implementation, depending on the speed of diffusion of the new technology and the extent to which resources are re-diverted from the old to the new production process. Petsas (2003) focuses on the rising product quality of final goods (rather than the expanding variety of components) as impact channel of a new GPT. The GPT affects long-run growth by enhancing (1) the scale of future innovations, and (2) research productivity, thus accelerating innovation rates.

Second-generation models

The GPT growth literature has been further extended by second-generation models (Cantner and Vannuccini 2012), each contributing novel aspects to the existing body of work:

Van Zon and Kronenberg (2005) introduce stochastic R&D processes, distinguishing between "core" technologies (GPTs) and "peripherals" (components). The model allows for the possibility of GPT failure if insufficient components are developed. Carlaw and Lipsey (2006, 2011) introduce uncertainties in the arrival time and the performance of the GPT, also addressing competing GPTs in their evolutionary-economic model. Afonso and Bandeira (2013) use a general-equilibrium model to examine how GPT diffusion from the Global North to the Global South affects wage inequality both within and between countries. Schaefer et al. (2014) expand on Petsas' (2003) quality-ladder model to examine how successive GPTs, emerging endogenously and at an accelerating pace, affect long-term growth. Coccia (2015) stresses the significant role of strategic behaviour of organizations, especially of leading nations (i.e. great powers) to stay on top of the GPT race.

Several papers focus on the effect of GPTs on structural change. Rainer and Strohmaier (2014) develop a multisectoral model of GPT diffusion, combining evolutionary game theory and input-output analysis to study skill-biased technical change, wage inequality and GPT co-existence. Andergassen et al. (2017) investigate GPT diffusion through "R&D races", finding that stronger linkages between sectors enhance adoption, technological proximity and sustained economic growth. Cantner and Vannuccini (2021) model conditions that enable GPT adoption across vertically related and networked industries.

Empirical application. The empirical GPT literature covers diverse aspects such as the sources of pervasive technological change (Coccia 2018), the main characteristics of GPTs (also vis-à-vis others; Jovanovic and Rousseau 2005), as well their economic and societal impact (see, e.g., David 1990, Rosenberg and Trajtenberg 2004).

The majority of quantitative-empirical studies have focused on knowledge flows between the initial technological breakthrough and subsequent innovations. These are typically measured by means of patent and patent citations data. The central assumption in this line of research is that a GPT's capacity to spawn innovations can be assessed by measuring the extent to which downstream inventions cite the original patent in their applications (i.e. by the number of forward citations). The larger the range of technology fields these inventions are assigned to, the bigger the generality, or pervasiveness, of the technology. Noteable contributions are Hall and Trajtenberg (2006) and Petralia (2018), who develop measures for detecting general purpose technologies in patent and patent citation data, and Nicholas (2004), who uses this type of data to track innovational complementarities regarding four technology fields (electricity, chemical, mechanical and other). Similar studies have been conducted for potential GPT candidates, such as nanotechnology (Youtie et al. 2008; Graham and Iacopetta 2014) and biotechnology (Appio et al. 2017; Feldman and Yoon 2012).

Some studies revert to input-output models to explore dynamics between the GPT-providing sector and application sectors, focusing on complementarities in the marketplace rather than at the innovation level. GPTs are analysed as technologies embodied in intermediates and capital goods. Verspagen (2004) employs linkage analysis to study the sectoral impact of ICT on the U.S. economy in the postwar period. Based on time-series input-output tables (1966-2009) for Denmark, Strohmaier and Rainer (2016) show that for ICT this data is able to capture the main characteristics of a GPT.

Other studies make use of national account data to measure empirically the impact of a generic technology on productivity. Castellacci (2010) combines the EU-KLEMS database with the Community Innovation Survey (CIS) to investigate sectoral labour productivity dynamics for 18 OECD countries over the period 1970–2005. Liao et al. (2016) examine the direct and indirect contribution of ICT to productivity dynamics in the US between 1977 and 2005, also using the EU-KLEMS database.

The rise of digital technologies has led to a significant increase in the availability of qualitative and quantitative indicators for measuring technological and socioeconomic change. These indicators are increasingly used in technology impact studies, such as Harb's (2017) analysis of the impact of Internet penetration on economic growth in Arab and Middle East countries.

3.5 In a nutshell: analyzing pervasive technological change

Pervasive technological change is not a novel topic in economic history and the history of economic ideas and has garnered significant interest, particularly in the last half century, owing to its presumed correlation with economic growth cycles. Nevertheless, the comprehension of the nature and evolution of technologies, which induce punctuated equilibria dynamics in the economy, has been less prominent than the recognition, conceptualization and empirical identification of the regularities behind incremental and localized technical change. It has also received less attention compared to the standard modeling of technological change, perceiving the latter as a rather homogeneous process (see Section 2.7). This disparity has resulted in a fragmented and parallel development of methodological approaches to measuring technological pervasiveness: European scholars have predominantly focused on "appreciative theorizing" (Nelson 2018) of discrete technological interventions, delving into various qualitative key factors that remain unexplored or unexplained by economic models. Studies have typically employed an evolutionary-economic and sociotechnical lens. In contrast, American scholars sought to integrate the phenomenon of pervasive technological change into endogenous growth modeling.

The GPT concept centers around market transactions and the economic realm, with a primary focus on technological complimentarities and their impact on the rate of economic growth. Since models like Helpman and Trajtenberg (1998a) exhibit a similar cyclical growth pattern akin to evolutionary-economic concepts, Verspagen (2004) refers to them as the "American counterpart of Schumpeterian economics".

Evolutionary-economic concepts offer a macroeconomic view on technological change. Radical or disruptive technological change acts as a catalyst for revitalizing growth, contingent upon the adaptability of the socioeconomic system. Examining the interplay between a particular technology and the economic and social structure, scholars identify broad patterns of change as characteristics of a specific technological paradigm or revolution.

Sociotechnical studies, also employing a systemic perspective, similarly view radical technological change as a necessary but not sufficient condition for transformative change. They typically analyze specific technological trajectories, identifying reverse salients (LTS) or blocking mechanisms at the functional or systemic level ([T]IS), and explore the relationship between a new technology and the prevailing regime (MLP). Investigating disruptive, and not exclusively pervasive, technological change, these studies capture transitions to a new technological paradigm – often in the context of sustainability – as a co-evolutionary, non-linear and path-dependent process. Many studies delve into the direction of technological change, examining both the "direction of search" for new technical solutions and the "direction of progress" (e.g., just transition).

