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The hunt for *S*-shaped growth paths in technological innovation: a patent study*

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Abstract. Since the works by the business cycle theorists in the 1930s, no attempts have been made to study empirically the long term evolution paths of individual technologies starting with long time series. This is an empirical exploration and confirmation of the now almost assumed image or metaphor of the way technology develops; that it follows an *S*-shaped growth path which is commonly associated with a similar shaped diffusion function of entrepreneurial activity. The paper also confirms the diversity of technology dynamics and explores how technological cycle takeoffs appear to be clustered within certain historical epochs. The results have implications for our understanding of the evolution paths of individual technologies, and of the evolution of technological systems and waves of innovation.
By use of computational statistics, logistic growth functions are fitted to US patent stocks, 1920–1990, at a detailed level of aggregation, including chemical, electrical/electronic, mechanical, transport and non-industrial technologies. Some practical considerations when developing an empirically testable model of innovation cycles are addressed in the paper as well.

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Key words: Schumpeterian perspectives – Innovation cycles – Logistic biological growth – Patents – Diversity of technology dynamics and clusters

JEL-classification: O30, O31, P49

1 Introduction

1.1 Thinking in S-shapes

Following on Schumpeter's (1939) contribution to business cycle theory, which deals with the association between the distribution of entrepreneurial ability and cyclical movements in the rate of innovation (Kuznets, 1940, p.114), it is now commonly argued among Schumpeterian economists that the development and diffusion phase of a selected variable generally follows a Sigmoid curve (popularly termed an S-curve). Such studies have, for example, covered the areas of population growth, technology growth, diffusion of innovations and market shares, and much more.

Within economics the most prominent literature on S-curves concern the product life cycle literature (e.g. Kuznets, 1930a; Burns, 1934; Vernon, 1966; Utterback and Suarez, 1993; Utterback, 1996; Klepper and Simons, 1997), or are related to the diffusion process of technologies among firms (e.g. Mansfield, 1961; Silverberg, Dosi and Orsenigo, 1988; Cantwell and Andersen, 1996). However, the 'product life cycle'-based literature has been concerned with the characteristics of products, technologies and industries along associated life cycles, while treating the cycles themselves in a very informal way. The diffusion literature within evolutionary economics, likewise, seems to have just assumed that the diffusion curves were related to associated *S*-shaped development or growth curves. Related literature within the same tradition has focused on diffusion processes of technologies within societies (e.g. the extensive amount of literature on innovation systems, Lundvall, 1992; Nelson, 1992), or focused on cross-sectional analysis of the structural dimensions of the way technologies develop in an increasingly interrelated complex fashion (see e.g. Kodama, 1986, 1992; von Tunzelmann, 1995; Andersen, 1998). Finally, literature based on 'long waves' in economic life (Kondratieff 1979) has also been associated with S-curves. This has mostly been in relation to economic booms or crises or on identifying clusters of waves of innovations (e.g. Mensch, 1975; Freeman, Clark and Soete, 1982; Solomou, 1986; Kleinknecht, 1990), rather than identifying to what extent the individual development patterns themselves are *S*-shaped.

Hence, since the empirical works by the business cycle theorists in the 1930s (Kuznets, 1930a; Merton, 1935), no recent efforts have been made to study empirically the long term evolution paths of individual technologies starting with long time series[1]. Given the lack of empirical evidence on *S*-shaped growth patters, the S-curve is still merely an image or metaphor of

[1] Griliches (1957) studied output growth related to the diffusion of hybrid seed corn among farmers in 31 different states of the US.

the way technology develops, as argued by Lindquist (1994). Therefore, the key issue addressed in this paper is an empirical test of the theoretical use of the S-curve in relation to the *S*-shaped innovation growth cycle of technological development[2]. Thus, this study can be seen as a recent contribution to an analysis of the long term evolutionary growth paths of individual technologies. Patent data are appropriate for this kind of study as they are registered historically (1890–1990 in this case) and at a detailed level of disaggregation[3].

This paper also stresses some practical considerations concerning the development of an appropriate empirically testable model of *S*-shaped growth. Still, despite the great use of S-curves or *S*-shaped development patterns, up to the present there is no dominant theoretical framework relating to S-curves, or any associated statistical tests of such. Hence conceptual, technical and statistical issues are given importance in this paper.

The diversity of technology dynamics is also commonly recognised in post Schumpeterian approaches, in terms cycle duration, the timing of technological takeoff, technological opportunity, and the level of accumulated socio-economic capability or historical impact. These now almost stylised facts are also areas the paper attempts to measure. Special attention will be given to the notion of clustering of innovation in terms of the timing of takeoff which is still a controversial issue.

1.2 The organisation of the paper

The long run (1890–1990) US patent data on which this analysis is based will first be presented, and it will be shown how the patent data can be used as a proxy for innovation (Section 2). Then we set out to discuss the conceptual framework concerning the image of the shape of the

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[2] The aim of this paper is *not* a theoretical one discussing why it is believed that technology develops not in a smooth line but in cycles. These issues have been dealt with plentifully elsewhere in the business cycle literature on diffusion processes of innovations, 'entrepreneurial swarming' and processes of retardation, as well as in the literature on economic booms and crises or 'clustering of innovations' (see e.g. Schumpeter 1939; Kuznets, 1930a, 1940; Kondratieff, 1979; Freeman, Clark and Soete, 1982; Solomou 1986; and Kleinknecht 1990).

[3] In studying time series of US patenting activity, this paper can best be considered as being in line with the empirical works of Kuznets (1930a) and his student Schmookler (1966) and their work on US patenting activity, which they addressed in relation to production and prices as well as sectoral investment demand. However, as mentioned above, this paper is purely about evidence for cyclical *S*-shaped movements in technological activity (and related cycle attributes). Such *S*-shaped movements may of course be correlated with their counterpart industry specific patterns of innovation (e.g. chemical technological growth cycles may be strongly correlated with the chemical industry's pattern of innovation, Cantwell and Andersen, 1996; Andersen, 2000), although less so over time due to the increasing complexity of technological evolution associated with blurring of industry boundaries (Andersen and Walsh, 2000), but this is not an area this paper will elaborate upon.

technological growth curve (Sect. 3), so as to develop an empirical model from which the data can be analysed. The cyclical units of the growth curve and the position of cyclical phases – depression, revival, prosperity and recession – will be identified[4]. As these are relative measures, we also need to bring in notions of a system's 'theoretical norm' and equilibrium. The periods of possible cyclical growth in technological development will then be identified, and emphasis will be on distinguishing sustained growth cycles from fluctuations. Although the conceptual framework will mainly be based on Kuznets (1930s, 1940), it is synthesised with the views of Schumpeter. As Schumpeter was mainly a theorist, his theoretical innovation cycles were not directly testable[5].

Section 4 presents the fitting of logistic growth curves to patent data. The use and transformation of the logistic biological growth model of the type used by Grilliches (1957) is justified. There are numerous types of models which give raise to *S*-shaped paths, but they are quite different in the mechanism which actually produces this trajectory. We then examine whether technological development in different technological fields tends to follow *S*-shaped curves, and if so, the characteristics and properties of such curves are identified quantitatively. Each cycle will be characterised in relation to the parameters that guide its evolutionary path.