Given the conceptual overlaps between evolutionary-economic and sociotechnical studies, integrated approaches have been proposed: Markard and Truffer (2008), e.g, outline an extended framework for TIS, where regimes, landscapes (cf. MLP) and other technological innovation systems form the environment of the focal TIS. Schot and Kanger (2018) introduce the long-term perspective typical of the TEP framework to the MLP concept (see also Section 4.3).

Regarding empirical applications, studies measuring pervasive change can be grouped in the following way: (1) historical and cliometric studies, which delve into the characteristics of a specific technology and its interaction with the broader socioeconomic environment; (2) data analysis, often utilizing statistical models, focusing on R&D expenditures, knowledge flows (patents), national account data and input-output tables to detect changes in innovation and economic activities at the meso level (technology field, sector/industry); and (3) indicator analysis, often survey-based, offering expert insights and tacit knowledge into pervasive technological change.

Evolutionary-economic concepts have frequently been discussed within, and developed in tandem with, historical-descriptive studies (see, e.g., Perez 1985; Freeman and Louçã 2001). This type of analysis can capture the long-run perspective inherent in the theoretical frameworks while reflecting in detail on country-, region- or industry-specific circumstances. Sociotechnical studies, with a stronger focus on the micro level, employ established instruments in qualitative-empirical research (document and media analysis, expert interviews, focus group discussions, scenario analysis etc.). The emphasis is on understanding current and future technological development, particularly in the context of the sustainability agenda.The concept of GPTs has triggered a diverse body of empirical work, ranging from historical studies (see, e.g., Rosenberg and Trajtenberg 2004) to econometric and network models based on knowledge flows (see, e.g., Hall and Trajtenberg 2006; Petralia 2020).

Patent statistics have been a key resource for studying pervasive technological change at the micro level, offering detailed, long-term data on technologies and inventors. However, they also have limitations: Simple patent counts do not adequately capture innovation quality and many patents do not translate into practical technical solutions; patenting behaviours vary by sector and firm (Verspagen 2007); and language bias and country-specific patenting practices hinder comparability (van Raan 2004). Patent citation analysis has been particularly valuable for mapping technological trajectories and identifying macroinventions and GPTs. Nevertheless, the method only captures technology spillovers; missing broader effects such as when employing basic technologies (e.g., microcomputers) enables advancements in others (e.g. wind turbines) (Bresnahan 2010).

Other data sources used to measure pervasive technological change include intersectoral commodity flows,), as reflected in input-output tables (see, e.g., Verspagen 2004, Strohmaier and Rainer 2016) and national account statistics (e.g., Liao et al. 2016). These data highlight how technology impacts sectors differently. However, they have limitations: they cannot capture individual firm dynamics; certain industries may be over- or underrepresented; and some technologies may not align neatly with specific sector(s). For example, while ICT can be identified at the two-digit level in standard industry classifications, technologies like nanotechnology or biotechnology require more granular industry groupings, as their production spans multiple sectors.

Indicator analysis has also been used to measure pervasive technological change, often drawing on R&D and innovation activity surveys (see, e.g., Castellacci 2010) to capture the tacit knowledge of firms and businesses. Standardized surveys, such as the CIS or the U.S. Business R&D and Innovation Survey (BRDIS), provide data on innovative activities across major technology fields but may lack detailed insights into specific innovations. Consequently, some studies conduct their own surveys, tailored to the technology in question. This is typically a costly undertaking and requires a robust empirical basis, often challenging to achieve during the early stages of technology development. More recently, the expanding array of indicators has enabled more comprehensive systemic analyses, allowing for the assessment of technological change within its broader socioeconomic context (see, e.g., Strohmaier et al. 2019).

Quantitative-empirical studies of technological change frequently depend on well-defined model specifications. The S-shaped performance and diffusion curve (see, e.g., Aghion and Howitt 1998 in the GPT context) is particularly prominent for fitting past patterns of technological development or predicting future outcomes (see, e.g. Odenweller et al. 2022). Estimating the sigmoid fuction depends on assumptions about the upper limit, inflection point and factors shaping the curve – and not least, hinging on the empirical validity of the S-curve itself. Some scientists contest the general applicability of a sigmoid curve, suggesting exponential performance trends over the long term, more in line with Moore's law (see, e.g, Moore 1998).

Last but not least, the rise of new technologies has influenced the empirical measurement of pervasive technological change. Advances in modeling and AI, along with the availability of large datasets, have facilitated the prediction of technology performance, enabling the assessment of the future importance of specific technologies (Hoisl et al. 2015). For instance, Singh et al. (2021), predict the performance improvement rates for almost all technology fields, using a patent-based AI algorithm trained with 30 technology domains for which empirical performance data is available. Machine learning is also used to study specific effects of pervasive technological change (see, e.g. Frey and Osborne 2017 on the susceptibility of jobs to computerisation) or explore hidden thematic patterns through topic modelling, based on a large text corpus (see, e.g., Kumar and Ng 2022 on the success and growth factors of renewable energy). (For further discussion, see also Section 4.5)

In summary, the various approaches discussed in this chapter aim to illuminate the black box of pervasive technological change, contributing to a kaleidoscopic landscape characterized by multifaceted research perspectives and a comprehensive array of empirical measures and techniques.

Table 2: In a nutshell: concepts of pervasive technological change and their empirical application.

Concept	Focus	Data and methodology	Strengths	Problems and weaknesses	Reference
Evolutionary-economic concepts	Determinants of long-term economic development from macro- and microeconomic perspective	Mostly historical studies based on document and literature analysis, cliometrics	Coverage of long time periods Holistic view of technological and socioeconomic transformation, exploring the causes, drivers, and direction of technological change	Overemphasis on specific (macro-) technologies Results are difficult to generalize	Perez (1985) Freeman and Perez (1988) Mokyr (1990) Lipsey et al. (2005)
Socio-technical studies	Framework conditions, learning processes, functioning of technical and innovation systems, especially in the context of sustainability	Qualitative-empirical studies, based on desk research, expert interviews, focus group discussions, etc.	Detailed account of the factors driving/impeding technological change and transitions	Context-specifictiy of the research question usually limits generability of results. Difficult delineation between different technologies/technology systems, and purely technological and social aspects	Hughes (1983) Hekkert et al. (2007) Rip and Kemp (1998) Rotmans et al. (2001) Geels (2002)
General purpose technologies	Complementarities of technological change, spillover effects, cyclical growth pattern	Economic/stat-istical modeling for impact analysis, empirically often based on country-level or firm-level data; patent analysis for measuring the importance of the GPT and compementarities	Macroperspective on the relationship between technology and growth and productivity differentials across time, industries or countries Quantitative measuremnent of pervasive technological change	Overreliance on one type of data (e.g. patents) Unclear definition of pervasiveness (direct vs. indirect linkage)	Bresnahan and Trajtenberg (1995) Helpman and Trajtenberg (1998a, 1998b) Aghion and Howitt (1998)

4 Impact of new technologies on theory and measurement of technological change

4.1 Features of industrial modernity

Schumpeter (1939) argued that clusters of radical innovations drive long waves—extended periods of economic expansion and contraction lasting approximately 40 to 60 years—triggering oscillations in capital goods (see Section 2.4), investment clustering, and self-reinforcing behaviour. The historical narrative from 1790 to 1920 in the U.S., Britain, and Germany illustrates the uneven distribution of innovation (McCraw 2007).[7] Kurz et al. (2018) describe disruptive innovation and and technological revolutions from a post-Schumpeterian perspective, while Perez (1985) and Freeman and Perez (1988) introduced the *techno-economic paradigm* (TEP), linking cyclical technological evolution with path dependence, structural changes, and institutional dynamics.

Freeman and Louçã (2001) associated the TEP with Kondratiev long waves, which describe cyclical economic expansions and contractions driven by technological advancements. Pérez (2002) referred to them as great surges of development, emphasizing their transformative impact on industries and institutional structures. While Kondratiev waves focus on macroeconomic fluctuations, great surges highlight the role of technology in reshaping economies and societies. These perspectives highlight how institutions, path dependence, and guiding principles shape the historical dynamics and economic impacts of technological revolutions. Perez (2010) characterized these revolutions as clusters of interdependent technologies—a “system of systems.”

Perez (1983) emphasized that each TEP includes a dominant low-cost key sector encompassing energy sources, materials, technologies, products, and processes with distinctive organizational structures. Nelson (2005) stressed that changes in core inputs, physical technologies, and human-technology interactions are pivotal to the dynamics of each TEP. According to Perez (2002), each TEP goes through four distinct phases: (1) *irruption*, where new technology displaces older systems, driving initial economic disruptions and investment surges; (2) *frenzy*, marked by intense innovation, speculative investments, and rapid industry transformations; (3) *synergy*, during which the technology stabilizes, integrates into mainstream economic structures, and fosters widespread productivity gains; and (4) *maturity*, signaling the completion of diffusion and eventual stagnation in growth. A modern example of this cycle is the rise of the internet, which initially disrupted traditional industries, saw speculative investment bubbles in the late 1990s, integrated into all sectors during the 2000s, and is now in a phase of sustained but slower innovation. Perez also introduced a gestation period preceding each paradigm, analogous to the “laboratory-invention phase” in Freeman and Louçã, which predicts the emergence of the next wave of technological change. Perez (2002) conceptualized these stages as part of the S-shaped technology life cycle, capturing the dynamic progression of innovation and diffusion (see Section 3.3).

Industrial Revolutions and TEP Transitions

Table 3 summarizes five TEPs that have shaped industries and economies since Arkwright introduced the water frame in 1771. The first TEP, driven by waterpower and mechanical spinning machines, initially struggled due to the excessive costs and technical limitations of James Watt's steam engines. Later advances in machine tools and precision engineering led to smaller, more efficient steam engines, enabling further industrial progress (see also Knell 2013, 2024) on the connect between technological revolutions and energy transitions).

[7] In *The Theory of Economic Development*, Schumpeter (1934 [1912]: 229) stated that “every typical economic boom originates in one or a few specific industries—such as railway construction, electrical engineering, or the chemical sector—and derives its distinctive characteristics from the innovations within the industry where it first emerges.”

Table 3: Overview of key catalysts in industrial modernity

TEP	Key catalysts	Notable developments
1st TEP (1771)	Waterpower, machine tools, precision engineering	High costs and technical limits hindered steam engine adoption
2nd TEP (1829)	Steam-powered mechanization, declining resource prices	Agglomeration, standardization, and infrastructure like railways and telegraph networks
3rd TEP (1875)	Industrial electrification, electrical equipment	Steel advancements, Edison's R&D laboratory, networking inventions
4th TEP (1913)	Declining oil prices, moving assembly line	Mass production, economies of scale, post-WWII economic growth
5th TEP (1971)	Microprocessors, software, and the internet	Integrated circuits, telecommunications, robotics, and a lead to "smart systems"

Source: Own summary based on Freeman and Perez (1988), Perez (2002), and von Tunzelmann (1995).

The second TEP, characterized by steam-powered mechanization, benefited from declining resource prices and key developments like the Rainhill Locomotive trials and the Liverpool-Manchester railway. Agglomeration, standardization, and specialization boosted productivity, while railways and telegraphs improved connectivity. Nevertheless, working-class repression and inequality marked the period.

Industrial electrification and the expansion of the electrical equipment industry defined the third TEP. Advances in steel production and transportation were crucial, with Edison's New Jersey laboratory appearing as a hub for research and collaboration.

The fourth TEP began with the introduction of the moving assembly line in 1913, enabling mass production of goods such as the Ford Model T. Falling oil prices and post-World War II economic growth accelerated mass production and consumption, driving industrial expansion and innovative product designs.

Schot and Kanger (2018) define the first four technological paradigms as part of industrial modernity, marking the first deep transition. During this phase, machines increasingly complemented human labour, enhancing productivity and efficiency across various sectors. The second deep transition, associated with the fifth TEP, shifted this dynamic as machines moved beyond assisting human labor to automating cognitive functions, particularly symbol processing. This transformation redefined the relationship between humans and technology, as machines evolved from performing physical tasks to handling complex informational processes. The transition from industrial modernity to automation reflects the continuous evolution of technology, reshaping economies, labour, and society.