When identifying the diversity of technology dynamics (Sect. 5), each cycle will be characterised in relation to the four phases of development (depression, revival, prosperity and recession), their timing as well as total cycle duration. The cycle's socio-economic capability or impact at different cyclical stages as well as the cycle's overall technology opportunity are also identified. After a cross technology comparison of the timing of technological takeoff and cycle saturation, the notion of clustering of innovations will also be tested.

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[4] Economic concepts of the phase or state of the innovation cycle is here used as a proxy measure, as the paper builds upon Schumpeter's first approximation (prosperity and recession) and second approximation (depression and revival) which broadly read refer to innovation investment and hence innovative activity (Schumpeter, 1939, chapter IV). It can be compared to Kuznets's primary trends in production and prices which reflect the life cycle of a given technical innovation (Kuznets, 1930a).

[5] Kuznets and Schumpeter share some striking similarities and some equally striking differences. Whereas Schumpeter was a theorist and Kuznets an empirist they agreed that changes in technique are the decisive factor in growth. However, for empirical measurement purposes, Kuznets' conceptual framework differed rather sharply from Schumpeter, although the two were not inconsistent with one another (Rostow, 1990, pp. 233–246). Although they both agreed on the existence of *S*-shaped growth paths, Schumpeter (for theoretical reasons) focused on the movements from 'prosperity and recession' to 'depression and revival', whereas Kuznets (for technical statistical reasons) focused on the movements from 'depression and revival' to 'prosperity and recession' (i.e. from trough to peak, see also Sect. 3) (Kuznets, 1940). Also, whereas Schumpeter begins with a theory of an economic dynamic system of circular flows into which he introduces a disruptive, creative, innovating entrepreneur, Kuznets begins with a set of observations (long time series) based on empirical evidence and statistical methods. Finally, whereas Kuznets asserted that *S*-shaped curves were randomly distributed, Schumpeter believed that they were clustered (Kuznets, 1940).

Some concluding remarks will follow in the last section of the paper (Sect. 6).

2 Data and indicators

2.1 The patent data base

This study is based on all corporate and individual patents granted in the US between 1890 and 1990[6]. Each patent is classified by the year in which it was granted, and by the type of technological activity with which it is most associated. Various broad categories of technological activity can be derived by allocating classes or sub-classes to common groups of activity. In that way, patents have been allocated to one of 399 technological sectors (which indicate a class or occasionally a subdivision of a class), which in turn belong to one of 56 technological groups[7]. The 56 categories have been amalgamated into five broad technological fields: Chemical, Electrical/electronic, Mechanical and Transport technologies, plus a residual consisting of Non-industrial technologies[8]. For the purpose of this paper the analysis is carried out at the level 56 technological group level. The 56 technological groups are listed in Table 1.

2.2 Patent data as indicators

Applying this classification scheme the patent data in this paper serves as a proxy for three variables, as presented below.

Proxy 1: Patent data as a proxy for technological innovation/technological activity.

As patent data is only a direct measure of invention, there is a potential difficulty with this approach. To justify the relevance of this assumption, it is suggested that cumulative calculations (stocks) are appropriate when patents are used as a proxy measure for innovation, as that measure tends to capture the most central features of new technology. In this context it is argued that accumulated inventive activity does not take place unless

[6] The US patent data base is based at the University of Reading. It has been compiled by Professor John Cantwell with the assistance of the US Patent and Trademark Office.

[7] As the system of patent classes used by the US Patent Office changes, fortunately the Patent Office reclassifies all earlier patents accordingly, so the classification is historically consistent. The 1990 classification is used. Furthermore, although the US Patent Office has assigned most patents to more than one technological field or class, the Office identifies the most important or primary class of every patent, and in this study the primary classification was used in all cases.

[8] Note that the patent class as well as a technological group reflects an area of technological activity, as opposed to industrial activity, although the two may be interrelated (as mentioned in footnote 3).

Table 1. Identification of the 56 technological groups sorted by broad technological field

Broad technological field	Code	Technological group
Chemicals	2	Distillation processes
	3	Inorganic chemicals
	4	Agricultural chemicals
	5	Chemical processes
	6	Photographic chemistry
	7	Cleaning agents and other compositions
	8	Disinfecting and preserving
	9	Synthetic resins and fibers
	10	Bleaching and dyeing
	11	Other organic compounds
	12	Pharmaceuticals and biotechnology
	51	Coal and petroleum products
	55	Explosive compositions and charges
Electrical/electronics	30	Mechanical calculators and typewriters
	33	Telecommunications
	34	Other electrical communication systems
	35	Special radio systems
	36	Image and sound equipment
	37	Illumination devices
	38	Electrical devices and systems
	39	Other general electrical equipment
	40	Semiconductors
	41	Office equipment and data processing systems
	52	Photographic equipment
Mechanical	1	Food and tobacco products
	13	Metallurgical processes
	14	Miscellaneous metal products
	15	Food, drink and tobacco equipment
	16	Chemical and allied equipment
	17	Metal working equipment
	18	Paper making apparatus
	19	Building material processing equipment
	20	Assembly and material handling equipment
	21	Agricultural equipment
	22	Other construction and excavating equipment
	23	Mining equipment
	24	Electrical lamp manufacturing
	25	Textile and clothing machinery
	26	Printing and publishing machinery
	27	Woodworking tools and machinery
	28	Other specialised machinery
	29	Other general industrial equipment
	31	Power plants
	50	Non-metallic mineral products
	53	Other instruments and controls
Transport	42	Internal combustion engines
	43	Motor vehicles
	44	Aircraft
	45	Ships and marine propulsion
	46	Railways and railway equipment

Table 1 (Continued)

	47	Other transport equipment
	49	Rubber and plastic products
Non-industrial	32	Nuclear reactors
	48	Textiles, clothing and leather
	54	Wood products
	56	Other manufacturing and non-industrial

applied, so that accumulated patent stocks reflect the process of application and diffusion of new technology (i.e. the interaction-process between scientists, inventors, engineers, innovators and entrepreneurs, learning and market diffusion). Hence, by using accumulated patent stocks, this paper takes an appropriately broad view of technology, where it tends to include the interaction between (i) the universal element of technology relating to information or codified knowledge (for example patents), which is potentially tradable and potentially transferable; (ii) the tacit element of technology, which is context specific and tied to local technological competence or capability; and (iii) market diffusion. In this way (i) may serve as a proxy for (ii) and (iii), as well as being a direct measure of itself[9].

Cumulative stocks of patents were calculated for technological groups using the perpetual inventory method as in vintage capital models, with an allowance for a depreciation of the separate contribution of each new item of technological knowledge (reflected in a patent) over a thirty year period. This is the normal assumption for the average life time of capital, given that new technological knowledge is partly embodied in new equipment or devices, as well as the conventional method now used in patent statistics based on long time series[10].

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[9] The use of patent stocks is also consistent with the theoretical notion of technological accumulation (which again is analogous to capital accumulation), and which follows from the view that technological change is a cumulative, incremental and path-dependent process (Nelson and Winter 1982; Rosenberg 1982; Dosi et al. 1988). Analysing stocks also helps to reduce statistical problems that might otherwise be created by small numbers of patents and by year-to-year fluctuations in patenting, problems which are more serious at more detailed levels of disaggregation, and which causes only random results. Finally, when working historically we also have to take into account that the propensity to patent is not constant over time. The propensity to patent generally tended to increase over time (Cantwell 1998), and is of course also expected to be affected by wars and other random historical events. The effect this may have on the results is also reduced by working with stocks rather than absolute flows.