4.2 The Digital Revolution as the second deep transition

The second deep transition, encompassing the Digital Revolution (also referred to as the fifth TEP), began in the late 20th century with the development of the first electronic computers, such as ENIAC and UNIVAC. Based on Turing's computational principles, this paradigm enabled the rise of modern computing, which, in turn, drove the development of artificial intelligence (AI). This advancement allowed machines to process information, learn, and make decisions in ways once considered uniquely human. Key breakthroughs foundational to this revolution include the development of the vacuum tube in 1935 and the transistor in 1947. The transistor, a semiconductor device that regulates electronic currents, transformed electrical signal control. Bell Labs played a pivotal role in this transformation by developing prototypes and securing patents, catalyzing the rise of Silicon Valley (Lécuyer 2006).

Box: Digital vs. digitalization.

Digitization converts analogue data into computer-readable formats. Digitalization employs digital technologies to create or alter activities. Digital transformation encompasses the broader economic and social implications of these processes (OECD 2019b).

The Intel microprocessor is essential to the digital revolution

A key milestone in digital technology occurred in 1969 when Intel announced its plan to develop the world's first commercially viable microprocessor, the Intel 4004, which debuted in November 1971. In the same year, the U.S. Department of Defense deployed computers on the Advanced Research Projects Agency Network (ARPANET), the precursor to the Internet. Integrating central processing unit (CPU) functions into a single chip revolutionized computing, marking a foundational moment in the digital era. However, the Apollo 11 moon landing initially overshadowed the microprocessor's debut (Isaacson, 2014). Advances in photolithography and planar technologies made the microprocessor possible, fueling the fifth technological revolution, or digital techno-economic paradigm. Over the next five decades, this paradigm transformed communication, information access, business practices, and societal interactions, driving sustained economic growth and innovation (Knell, 2021; Knell and Vannuccini, 2022).

According to Perez (1983), the diffusion of the Digital Revolution follows a pattern similar to the spread of a Technical Innovation System (TIS) (Hughes, 1983). As outlined in Section 3.3, the digital revolution has progressed through four phases: early exploration, a financial bubble followed by a crisis at the turn of the century, and the eventual widespread diffusion of knowledge across the techno-economic paradigm. This transformation began with a prolonged gestation period, often referred to as the laboratory-invention phase, followed by a revolutionary breakthrough (or big bang) that defined the digital TEP. Over the next five decades, this paradigm gradually reshaped communication, information access, business practices, and societal interactions, driving innovation, economic growth, and social progress (see Singh et al. (2021), for a patent-based analysis)

Moore's law as a reflection of the digital revolution

The evolution of the techno-economic paradigm (TEP) has been shaped by Moore's Law (Moore, 1965), which states that transistor density on integrated circuits doubles approximately every two years, driving significant increases in computing power and reductions in cost. Advances in transistor technology, particularly the development of metal–oxide–semiconductor field-effect transistors (MOSFETs) and complementary metal–oxide–semiconductor (CMOS) technology, have sustained this rapid progress, enabling faster processing speeds, greater miniaturization, and widespread technological innovation (Kahn et al., 2018). Braun and Macdonald (1982) emphasize the role of miniaturization in accelerating technological development, while Nordhaus (2007) examines its economic implications, showing how the continuous expansion of computing power has transformed industries and enhanced global productivity.

One striking example of Moore's Law in action is Apple's introduction of the M3 family of chips in October 2023. These chips, built using 3-nanometer process technology, contain up to ninety-two billion transistors—a dramatic increase from the original Intel microprocessor, which had only 2,250 transistors. Such advancements have fueled diverse technological trajectories, fostering dynamic clusters of innovations across industries. The resulting developments have not only transformed products and services but have also stimulated the emergence of new enterprises, strengthened industry networks, and contributed to the expansion of global digital infrastructure. This includes the proliferation of the Internet and various electronic services, such as email and cloud computing.

However, as transistor miniaturization approaches its physical limits, researchers are turning to alternative computing paradigms. One promising frontier is quantum computing, which represents a fundamental shift from the classical binary system. Unlike traditional computers that rely on electrical signals to represent ones and zeros, quantum computers use quantum bits (qubits), derived from subatomic particles, which can exist in multiple states simultaneously. This capability allows quantum systems to perform computations at unprecedented speeds, holding transformative potential for fields such as cryptography, optimization, and AI (Kaku 2023).

Digital revolution and artificial intelligence

While the concept of crafting automatons and artificial entities has ancient roots, the formal start of modern robotics and AI predates the digital revolution, emerging in the mid-20th century. A pivotal moment occurred in 1961 with the introduction of the first programmable robot, which transformed industrial assembly-line applications. Since then, robotic advancements have progressed rapidly, leading to increasingly sophisticated machines capable of executing diverse tasks (Raj and Seamans 2019). Progress in sensors, actuators, and AI algorithms has enabled robots to navigate complex environments, interact with humans, and function across various sectors, including manufacturing, warehousing, agriculture, autonomous vehicles, healthcare, and education (Hudson 2019, Ford 2021). Despite advancements in AI through statistical learning algorithms, robots still face limitations in solving everyday problems (Mitchell 2019)

The foundational work for AI emerged from a 1956 Dartmouth College conference, where Allen Newell and Herbert Simon introduced the term "artificial intelligence" (AI), intertwining logical reasoning, problem-solving, symbolic reasoning, and machine learning (ML). Unlike traditional AI methods that require extensive datasets, early AI research focused on commonsense intelligence (Levesque, 2017). Generative AI, a subfield gaining prominence around 2014, involves AI systems that create text, images, or other media in response to prompts (Roser, 2022; Crawford, 2021). These models, trained using neural networks and machine learning techniques, can generate new data reflecting inherent patterns (Mitchell, 2019; Wooldridge, 2021; Agrawal et al. 2019, 2022; Craglia et al. 2018, for a European perspective).

AI as a General-Purpose Technology?

There is an ongoing debate about whether AI qualifies as a general-purpose technology. Cockburn et al. (2019) and Crafts (2021) argue that AI has the characteristics of a general-purpose technology, emphasizing its transformative potential across various sectors, while Knell and Vannuccini (2022) question this assertion, highlighting concerns about limitations, ethics, and societal implications. The discourse revolves around assessing the true nature and scope of AI's impact on diverse domains.