[10] John Cantwell and his associates pioneered the use of accumulated stocks of long time series within patent statistics [see. e.g. Andersen (1998, 2000), Cantwell and Andersen (1996) and Fai and von Tunzelman (1999) concerning technology and industry dynamics issues; Cantwell (1995) concerning the product cycle model; as well as Cantwell and Fai (1999) concerning firm dynamics issues].

We see that the stock in 1919 represents a weighted accumulation of patenting between 1890 and 1919, a thirty year period with weights rising on a linear scale from 1/30 in 1890 to unity (30/30) in 1919, using 'straight line depreciation'. The analysis covers the period 1920–1990. Although all innovations are not necessarily embodied in plant and equipment, this method of a 30 years depreciation takes into account (or is a proxy for) the lifetime of the underlying *technological knowledge* and the tangible devices with which it is associated. (i.e. it is *not* intended to capture lifetime of the patent (which is shorter) or the life of the *economic value* of the patent[11].)

Proxies 2 and 3: Patent data as proxies for technological opportunity and socio-economic capability or historical impact.

Within post-Schumpeterian approaches it is now commonly believed that the rate of technological activity is related to the degree of technological opportunity, and that the size of the accumulated patent stock is related to the collective accumulated technological capability or socioeconomic competence in society.

Accordingly:

- The rate of growth of the patent stock over a given period can serve as a proxy for the extent of technological opportunity in the technology in question over that period, in which a high rate of growth in a technological field reflects an area of high technological opportunity.
- The size of the accumulated patent stock can serve as a proxy for the collective accumulated technological capability or socio-economic competence, in which a large stock reflects an area of high capability or competence, acquired from a succession of innovations over time.

The latter two proxy measures play an important part in section 5 only, when identifying cycle properties and the diversity of technology dynamics[12].

[11] The assumption of a thirty year life is admittedly arbitrary. However, although patent stocks would fluctuate more if a shorter life time was assumed, as the smoothing process associated with accumulation would be less pronounced, the identification of 'innovations cycles' (as opposed to 'random fluctuations') depends on the cut-off points between what is recognised as a cycle and what is taken as a random fluctuation on the cycle and not by the rate of depreciation. As some stability has been built into the data by allowing for a thirty years depreciation, this analysis very strictly allows for *only* one year fluctuation on the cycle before identifying a cyclical break. This principle, when distinguishing between sustained growth periods and fluctuations, is taken from Franses (1996, p. 85) and Watson (1994, pp. 24–46) who determine turning points in US industrial production data while investigating seasonality in business cycle turning points. See Section 3.2.

[12] As the aim of this article is not to review the literature on the last two mentioned proxies, which is now commonly used in the literature, this article here refers to Andersen (1998a) and especially Andersen (2000) which discuss and justify these proxy measures in detail while reviewing literature concerning the possibilities and problems of these measures.

3. The *S*-shaped image of the technological growth curve[13]

3.1 The conceptual framework

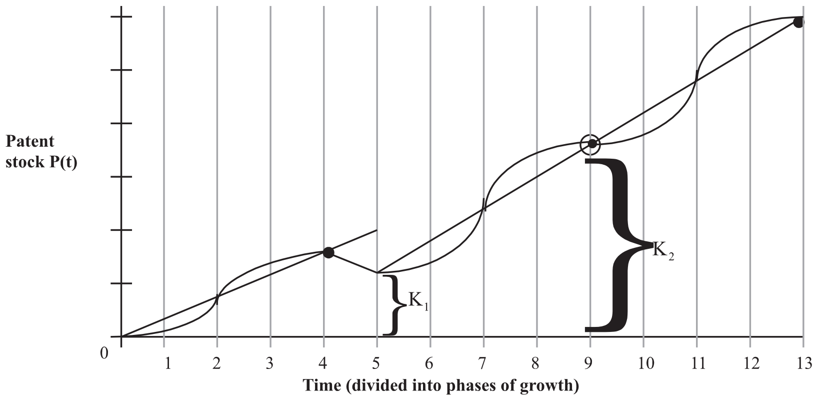
The aim of this section is conceptual, dealing with how best to identify cyclical units (i.e. when a cycle starts and ends) and to identify the cyclical phases and saturation levels, in order to perform empirically the model fitting of patent stocks to *S*-shaped growth functions. This is an area where there is still no dominant approach.

In the definition of cyclical units, this paper uses troughs and peaks as turning points (commonly used by national statistical offices). Between the turning points, indicating the growth cycle from trough to peak, the cycle passes through four cyclical phases of development, moving from depression to revival to prosperity and to recession. Instances of negative growth will be disregarded, and will instead be referred to as periods of crisis.

Hence, the analysis is based on Kuznets' conceptual approximation of a cycle using troughs and peaks as turning points. There is a dispute between Schumpeter and Kuznets concerning how to define the cyclical units of analysis. Schumpeter suggests that cyclical units should be defined from the beginning of prosperity (the point at which the time series begins to rise above the 'normal' level) to the end of revival (the point at which the time-series again reaches the new 'normal'). Kuznets stressed the empirical difficulty of developing statistical procedures that would correspond to Schumpeter's theoretical model: "By refusing to accept peaks and troughs as guides in the determination of cycles he [Schumpeter] scorns the help provided by statistical characteristics of cycles in time series. One cannot escape the impression that Professor Schumpeter's theoretical model in its present state cannot be linked directly and clearly with statistically observed realities" (Kuznets, 1940, p. 116). "[N]o proper link is established between the theoretical model and statistical procedure" (Kuznets, 1940, p. 123). That is, we have technically developed statistical growth functions which illustrate a path from trough to peak, as opposed to Schumpeter's growth functions illustrating evolution path from the beginning of prosperity to the end of revival. Schumpeter's and Kuznets' conceptual approximations of innovation cycles are illustrated in Figure 1.

The cyclical phases (i.e. depression, revival, prosperity, recession, crises) or stages of the cycle introduced by Schumpeter represent a relative measure. As Schumpeter argues, the different cyclical phases of development must be around something and, if pressed, that something is more or less related to

[13] Throughout, the paper refers to innovation 'cycles' and the 'cyclical' character of innovations with respect to *S*-shaped growth patterns. [The appropriate application of such phrases are discussed in Solomou (1986) and Kleinknecht (1990).] The use of the term 'cycle' in this paper is justified by the subsequent application of an evolutionary model endogenously producing *S*-shaped (cycle-like) growth patters. Hence they are investigated as 'real' phenomena rather than purely statistical coincidence. However, the analysis does not to the same extent establish the 'cyclical' character of innovation cycles (i.e. their endogenously caused regular recurrence), so the paper admittedly uses this concept in relation to a post-schumpeterian theoretical belief on the behaviour of many economic variables.