Over time, digitalization has enabled the development and adoption of innovative technologies, including AI, big data analytics, cloud computing, and the Internet of Things (IoT) (Brynjolfsson and McAfee 2014, Acemoglu and Johnson 2023). The fusion of robotics and AI has revolutionized business operations, prompting fundamental changes in organizational strategies, processes, and customer interactions (Isaacson 2014). These technologies have enhanced efficiency, scalability, and innovation across diverse sectors, transforming industries, societies, and human-machine interactions.

Technological trajectories and the digital revolution

Dosi (1982) identified several key technological trajectories relevant to the digital revolution (see Section 3.1 and Nordhaus 2007). Within a techno-economic paradigm, multiple technological trajectories may coexist, each contributing to broader patterns of innovation and structural change. Although the concept of technological trajectories predates this framework, Dosi's analysis provides a systematic understanding of how these pathways influence economic and social structures. The following trajectories illustrate distinct evolutionary trends in digital technology:

(1) ***Mobiles, Internet, and Broadband****:* The rise of mobile telephony, the Internet, and broadband networks reshaped global communication, culminating in 5G technology. Mobile telephony traces its roots back to 1928 when Detroit police introduced a voice-based radio system, evolving from one-way paging. The transistor, introduced by Bell Labs in 1947, paved the way for cellular networks in the 1960s (Gertner 2012). Technological advancements in the 1960s and 1970s furthered the shift toward digital communication. Martin Cooper's groundbreaking call in 1973 led to the launch of Motorola's DynaTAC, enabling portable communication through handheld devices. Key milestones like the Nordic Mobile Telephone (NMT) system in 1981 and Global System for Mobile communication (GSM) standardization in 1989 contributed to the widespread adoption of digital protocols. According to the International Telecommunication Union (ITU 2023), global 4G LTE subscriptions surpassed 5.3 billion in 2022, with overall mobile cellular subscriptions exceeding eight billion, highlighting global connectivity in mobile telecommunications. The adoption of 5G technology since 2019 has further advanced communication, providing faster data speeds, increased capacity, and lower latency.

(2) ***Internet of Things (IoT)****:* Building on these advancements, 5G has also facilitated the expansion of the Internet of Things (IoT) by supporting low-rate IoT applications (Mendonça et al. 2022). Alongside these developments, the internet emerged as a transformative force. Originally a collaborative research initiative, the internet has profoundly reshaped global communication and economic systems (Bonaccorsi & Bonaccorsi, 2020). The late 1990s introduced IoT, enabling physical objects to connect to the internet and paving the way for a more interconnected, data-driven environment (Li et al. 2015, OECD 2023).

(3) ***Big Data and Machine Learning (ML)****:* Advances in data science and predictive analytics have transformed various industries. Big data platforms efficiently manage extensive datasets, enabling ML to extract valuable features and enhance model performance (Mayer-Schönberger and Cukier 2013, Brynjolfsson and McAfee 2014). The term "Big Data" refers to an enormous amount of information gathered from diverse sources, serving as input for ML algorithms. ML, a subset of AI, improves computer performance by analyzing large datasets through algorithms and statistical models. Big data also presents challenges in capturing, storing, analyzing, sharing, and visualizing data. The introduction of the concept of veracity underscores the importance of data quality, with a current emphasis on predictive analytics and advanced methods for extracting value from big data. Increased data collection from cell phones and the IoT (OECD 2023) provides opportunities for healthcare and government administration to use big data creatively and effectively, generating value and cost savings.

(4) ***Blockchain Technology****:* Initially tied to cryptocurrencies, blockchain now facilitates secure transactions across multiple sectors. Blockchain acts as a distributed ledger with interconnected blocks including transaction data, timestamps, and cryptographic hashes, ensuring the integrity of recorded information and resisting retroactive alterations. Managed by a peer-to-peer network, blockchain employs consensus algorithms for validating and adding new blocks (Narayanan 2016). While its origins are in finance, blockchain's influence now extends to sectors such as supply chain management, healthcare, and secure data sharing (Tapscott and Tapscott 2016). Blockchain technology has gained attention for enhancing transparency, traceability, and security across industries (Smith and Kumar 2018).

(5) ***Platform Economy:*** Digital platforms revolutionize business models, foster network effects and reshape global commerce. The platform economy, exemplified by major players like Amazon, Airbnb, Uber, and Baidu, heavily relies on online sales and technological frameworks (Gawer 2009, Evans and Schmalensee 2016). Apple,

Microsoft, Google, and Intel are innovation platforms that contribute diverse technological frameworks. Academic interest in economic platforms emerged in the 1990s, describing the growing influence of major companies on internet-related cultural content. The study of platforms captures how communication and expression are both enabled and constrained by new digital systems and new media (Plantin et al. 2018). Whether catering to diverse users like Amazon or focusing on specific types as seen on Facebook, the platform business model capitalizes on network effects, fostering interactions and shaping complex market dynamics. Highlighting the significance of platform architecture, design should center around a core interaction that defines the enterprise. Parker et al. (2016) explore the challenges and considerations in the "Platform Revolution," addressing aspects such as attracting users, monetization, openness, governance, metrics, strategy, and policy. As platform-based businesses evolve, strategic design has become crucial.

(6) ***Automated Systems:*** Robotics and 3D technology have enhanced operational efficiency and production methodologies across various industries (Acemoglu and Restrepo 2019, Acemoglu and Johnson 2023). Automated systems integrate sensors, controls, and actuators to perform functions with minimal or no human intervention. These processes boost operational efficiency, streamline production, and reduce manual labor while driving advancements in manufacturing and rapid prototyping. The integration of robotics and 3D technology significantly improves industrial workflows, influencing production methodologies across sectors for enhanced efficiency, quality, and innovation (Ford 2015, Hudson 2019).

These trajectories, as outlined by Dosi (1982), show how digital innovations align with broader techno-economic paradigm shifts, influencing industries, institutions, and societal structures.

4.3 From the Digital Revolution to the Quantum Age

While the techno-economic paradigm (TEP) discussed in Section 4.1 and the digital revolution outlined in Section 4.2 gradually transformed technology, the economy, and society, recent advancements have accelerated these changes at an unprecedented pace. The rapid integration of automation, data-driven decision-making, interconnectedness, and robotics has led to what experts refer to as the “Fourth Industrial Revolution” or “Industry 4.0.” Coined in 2011, these terms encapsulate the transformative impact of digital technologies and emerging breakthroughs, including biotechnology, nanotechnology, artificial intelligence (AI), robotics, 3D printing, the Internet of Things (IoT), and quantum computing. The World Economic Forum’s 2016 theme, Mastering the Fourth Industrial Revolution, contextualized this shift within the broader historical framework of industrial transformation, following water- and steam-powered manufacturing, electricity-driven mass production, and the digitalization of industry—marking the preliminary stages of a post-Silicon revolution.[8]

Despite its widespread adoption, the concept of the Fourth Industrial Revolution remains contested. Critics such as Schiølin (2020) argue that it reflects “future essentialism” and may function more as a strategic narrative than a robust analytical framework. The ongoing debate between techno-optimists and techno-pessimists highlights divergent perspectives on digitalization and automation. Advocates such as Rifkin (2011) foresee a new industrial era driven by *green* technologies, while Brynjolfsson and McAfee (2014) characterize this phase as the *Second Machine Age*, emphasizing

[8] Schwab (2016, 2018) named four long waves of technological change, corresponding to water- and steam-powered mechanical manufacturing (first and second TEPs), electricity-powered mass production (third and fourth TEPs), digitalization, and cyber-physical systems (fourth and sixth TEPs). In contrast, Freeman and Perez (1988) identified Schwab's waves as two distinct techno-economic paradigms, including the anticipation of a sixth wave on the horizon (Knell and Vannuccini 2022).

digitization and the growing importance of intangible assets. Schot and Kanger's (2018) concept of the second deep transition also recognizes profound shifts in skills, organizations, and institutions.

The late 1990s witnessed the emergence of the IoT, which extended internet connectivity beyond traditional computing devices to everyday objects, fostering an increasingly interconnected and data-driven environment. However, as the digital revolution matures, a new phase—the *Quantum Age*—is beginning to take shape. Future eras will be characterized by the integration of advanced smart technologies, including nanotechnology and nanobiotech-nology, with substantial implications for materials science, healthcare, and electronics.

Distinguishing between cyber-physical systems and the ongoing digital revolution is crucial in understanding emerging technologies such as nanotechnology, biotechnology, AI, and quantum computing. Lombardi and Vannuccini (2021) propose that the convergence of physical, digital, and biological systems will give rise to a “cyber-physical universe,” marking the onset of the sixth technological revolution. This concept traces its origins to Richard Feynman’s seminal 1959 lecture, There’s Plenty of Room at the Bottom, in which he envisioned the manipulation and control of individual atoms and DNA molecules. The subsequent development of transistors and microprocessors initiated a trend toward miniaturization, laying the foundation for nanoscience and nanotechnology. These advancements have since influenced multiple scientific disciplines, including chemistry, biology, physics, materials science, and engineering. Feynman's early insights foreshadowed not just the digital revolution, but also the impending quantum revolution, which will reshape economies, societies, and frameworks for measuring technological progress.

According to Kaku (2023), humanity is on the brink of a post-Silicon or Quantum Age, characterized by the convergence of nanotechnology, biotechnology, AI, and quantum computing. Unlike conventional computing, which relies on binary transistors, quantum computing harnesses quantum mechanics to encode information on electrons, exponentially increasing data processing capabilities. However, realizing a general-purpose quantum computer remains a formidable challenge, requiring breakthroughs in maintaining low temperatures, eliminating electrical resistance, and achieving quantum coherence. The potential of quantum computing is immense, particularly in solving complex problems in physics, chemistry, engineering, and medicine. For instance, simulating protein behavior—critical to regulating all life—could revolutionize healthcare by advancing drug discovery and medical research.

The convergence of independent technological systems into a system of systems could trigger the sixth technological revolution (Roco and Bainbridge 2003, Knell 2013, Suleyman and Bhaskar 2023, Knell 2024). Foundational elements such as atoms, DNA, qubits, and synapses are expected to enhance the integration of emerging technologies, including nanotechnology, biotech-nology, quantum biology, information technology, and cognitive science, into multifunctional systems. The intersection of AI and healthcare exemplifies the broader transformative potential of this integration, underscoring its profound implications for medical innovation, healthcare delivery, and the unfolding technological paradigm.

4.4 New technologies, economic impacts, and models of technological change

New, innovative technologies have increased the complexity and interconnectivity of systems (Arthur 2014). Automation and digitalization play pivotal roles in integrating diverse processes and data streams, creating a challenge in assessing individual technology impacts (Acemoglu and Johnson 2023). AI and ML systems function differently from conventional software, independently adapting and evolving over time (Agrawal et al. 2019). This characteristic poses challenges in accurately modelling and predicting their behaviour. These complex interactions and emergent behaviours may be difficult to account for in traditional marginalist theoretical frameworks (Goldfarb and Tucker 2019). Greenan and Napolitano (2023) provide an alternative perspective.

Endogenous Growth Theory and the Digital Revolution

The modeling of technological change within the digital revolution aligns with endogenous growth theory, which emphasizes internal drivers of innovation and economic expansion (Helpman 2004; Acemoglu 2009; see also Section 2.7). Human capital plays a fundamental role in the digital era, as skill accumulation fosters technological progress and innovation. Unlike traditional neoclassical models, endogenous growth theory views innovation as an internal process, highlighting the significance of investments in education, research and development (R&D), and entrepreneurship within the rapidly evolving digital economy (see Nelson (2018), for an evolutionary perspective).

Since the onset of the digital revolution, the pace of R&D and knowledge creation has accelerated significantly. Digital technologies have facilitated open innovation, challenging the traditional closed innovation systems within firms. As new technological trajectories emerge, disruptive innovations necessitate models capable of capturing these dynamic shifts. The rise of digital start-ups introduces complexities not fully addressed by conventional economic theories. Additionally, digitalization has led to intricate intellectual property rights challenges, requiring new economic frameworks that balance innovation incentives with the protection of digital assets.

Data, Modeling, and Economic Implications

The proliferation of big data and advanced analytics has deepened economists' understanding of technological change. These tools enable analysis of the economic impact of data-driven innovation, including privacy concerns, data ownership, and monetization. Data science plays a critical role in forecasting by identifying patterns in historical data, corresponding with the rational decision-making and market equilibrium principles central to economic theory. The concept of *data as a factor of production* has become fundamental to understanding the economics of technology and innovation.