PHASES OF GROWTH
0-1; 5-6 and 9-10: Depression
1-2; 6-7 and 10-11: Revival
2-3; 7-8 and 11-12: Prosperity
3-4; 8-9 and 12-13: Recession
4-5: Crises
2-7 and 7-11: Illustrative examples of Schumpeter's innovation cycles
0-4, 5-9 and 9-13: Illustrative examples of Kuznet's innovation growth cycles (the one adopted in this analysis)
Equilibrium (or level of saturation): ●
Punctuated equilibrium:
K: Offset
:The system's 'theoretical normal'
or : The innovation cycle

Fig. 1. Conceptual framework

an equilibrium concept (Schumpeter, 1939, p. 44). For analysis and diagnosis purposes Schumpeter refers to equilibrium in a dynamic context (as opposed to the Walrasian system) in which any stage of a cycle can conveniently be defined in relation to its distance from a theoretical normal or 'theoretical norm' (Schumpeter, 1939, p. 23). Kuznets also acknowledges making business cycle theory an integral part of an economic system by coupling it to the achievements of equilibrium economics: "Instead of a system we are likely to find ourselves with a chaotic description" (Kuznets, 1930b, p. 31), and he agreed with Schumpeter that the stable static equilibrium has to be substituted with a general recognition of the time element.

The growth cycle, wrapping around the system's theoretical norm, moves from one level of equilibrium to another at a qualitatively different level. If the troughs and peaks of every two successive growth cycles coincide in time, the technological development may have a pulsating character causing punctuated equilibrium (in the way argued by Yakovets, 1994, p. 400), although it is also argued here that this may not always be so if there is a long period of a crisis or a structural break when developing and adjusting to a new technological trend. As stated by Schumpeter, the equilibrium reached by recovery is not necessarily identical with that which would have been attained had the crisis not taken place.

As growth cycles between equilibrium points both for statistical technical purposes and theoretical purposes needs to be understood individually (cf. each growth cycle being of different qualitatively kind – the nature of each cycle being unique), an offset – provided by a constant K – is inserted in the beginning of each cycle to avoid the previously accumulated patent stock entering the analysis. Hence, K reflects the size of the accumulated patent stock for each cycle's initial level, and is therefore of different value for each new cycle (see Fig. 1 and Sect. 4.2)[14].

3.2 Identification of periods of potential technological growth cycles

When identifying periods of potential technological growth cycles, it is important to distinguish between sustained cyclical growth periods and random fluctuations.

Using troughs and peaks as turning points, a growth cycle is considered to end or move into a crisis when two consecutive years display negative growth. The year before a sequence of two such negative growth observations is considered to be a peak, while the last observation of two consecutive years is considered to be a trough. By definition, a trough for a new growth cycle can at the earliest come two years after a peak of an earlier growth cycle, as we allow for one-year fluctuations within the growth cycles[15]. Thus, in the context of this analysis, if a trough for a new growth cycle comes two years after the peak of an earlier cycle, we have defined this as a series of punctuated equilibria. However, if a trough for a new cycle comes more than two years after an earlier cycle, we have a series of negative growth rates reflecting a crisis.

Using this principle, the turning points in technological development of the technological groups have been identified and will subsequently be used for model fitting to test for the existence of *S*-shaped growth paths. Periods of sustained decline in the patent stock (i.e. periods of crisis, see Fig. 1) are cut out of this analysis, and the remaining periods illustrate potential growth cycles. As much as 172 sustained growth periods were found across all the 56 technological groups and the structure of those are illustrated in Table 2.

Of the 172 sustained growth periods, 6 technological groups of the 56 in total experienced only 1 sustained growth period, 14 groups experienced 2 sustained growth periods, 13 experienced 3, 17 experienced 4, 5 experienced 5, and finally, 1 technological group experienced 6 sustained growth periods between 1920 and 1990. Hence, the technological groups, identified in Table 1, show a notable difference in the number of growth periods.

Table 2 also indicates that in general we have longer periods of growth than periods of decline (which are left out), because (i) the total periods of sustained growth are longer than the total periods of sustained decline, and (ii) we often have one growth period after another, suggesting a series of punctuated equilibria between growth cycles. Of

[14] It is relevant to mention that, as this paper is based on a patent data classification scheme, we only measure technological activity in a certain technological area rather than a specific innovation. However, the type and nature of the technological activity varies over time.

[15] The principle is taken from Franses (1996, p. 85) and Watson (1994, pp. 24–46), who determine turning points in US industrial production data while investigating seasonality in business cycle turning points.

Table 2. Structure of sustained growth periods between turning points*

Numbers of technological groups by broad technological field derived from Table 1	Number of 'technological groups' with sustained growth, between 1920 and 1990, for more than 40/50/or 60 years in total, respectively	Total number of 'sustained growth periods from trough to peak' across all technologies/ (Sustained growth periods of at least five observation years)	Total number of 'sustained growth periods linked with punctuated equilibria' across all technologies. (Assuming they can be fitted to *S*-shaped growth cycles)
Chemical: 13	12/10/7	31/(25)	6
Electrical: 11	9/7/4	38/(32)	6
Mechanical: 21	12/7/1	66/(56)	15
Transport: 7	3/0/0	23/(16)	4
Non-industrial: 4	1/0/0	14/(11)	6
Total: 56	37/24/12	172(140)	37

* Documentation of all the observed sustained growth periods (in years) for each of the individual technological groups are omitted here, but they are forthcoming in Andersen (2000). However, Tables a, b, c, d, and e in the Appendix include the identified years of sustained growth with respect to those cycles, which have been successfully fitted to *S*-shaped growth paths.

the 56 technological groups in total, 37 experienced sustained growth between 1920 and 1990 (a total of 70 years) for more than 40 years in total, and among those 37 groups, 24 experienced sustained growth for more than 50 years, and 12 even experienced sustained growth for more than 60 years. Hence, it is not surprising that we also find that as many as 37 of the 172 sustained growth periods can be linked with punctuated equilibrium (i.e. one growth cycle after another without any decline in accumulated patent stock) assuming they subsequently can be fitted to *S*-shaped growth cycles. Accordingly, (i) and (ii) above also indicate that the critique often raised, that technological growth curves used for picturing technological development only depict half of the technology's 'life', as they ignore the period of absolute technological decline (see e.g. Lindqvist, 1994), is proven not to be the case when using patent data as a source of evidence.

In the further analysis only those sustained growth periods which have at least 5 observation years will be used (as this is the minimum time series number for fitting an S-curve to the data). Of these, Chemicals represents 25 potential growth curves, Electrical/electronics 32, Mechanical 56, Transport 16 and the Non-industrial technological group 11, which gives a total of 140 potential growth curves.

4 Fitting *S*-shaped growth paths

4.1 Model selection

Just as there is no dominant approach to the study of S-curves, there are no conclusive S-curve models associated with definite statistical tests. There are numerous types of models which give raise to *S*-shaped curves (see e.g. Mahajan and Peterson, 1985), but they are quite different in the mechanism that actually produces this trajectory. Each development or diffusion model usually facilitates a theoretical explanation of the dynamics of the development or diffusion process in terms of certain general characteristics, as well as permits predictions concerning the continued evolution of the development or diffusion process. Several different kinds of such models have been applied in economics.