Haavelmo's (1944) seminal work on the probability approach to econometrics underscored the importance of statistical modeling in measuring innovation and technological change. In the early twentieth century, economists largely disregarded the relevance of probability theory for economic data. The Kondratiev long-wave cycle exemplifies narrative inference in economic analysis (Morgan 2021). However, Haavelmo's contribution, highlighted by Morgan (1990) and Hendry and Morgan (1995), disrupted this conventional view, influencing applied economists who sought stable and generalizable economic laws. Morgan's (2012) typology of models—including recipes, idealizations, visualizations, and analogies—illustrates how modeling has replaced earlier theory-driven economic approaches. Economists now employ models in two distinct ways: to investigate theoretical economic phenomena and to analyze real-world trends. Tracing the history of economic modeling, Morgan (2012) highlights how models evolved from conceptual tools in the early 19th century to the dominant form of economic reasoning by the late 19th century.

The Role of Mathematical Modeling and Simulations

Mathematical modelling and simulations significantly enhance understanding and forecasting, particularly in macroeconomics. However, it is crucial to differentiate between model-land and real-world values. Decisions grounded in estimating real-world values with clear uncertainty information are more dependable than relying solely on "optimal" model-land quantities. Thompson and Smith (2019) caution against the challenges of model-land, emphasizing the necessity for adaptable models, particularly in complex scenarios such as long-term GDP or localized predictions. In her book "Escape from Model Land," Thompson (2022) advocates for a critical examination of the use of mathematical models and simulations. Emphasizing the necessity of meticulous analysis of the nature and impacts of these models, Thompson proposes five principles for responsible modelling, highlighting the critical role of human cognitive abilities in navigating the imperfect knowledge within models.

Mathematical modeling and simulations have significantly enhanced economic forecasting, particularly in macroeconomics. However, it is essential to distinguish between *model-land*—theoretical constructs within models—and real-world values. Economic decisions based on real-world estimations with well-defined uncertainty measures are more reliable than those derived solely from "optimal" model-land quantities. Thompson and Smith (2019) highlight the limitations of over-reliance on models, particularly in long-term GDP forecasts and localized predictions. In *Escape from Model Land*, Thompson (2022) argues for a critical reassessment of mathematical modeling and simulations. She proposes five principles for responsible modeling, emphasizing the importance of human cognitive abilities in addressing the limitations of models and managing uncertainty.

Key Challenges in Modeling Technological Change

Several key issues emerge in the economic modeling of technological change:

(1) ***Modeling and simulation techniques:*** Feynman (1960) underscored the importance of modeling and simulation in understanding the diffusion of digital technologies. Shubik's (1960) bibliography demonstrates that by the mid-20th century, simulation had become a prevalent concept in the social sciences and statistics. Morgan (2004, 2012) emphasizes that simulations blend multiple elements—including experiments, role-playing, computation, probability setups, statistical data, mathematical models, and games—making their precise definition complex. She also highlights the epistemic function of narratives in economic modeling, as they can reveal hidden aspects of technological change and innovation diffusion. These insights are critical for refining economic growth theories to account for the rapid adoption and disruptive impact of digital technologies.

(2) ***Incorporating uncertainty and innovation:*** Simulation and agent-based models (ABMs) help economists navigate the uncertainty associated with the digital revolution (Rosenberg 1998; Arthur 2009). Chiffi et al. (2022) argue that economists must distinguish between quantifiable uncertainties and deep uncertainties when modeling technological change, aligning their analyses with societal preferences and economic contingencies.

(3) ***Agent-Based Models (ABMs):*** ABMs offer a powerful tool for simulating innovation by capturing the decentralized and interactive nature of economic agents in the digital era. Unlike traditional models that assume homogeneous agents, ABMs account for heterogeneous entities, including individuals, firms, and governments (Delli Gatti et al. 2018). Given that digitalization is characterized by decentralized decision-making and dynamic interactions, ABMs provide valuable insights into emergent phenomena, innovation diffusion, and network effects. By simulating agent behavior in response to technological change, ABMs contribute to a deeper understanding of economic growth in the digital age (Watts & Gilbert 2014; Gilbert 2014)

(4) ***AI Agents and Economic Thought***. AI-driven systems enhance economic modeling by enabling autonomous, goal-directed decision-making. Intelligent agents—designed to perceive their environment, make decisions, and optimize performance over time—represent a novel form of digital agency. AI agents exhibit similarities to traditional economic agents in various theoretical contexts.

- Adam Smith's principle of *specialization and productivity* is reflected in AI's ability to automate human tasks, enhancing efficiency (see Section 2.2; Acemoglu and Restrepo 2019).
- Marx's concerns about *labour displacement* (see Section 2.3) are increasingly relevant in discussions of AI-driven automation.

- Innovative AI sectors disrupt traditional economic structures in a way similar to Schumpeter's concept of creative destruction (see Section 2.4).
- Herbert Simon’s (1996) theory of *bounded rationality* applies to AI agents, which approximate solutions rather than optimizing due to computational constraints. AI systems mimic satisficing behavior by using heuristics and reinforcement learning in decision-making processes across markets, from algorithmic trading to supply chain optimization.
- Simon (2001) also viewed creativity as a structured problem-solving process, an idea relevant to AI-generated content, design, and innovation.

The ongoing evolution of technological change requires adaptable economic models that integrate automation, digitalization, and AI. Traditional economic frameworks are being challenged by the rapid pace of innovation, necessitating interdisciplinary approaches that incorporate big data, agent-based simulations, and probabilistic modeling. As AI systems become more integral to economic processes, their role in shaping economic structures and policy considerations will continue to expand, reinforcing the need for dynamic and flexible models of technological change.

4.5 In a nutshell: new technologies and measurement of technological change

Traditional measures of technological change include patent counts, R&D expenditures, and innovation surveys. While these metrics provide valuable insights into innovation and its economic effects, they fail to capture the full impact of emerging technologies. This limitation has driven the search for alternative measures. Established metrics face increasing challenges in the digital era. Patent counts may overlook critical advancements, and innovation surveys may not fully capture the effects of disruptive digital technologies. Additionally, conventional productivity measures struggle to keep pace with the rapid evolution of AI and automation. Addressing these gaps requires exploring alternative methodologies to better understand the transformative effects of technological innovation (Mohnen 2019).