For the purpose of this study the biological internal-influence (i.e. endogenous) growth model, which has been applied by, e.g. Griliches (1957), is most applicable. The advantage of this type of internal-influence biological growth model is that it illustrates a growth process in which technology is the variable that grows over time and is not of a constant size which then diffuses, as in the internal-influence epidemic diffusion model (e.g. the one applied by Mansfield, 1961). However, the disadvantage of the simple internally-influenced diffusion model is that it is of limited flexibility in terms of the two alternatives (i.e. symmetry or positively skew), as opposed to the flexible cumulative lognormal density models (e.g. used by Bain, 1964)[16]. That is, they are generally built around a logistic or a Gompertz growth curve.

As Kuznets (1930a, p. 197), in his empirical research, finds that the simple logistic model (as compared to the Gompertz model (e.g. used by Chow, 1967)) best describes long term movements of growing industries, and subsequently links these results to the technology life cycle (using cumulative stocks of US patent data) the logistic model is the most obvious to consider. The logistic model is also the most widely used, e.g. by Griliches (1957), who studied the output growth related to the diffusion of hybrid seed corn among farmers in the US, and by Mansfield (1961) who studied the diffusion (or rate of imitation) of several industrial innovations among major firms. Metcalfe (1981) used the logistic curve in his extended model of innovation diffusion, which built partly upon the work of Kuznets' theory of industrial growth and retardation; and Andersen (Andersen E.S., 1994, Chapter 3) illustrated the way in which the logistic equation can provide us with a rough theoretical scheme which may help to organise the study of several of the issues raised by Schumpeter.

As the logistic function is symmetric around the inflection point the growth of the patent stock (or innovation growth) in the internal-influence

[16] The limitations of the flexible density model is however that, although it can deal with any skewness, it is basically a distribution function providing information concerning when you have the highest probability for growth or diffusion, but it does not provide any explanation concerning the mechanism behind the *S*-shape. It could be argued that any density model would fit any smooth movements in long time series, but as it does not provide any explanation concerning the mechanism of the movements, the results concerning the highest probability for growth or diffusion may be a pure illusion. (a statistical coincidence). Also, in relation to this present study the density model is inappropriate, as we do not in all cases have the data from the initiation of the technological growth curve all the way to its long run potential.

growth model is proportional to the growth already received and to the distance from the ceiling[17].

4.2 Model fitting

Accordingly, the logistic internal-influence biological growth model is very useful when examining time series of patent data, and the parameters in the model are subject to simple and meaningful interpretation. The fundamental logistic internal-growth model as provided by Griliches (1957, p. 504) and applied to patent growth, is given here by:

$$\mathrm{P(t)} = \frac{\bar{\mathrm{P}}}{1 + \exp[-(\mathrm{a} + \mathrm{bt})]} \tag{i}$$

P(t) represents the accumulated patent stock at time t, $\bar{\mathrm{P}}$ represents the ceiling (or long run equilibrium) value, 'b' represents the rate of growth coefficient, and 'a' is a constant of integration which positions the curve on the time scale.

As Griliches (1957), Mansfield (1961), Bain (1964) etc. worked with diffusion expressed in percentage terms (and not real values), their model's initial stage, $\mathrm{P(t_{initial})}$, is by definition close to zero, so the simple logistic model could be applied directly. The technological growth model will also subsequently be constructed along similar lines, by transforming the time-series of patent stocks for each growth curve into a percentage share of the long term technological potential or ceiling.

However, when constructing the model we can gain a better impression of the diversity of technology dynamics (see Section 5), derived from the cycle properties, if the cycle's origin, takeoff point, inflection point, saturation level, and phases of depression, revival, prosperity and recession are expressed in terms of patent stocks and time. In this way it is also possible to see by how much the technological field has increased in absolute importance or impact during the growth cycle, and it is possible to estimate directly the duration of the growth cycle. This is done by adding an offset K to the growth function provided in equation (i) (K being a constant and different for each cycle), so that when calculating the accumulated patent stock in absolute terms, $\mathrm{P(t_{initial})} = \mathrm{K}$ reflects an initial level of zero development (see also Fig. 1). In this way, P(t) for any stage of development will always reflect a true value of the accumulated patent stock. Also, as the cycles do not start at year 0, a variable t_0 (t_0 being different for each cycle) has been inserted to represents the year of the first empirical observation of each growth curve, as listed in Table 1. In this way the estimated t value for each stage of development will represent a true year.

Hence, the fundamental logistic biological growth model of patent growth over time is here rewritten as:

[17] It is the last property which has made the logistic function useful in relation to Wolf's law of retardation, the importance of which was stressed by Kuznets.

$$P(t) = \frac{\bar{P}}{1 + \exp[-(a + b(t - t_0))]} + K \qquad \text{(ii)}$$
$$\text{where} \lim P(t) \approx (\bar{P} + K) \text{ for } t \to \infty$$

P(t) represents the accumulated patent stock at time t. As the cycles does not start at year 0, t_0 (t_0 being different for each cycle) represents the year of the first empirical observation of each growth curve. $\bar{P}$ represents the cycle ceiling value, 'b' represents the rate of growth coefficient, 'a' is a constant of integration which positions the curve on the horizontal time scale. K is the constant of integration which positions the curve on the vertical patent stock scale. (K is the size of the accumulated patent stock at which the curve is initiated (i.e. ($t_{initial}$) or P(t) for $t \to -\infty$).)

Computational statistics based on non-linear least squares regression are then used to fit logistic curves to the sustained growth periods identified in Section 3.2. In this process the computer simultaneously optimises or fits the parameter values of the origin or K, the cycle ceiling $\bar{P}$ (from which we can calculate $P(t_{ceiling}) = (\bar{P} + K)$), the integration coefficient on the time scale 'a', and the growth coefficient 'b'.

4.3 Model fitting results: The existence of S-shaped growth paths

The results of the parameter estimates can now be used to identify the characteristics, or cycle properties, of the *S*-shaped growth paths (identified in Section 3.2) successfully fitted to the logistic biological growth model; subject to a few constraints. *First*, the goodness of fit, R^2, has to be greater than 0.94. *Second*, it might be expected that the technological growth cycle will be interrupted or be the subject of structural breaks due to random historical events before its estimated long run performance level or full potential is reached. Thus, another constraint is that an empirical break from the growth cycle model (i.e. the time of the last empirical observation of the cycle) has to be at least after 60% of the long run estimated technological cycle potential in terms of accumulated patent stock, i.e. $(P(t) - K)/\bar{P}$ has to be at least 0.6 (60%). This includes even those technological groups whose cycles break empirically in 1990 owing to data constraints. It is necessary to go beyond the point of inflection of 50% in order to make sure that we actually have an S-curve and not exponential growth. A *third* constraint is that the accumulated patent stock at the first empirical observation of the cycle, i.e. t_0, has to be below 10% of the patent stock at the cycle ceiling (i.e. full estimated growth cycle). This means that we allow the technology to 'die' relatively young (already after 60% of its full potential) but, as in biology, it cannot by definition be 'born' old in terms of empirical observations. However, as there is no reason to believe that these technology growth cycles first entering in 1920 due to constraints in the data source were actually born in 1920, we allow them into the model as long as 1920 is still in the first phase of the growth cycle, i.e. below 25% of the full cycle (i.e. $(P(t) - K)/\bar{P}$ can be up to 0.25 (25%) in 1920), which also represents the initial growth phase before takeoff and revival.