Novel approaches in empirical measurement include:

(1) *Measurement of scientific, technological, and innovation activities.* Innovation and R&D surveys offer detailed insights into business innovation, technology adoption, and R&D activity. The OECD Frascati Manual 2015, now in its seventh edition, ensures consistency and international comparability in R&D data. Originally drafted by Christopher Freeman in 1963, this manual provides guidelines for collecting and processing national R&D data. While the primary R&D definitions remain consistent, revisions have enhanced comparability between countries and improved alignment with societal developments. As a global standard for R&D studies, the manual fosters a common language for discussing research and innovation policy, emphasizing the importance of comparable statistics through shared definitions. The evolving metadata in the OECD Main Science and Technology Indicators (MSTI) reflects ongoing improvements in national R&D statistics.

The OECD Oslo Manual 2018, now in its fourth edition, guides the collection, reporting, and analysis of innovation data through a biennial survey across EU countries (known as CIS). This survey covers innovation inputs, outputs, and modalities, defining innovation across multiple creative activities, including R&D, engineering, design, and marketing. Although challenges exist, such as subjective data and the absence of quantitative measures for certain innovations, the survey provides valuable insights into factors influencing innovation and its impact on economic performance (Mohnen 2019). A microeconomic perspective on innovation examines the diffusion and adoption of innovations and the effects of digital technology on firms. Innovation surveys conducted across twenty OECD countries (2009, 2010) reveal the complexities of technological change, business strategies, and priorities in the digital economy (Gault et al. 2023).[9]

The OECD (2009) Patent Statistics Manual utilizes new patent statistics to harmonize methodologies for patent-related indicators. This manual facilitates the analysis of inventive processes, emerging technologies, and innovation networks. By integrating patent data with other datasets, researchers can assess the role of intellectual property in economic performance, entrepreneurship, and innovation networks. Recent OECD (2023) analyses highlight AI-related patents featuring core technologies such as general AI, robotics, computer vision, and recognition/detection. Autonomous driving and deep learning have gained increasing prominence in recent years.

(2) *Bibliometric analysis.* Bibliometric analysis systematically examines large volumes of scientific data. The OECD (2016) Compendium of Bibliometric Science Indicators presents bibliometric data from Scopus, illustrating trends in scientific production across OECD countries and other major economies. Despite its origins in the 1950s, bibliometric analysis remains relatively underdeveloped in business, economics, and innovation studies (Mukherjee et al. 2022, Donthu et al. 2021, Rossetto et al. 2018). Systematic analysis of scientific publications, patents, and academic literature offers insights into technology diffusion and impact. Citation patterns and co-authorship networks reveal how knowledge flows and collaboration dynamics shape technological advancements. Qin's (2023) bibliometric analysis highlights the exponential growth of AI research, underscoring the increasing sophistication of bibliometric methodologies.

(3) *Composite indicators.* Composite indicators provide a holistic view of technological change by integrating multiple measures. The OECD (2008) Handbook on Constructing Composite Indicators outlines methodologies such as weighting, normalization, and aggregation techniques. The process involves selecting relevant indicators, assigning appropriate weights, normalizing values, and aggregating components into a unified measure. Multivariate analysis employs dimensionality-reducing techniques, including principal component, factor, correspondence, and cluster analysis, to identify correlation patterns, assess variable relevance, and decompose variance. These techniques help uncover the influence of specific dimensions on aggregate technological change.

(4) *Big data analytics.* Big data analytics has transformed the measurement of technological change by leveraging vast datasets to provide real-time, granular insights into technological dynamics (Mayer-Schönberger and Cukier 2013). Unlike traditional metrics, big data approaches track technology adoption rates, user behaviors, and diffusion patterns, revealing complexities in speed and breadth. Machine learning (ML) and AI enhance this analysis through pattern recognition and predictive modeling, using tools such as R and Python (James et al. 2023). Beyond identifying trends, ML and AI forecast disruptions and reveal hidden relationships within extensive datasets, enriching the understanding of technological innovation and its economic implications. Real-time analysis of digital footprints offers further insights into technology adoption, user behavior, and societal impact.

The intersection of big data and ML raises important questions about the role of theory in data-driven analysis. Traditional economic models emphasize explicit theoretical frameworks, while data science often operates as a predictive black-box approach. Neoclassical economics integrates data science techniques to analyze historical

[9] Cutting-edge empirical studies increasingly integrate data from multiple datasets. Greenan and Napolitano (2023) provide empirical evidence from a unique dataset combining European Union (EU)-wide employer and employee surveys at the sector level within each country. This dataset includes the CIS, the Community ICT Usage and E-Commerce in Enterprises Survey conducted by Eurostat, and the European Working Conditions Survey by Eurofound.

patterns and predict future outcomes, reinforcing rational decision-making and market equilibrium. Balancing predictive capabilities with an understanding of causal relationships remains a key challenge. Heterodox perspectives critique neoclassical models for oversimplifying economic complexity, advocating alternative approaches for a more nuanced understanding of technological change (Nelson and Winter 1982, Kirman 2011)

Challenges and Ethical Considerations

Despite offering valuable insights, novel measurement approaches encounter significant challenges. The reliance on extensive datasets raises ethical concerns, particularly regarding data privacy. Biases in ML models introduce additional complexities, requiring continuous adaptation of methodologies to ensure accuracy and fairness. Addressing these challenges remains essential for maintaining the reliability of technological change measurements. Ethical and social considerations gain importance as emerging technologies integrate further into society, necessitating the evolution of existing frameworks to address privacy, bias, and social impact concerns (O'Neil 2016). Digitalization creates new opportunities, yet the rise of AI and digital platforms heightens concerns about privacy and security (Zuboff 2019). Traditional economic growth models may fail to account for the influence of data-driven decision-making, underscoring the need for robust ethical data practices (Joque 2022 provides an alternative perspective). As emerging technologies push conventional boundaries, integrating insights from diverse disciplines becomes essential for developing theoretical models that effectively capture their global impact.

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List of abbreviations and definitions

ABM	Agent-Based Model
AI	Artificial Intelligence
CIS	Community Innovation Survey
GPT	General Purpose Technologies
ICT	Information and Communication Technologies
IoT	Internet of Things
IS	Innovation Systems
ITU	International Telecommunication Union
LTE	Long Term Evolution (standard for wireless data transmission)
ML	Machines Learning
MLP	Multi-Level-Perspective approach
LTS	Large Technical Systems
R&D	Research and Development
SNM	Strategic Niche Management
TEP	Techno-Economic Paradigm
TIS	Technical Innovation Systems
TM	Transition Management

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