Among the growth paths identified in Section 3.2 that were eligible for estimation, the broad Chemical group went down by 4 (from 25 to 21), Electrical/electronics down by 9 (from 32 to 23), Mechanical down by 11 (from 56 to 45), Transport down by 8 (from 16 to 8), and the Non-Industrial technological group went down by 2 (from 11 to 9). Hence 106 technological growth curves out of 140 survived the constraints, and could be fitted to the selected S-curve model. The results of the parameter estimates are listed in Tables a, b, c, d and e in the Appendix.

With respect to the first and third constraint, the results in the Appendix also show that the goodness of fit is usually at the 0.99 or 0.98 level (applying to 86 out of the 106 S-curves), and that the accumulated patent stock at the time of the first empirical observation is below 5% of the full technological potential for most of the growth cycles (applying to 65 out of the 106 S-curves).

Finally, as mentioned in constraint two, it might be expected that the technological growth cycle will be interrupted or be the subject of structural breaks due to random historical events before its estimated long run performance level or full potential is reached. It is interesting here to compare the estimated accumulated patent stock at the time of the last empirical observation (identified in Appendix in Tables a–e) of the cycle with the estimated cycle potential (or cycle ceiling) to see to what extent the cycle reaches it long run potential (identified in Tables 3–7) (The calculation of the percentages share of technological development in relation to the potential ceiling of the growth curve is represented in Section 5.) Evidence from such analysis shows that almost all cycles (i.e. 72 out of 106 in total) survive more than 90% of their long run potential or ceiling level without any external shocks to break the cycle, and that it is very rare (i.e. only 10 out of 106) that they get interrupted before 80% of their estimated ceiling value. Actually, as many as 44 out of the 106 growth cycles represent a full cycle (i.e. more than 95% of their long run potential or ceiling level) without any breaks. Here it ought to be mentioned that many of the cycles ending empirically in 1990 are most likely because of data constraints (as the compiled data used for this study range from 1890 to1990) than anything else. So although external factors and 'history' have a large influence on change and growth, it is still important to understand the mechanism and the internal system dynamics.

These factors indicate that we have good model-fitting results, which in turn justifies the use in evolutionary economics of the *S*-shaped image or metaphor concerning the way technology develops.

5 Diversity of technology dynamics

5.1 Fitting cycle properties

When fitting cycle properties (see "*Cycle properties*" below) concerning the diversity of technology dynamics (including timing and socio-economic capability or impact at the year of takeoff and for the four phases of the growth curves, (depression, revival, prosperity and depression), as well as

Table 3. Cycle properties: Chemicals

Code**	Depression*		Revival		Prosperity		Recession					
	Socio-economic capability at: $P(t_{5\%})$*	Year	Socio-economic capability at: $P(t_{25\%})$	Takeoff year	Socio-economic capability at: $P(t_{50\%})$	Year	Socio-economic capability at: $P(t_{75\%})$	Year	Socio-economic capability at: $P(t_{95\%})$	Year	Cycle duration in years	Cycle opportunity***: (Growth rate)%
2	94.24	1900	456.01	1931	908.22	1949	1360.43	1967	1722.2	1998	98	1727.46
3a	2760.71	1924	3157.18	1928	3652.76	1931	4148.34	1934	4544.81	1939	15	64.62
3b	3900.09	1954	5062.29	1963	6515.05	1968	7967.81	1973	9130.02	1982	28	134.10
4a	318.30	1930	350.96	1932	391.78	1933	432.61	1934	465.27	1936	6	46.17
4b	619.36	1954	1511.31	1968	2626.26	1977	3741.21	1986	4633.17	2000	46	648.06
5a	4476.57	1921	5901.40	1928	7682.43	1932	9463.47	1937	10888.29	1944	23	143.23
5b	11829.40	1956	17701.50	1967	25041.70	1973	32381.90	1980	38254.07	1991	35	223.38
6	1115.90	1947	4038.83	1966	7692.50	1977	11346.20	1989	14269.1	2008	61	1178.71
7a	3497.91	1922	4873.04	1931	6591.94	1937	8310.84	1943	9685.96	1953	31	176.91
7b	8980.24	1954	9301.22	1958	9702.44	1960	10103.70	1963	10424.64	1966	12	16.08
7c	10260.40	1963	11684.10	1970	13463.80	1975	15243.50	1979	16667.24	1986	23	62.44
8a	40.25	1915	54.72	1926	72.82	1933	90.91	1939	105.38	1950	35	161.81
8b	122.25	1955	212.85	1968	326.10	1976	439.34	1984	529.94	1997	42	333.49
9	2727.71	1939	11488.70	1959	22439.90	1971	33391.10	1983	42152.03	2003	64	1445.33
10a	725.26	1924	1095.25	1930	1557.74	1934	2020.22	1938	2390.21	1944	20	229.57
10b	1758.39	1963	2135.39	1968	2606.66	1972	3077.92	1975	3454.93	1980	17	96.48
51a	1186.40	1923	2668.94	1931	4522.10	1935	6375.26	1940	7857.80	1948	25	562.32

Table 3 (Continued)

51b	7686.60	1956	7881.22	1957	8124.49	1958	8367.77	1958	8562.39	1959	3	11.39
51c	8560.36	1963	8937.13	1967	9408.10	1969	9879.07	1971	10255.84	1975	12	19.81
55a	412.25	1929	426.90	1930	445.22	1931	463.54	1932	478.20	1934	5	16.00
55b	415.02	1957	635.23	1964	910.50	1968	1185.76	1973	1405.97	1980	23	238.77

* Phases of growth are expressed as % share of cycle developed in comparison to the cycle ceiling: $(P(t) - K)/\bar{P}$ (see Sect. 5.1.). The time (year) and accumulated patent stock (or socio-economic capability or importance) for any such phase (i.e. for $(P(t) - K)/\bar{P} = 0.05$ (5%), 0.25 (25%), 0.50 (50%), 0.75 (0.75%) and 0.95 (0.95%)) are calculated.

** a, b, and c, after the technological group code number, denote different cycles of same technological group across different periods in time (see Year columns).

*** Cycle opportunity is expressed as the percentages growth in patent stock across the estimated cycle duration: $[P(t_{95\%}) - P(t_{5\%})] * 100\%/P(t_{5\%})$.

Table 4. Cycle properties: Electrical/Electronics

	Depression*		Revival		Prosperity		Recession					
Code**	Socio-economic capability at: $P(t_{5\%})$*	Year	Socio-economic capability at: $P(t_{25\%})$	Takeoff year	Socio-economic capability at: $P(t_{50\%})$	Year	Socio-economic capability at: $P(t_{75\%})$	Year	Socio-economic capability at: $P(t_{95\%})$	Year	Cycle duration in years	Cycle opportunity***: (Growth rate) %
30a	4711.09	1921	4773.59	1923	4851.70	1924	4929.82	1925	4992.32	1927	6	5.97
30b	2572.21	1971	2605.83	1972	2647.87	1973	2689.90	1974	2723.53	1976	5	5.88
30c	2674.32	1980	2907.04	1985	3197.95	1988	3488.85	1991	3721.58	1996	16	39.16
33	5157.97	1919	6151.88	1926	7394.25	1930	8636.63	1935	9630.53	1941	22	86.71
34	2093.30	1928	2276.23	1934	2504.90	1937	2733.56	1941	2916.50	1946	18	39.33
35a	463.28	1928	1883.58	1947	3658.95	1958	5434.33	1969	6854.63	1988	60	1379.59
35b	5719.06	1986	5780.75	1987	5857.87	1988	5934.98	1990	5996.67	1991	5	4.85
36a	5469.15	1924	5841.90	1927	6307.83	1929	6773.77	1931	7146.51	1933	9	30.67
36b	6302.64	1961	10555.30	1977	15871.20	1986	21187.00	1995	25439.70	2010	49	303.64
37a	7119.99	1918	8261.84	1926	9689.15	1930	11116.50	1935	12258.30	1942	24	72.17
37b	10708.80	1956	10977.00	1957	11312.20	1958	11647.40	1959	11915.50	1960	4	11.27
38a	8140.86	1910	13366.20	1922	19897.80	1929	26429.50	1936	31654.80	1948	38	288.84
38b	28029.60	1948	28472.60	1949	29026.30	1950	29580.10	1951	30023.10	1952	4	7.11
38c	30966.10	1956	36214.70	1963	42775.40	1968	49336.10	1972	54584.70	1980	24	76.27
38d	50262.80	1985	51151.70	1987	52262.70	1988	53373.80	1989	54262.70	1991	6	7.96
39a	12890.20	1919	14893.90	1926	17398.40	1930	19902.90	1934	21906.50	1940	21	69.95
39b	20612.10	1948	20900.40	1949	21260.80	1949	21621.10	1950	21909.40	1950	2	6.29
39c	22776.30	1957	27013.30	1966	32309.60	1972	37605.90	1978	41842.90	1987	30	83.71
40	510.50	1955	2379.97	1963	4716.81	1968	7053.65	1973	8923.12	1981	26	1647.92
41	5197.61	1957	15191.90	1974	27684.80	1985	40177.70	1995	50172.00	2013	56	865.29
52a	2022.60	1919	2044.61	1921	2072.13	1923	2099.64	1925	2121.65	1928	9	4.90
52b	2546.62	1948	2592.96	1949	2650.88	1950	2708.80	1950	2755.14	1951	3	8.19
52c	2436.16	1955	4760.59	1968	7666.14	1976	10571.70	1984	12896.10	1997	42	429.36

*, **, *** See Table 3.

Table 5. Cycle properties: Mechanical

Code**	Depression*		Revival		Prosperity		Recession					
	Socio-economic capability at: $P(t_{5\%})$*	Year	Socio-economic capability at: $P(t_{25\%})$	Takeoff year	Socio-economic capability at: $P(t_{50\%})$	Year	Socio-economic capability at: $P(t_{75\%})$	Year	Socio-economic capability at: $P(t_{95\%})$	Year	Cycle duration in years	Cycle opportunity***: (Growth rate) %
1a	3242.87	1922	3769.34	1929	4427.42	1934	5085.50	1938	5611.97	1945	23	73.06
1b	5339.40	1959	6194.82	1966	7264.09	1971	8333.36	1975	9188.78	1983	24	72.09
1c	9123.89	1988	9271.75	1988	9456.57	1989	9641.38	1989	9789.24	1990	2	7.29
13a	5613.79	1916	7197.26	1925	9176.61	1930	11156.00	1935	12739.42	1944	28	126.93
13b	10360.20	1958	13291.30	1966	16955.13	1970	20619.00	1975	23550.02	1982	24	127.31
14a	76082.20	1915	79419.10	1922	83590.27	1926	87761.40	1930	91098.36	1937	22	19.74
14b	64675.30	1986	66335.70	1988	68411.22	1989	70486.70	1990	72147.15	1992	6	11.55
15a	2905.69	1950	2943.09	1950	2989.84	1951	3036.59	1951	3073.99	1952	2	5.79
15b	1955.10	1955	1956.07	1956	1957.27	1957	1958.48	1958	1959.45	1960	5	0.22
15c	2901.69	1964	3042.89	1967	3219.39	1969	3395.89	1972	3537.09	1975	11	21.90
16a	25115.90	1921	26720.80	1926	28726.96	1929	30733.10	1933	32338.06	1938	17	28.76
16b	26819.70	1950	26944.70	1951	27100.91	1951	27257.20	1952	27382.16	1952	2	2.10
16c	27799.60	1961	30815.50	1967	34585.36	1971	38355.20	1974	41371.14	1981	20	48.82
17a	25555.10	1963	27595.10	1968	30145.09	1970	32695.10	1973	34735.09	1978	15	35.92
17b	32005.10	1984	32173.20	1985	32383.45	1986	32593.70	1987	32761.86	1989	5	2.36
18a	6257.36	1923	6961.61	1928	7841.91	1931	8722.21	1934	9426.45	1938	15	50.65
18b	7738.91	1957	8823.71	1964	10179.72	1968	11535.70	1972	12620.53	1979	22	63.08
19a	4203.81	1920	4375.62	1923	4590.38	1925	4805.13	1927	4976.94	1931	11	18.39
19b	2882.51	1962	3054.75	1966	3270.05	1969	3485.35	1971	3657.59	1976	14	26.89
20	19374.30	1950	23515.10	1961	28690.95	1967	33866.90	1974	38007.58	1984	34	96.18
21a	5705.55	1947	5899.76	1952	6142.52	1956	6385.28	1959	6579.48	1964	17	15.32
21b	6603.58	1968	6733.28	1969	6895.40	1970	7057.52	1971	7187.21	1972	4	8.84

Table 5 (Continued)

22a	2520.50	1922	2574.21	1923	2641.35	1924	2708.48	1925	2762.19	1926	4	9.59
22b	2722.02	1928	2766.11	1930	2821.21	1931	2876.32	1932	2920.40	1934	6	7.29
22c	1804.40	1958	1934.24	1964	2096.53	1968	2258.83	1971	2388.66	1977	19	32.38
23a	1952.67	1919	2603.99	1926	3418.14	1931	4232.28	1935	4883.60	1942	23	150.10
23b	4186.17	1954	5288.75	1962	6666.98	1966	8045.21	1971	9147.79	1979	25	118.52
24a	83.61	1924	126.07	1929	179.15	1932	232.22	1935	274.68	1940	16	228.53
24b	358.53	1959	435.12	1966	530.86	1969	626.60	1973	703.20	1979	20	96.13
25	17997.40	1921	18788.80	1926	19778.17	1930	20767.50	1933	21558.99	1938	17	19.79
26a	4957.13	1964	5015.73	1965	5088.98	1965	5162.23	1966	5220.83	1966	2	5.32
26b	5141.90	1969	5245.50	1972	5375.00	1973	5504.50	1975	5608.10	1978	9	9.07
27a	943.54	1949	1013.69	1953	1101.39	1955	1189.08	1958	1259.24	1962	13	33.46
27b	1261.22	1963	1325.75	1968	1406.43	1971	1487.10	1974	1551.64	1979	16	23.03
28a	32208.40	1919	33904.60	1924	36024.82	1927	38145.10	1930	39841.29	1935	16	23.70
28b	28911.60	1950	29046.00	1951	29214.04	1951	29382.10	1952	29516.48	1953	3	2.09
28c	29220.80	1956	31832.20	1963	35096.42	1967	38360.70	1971	40972.09	1979	23	40.22
29a	57679.00	1921	60275.90	1926	63522.00	1929	66768.10	1931	69364.99	1936	15	20.26
29b	48381.90	1961	51296.90	1966	54940.65	1969	58584.40	1972	61499.42	1976	15	27.11
29c	60835.70	1984	61295.50	1986	61870.31	1988	62445.10	1989	62904.90	1992	8	3.40
31	2377.85	1944	3632.17	1955	5200.06	1962	6767.96	1968	8022.27	1979	35	237.37
50a	11841.90	1920	13362.80	1927	15263.85	1931	17165.00	1935	18685.84	1941	21	57.79
50b	13654.10	1958	18231.40	1969	23953.01	1975	29674.60	1981	34251.89	1992	34	150.85
53a	35016.30	1918	37063.20	1924	39621.74	1927	42180.30	1931	44227.19	1936	18	26.30
53b	37880.90	1946	56444.60	1966	79649.09	1978	102853.62	1990	121417.30	2009	63	220.52

*, **, *** See Table 3.

Table 6. Cycle properties: Transport

Code**	Depression*: Socio-economic capability at: $P(t_{5\%})$*	Depression*: Year	Revival: Socio-economic capability at: $P(t_{25\%})$	Revival: Takeoff year	Prosperity: Socio-economic capability at: $P(t_{50\%})$	Prosperity: Year	Recession: Socio-economic capability at: $P(t_{75\%})$	Recession: Year	Socio-economic capability at: $P(t_{95\%})$	Year	Cycle duration in years	Cycle opportunity***: (Growth rate) %
42	4914.41	1970	7012.02	1978	9634.02	1983	12256.00	1988	14353.60	1997	27	192.07
43	3107.28	1954	4056.74	1966	5243.58	1972	6430.40	1979	7379.88	1991	37	137.50
44	2690.01	1923	3240.01	1927	3927.51	1930	4615.00	1933	5165.01	1938	15	92.01
45a	3726.74	1929	3777.05	1930	3839.94	1930	3902.80	1931	3953.14	1932	3	6.08
45b	2219.79	1956	2936.47	1963	3832.32	1968	4728.20	1972	5444.85	1979	23	145.29
46	4506.33	1969	4669.33	1971	4873.08	1973	5076.80	1974	5239.83	1976	7	16.28
49a	7115.35	1919	7376.53	1920	7703.02	1921	8029.50	1922	8290.69	1924	5	16.52
49b	4173.85	1952	5616.16	1963	7419.06	1969	9222.00	1976	10664.30	1987	35	155.50

*, **, *** See Table 3.

Table 7. Cycle properties: Non-industrial

Code**	Depression*: Socio-economic capability at: $P(t_{5\%})$*	Depression*: Year	Revival: Socio-economic capability at: $P(t_{25\%})$	Revival: Takeoff year	Prosperity: Socio-economic capability at: $P(t_{50\%})$	Prosperity: Year	Recession: Socio-economic capability at: $P(t_{75\%})$	Recession: Year	Socio-economic capability at: $P(t_{95\%})$	Year	Cycle duration in years	Cycle opportunity***: (Growth rate)%
32a	127.31	1956	636.54	1961	1273.08	1965	1909.61	1968	2418.84	1974	18	1799.96
32b	2773.45	1985	2867.88	1986	2985.93	1987	3103.97	1987	3198.40	1988	3	15.32
48	7767.33	1917	8118.79	1922	8558.12	1925	8997.44	1928	9348.90	1934	17	20.36
54a	4636.08	1949	4768.68	1950	4934.43	1951	5100.18	1952	5232.78	1953	4	12.87
54b	5298.74	1957	5477.03	1961	5699.89	1964	5922.76	1966	6101.05	1971	14	15.14
54c	5924.46	1970	5986.46	1972	6063.96	1972	6141.46	1973	6203.46	1975	5	4.71
54d	5419.52	1984	5615.63	1987	5860.78	1988	6105.92	1989	6302.04	1991	7	16.28
56a	27945.10	1920	28791.60	1923	29849.80	1924	30908.10	1926	31754.60	1929	9	13.63
56b	23358.40	1961	25789.00	1967	28827.30	1970	31865.70	1974	34296.30	1980	19	46.83

*, **, *** See Table 3.

the cycle duration and technological opportunity of the cycle), the time and level of accumulated patent stock for any stage on the cycle first need to be identified. For this purpose, the growth model is transformed so as to calculate the share of the technology (i.e. patent stock) which has been developed in relation to its long run level of technological potential or equilibrium. Hence, the technological relative position at a given time will always be in terms of the share of its long run potential[18].

By first subtracting K from P(t) (in order to scale the model so that $P(t_{\mathrm{initial}}) \approx 0\%$ of development), and then dividing both sides of the logistic model (see equation ii) by $\bar{P}$ (in order to consider the stage of the growth cycle in relation to the long run level of its potential), we have the form:

$$\frac{(P(t) - K)}{\bar{P}} = \frac{1}{1 + \exp[-(a + b(t - t_0))]}$$

$$\text{where } \lim \left[\frac{(P(t) - K)}{\bar{P}}\right] \approx 1(100)\% \text{ for } t \to \infty \tag{iii}$$

Denoting 'x' as the stage, $(P(t) - K)/\bar{P}$, which the technology have developed out of its long run potential, the accumulated patent stock, P(t), for any given time, t, can then be calculated as $(P(t) = (x)\bar{P} + K$. By rewriting equation (ii) and inserting P(t), the time t for any stage of development can be calculated by:

$$t = \frac{-\left(LN\left[\frac{\bar{P}}{(x)\bar{P}} - 1\right]\right) - a}{b} + t_0 \tag{iv}$$

E.g. by inserting P(t) for the point of inflection, $x = 0.5$, we get the time, t, of cycle inflection to be $-a/b + t_0$.

Cycle properties

As the logistic model is symmetrical around the inflection point, the model can now be directly associated with the following properties, concerning different cyclical points (initiation, takeoff and ceiling) and concerning the four phases of the growth cycle (depression, revival, prosperity and recession), which are playing an important part in identifying the diversity of technology dynamics.

- Initial level of potential technology growth curve, if $(P(t) - K)/\bar{P} \approx 0$ (0%)

[18] Although Griliches (1957), Mansfield (1961), Bain (1964) etc. worked with diffusion or growth expressed in relation to a given total, in which the total represents 100%, their ceiling value was not necessarily at the 100% level. For example, Griliches (1957) had some land which would never get planted with hybrid seed corn so the ceiling level would be below 100%. Similarly, in innovation diffusion studies, some firms may never adopt a new technology so the ceiling will be below 100%. However, in the current model concerning the growth of technology, the ceiling level is by definition 100% representing the technology's full potential.

- Depression, if $(P(t) - K)/\bar{P} < 0.25$ (25%) of the technological growth curve
- Takeoff of technology, if $(P(t) - K)/\bar{P} = 0.25$ (25%)
- Revival, if 0.25 (25%) $\leq (P(t) - K)/\bar{P} < 0.5$ (50%) of the technological growth curve
- Inflection point, if $(P(t) - K)/\bar{P} = 0.5$ (50%)
- Prosperity, if 0.5 (50%) $\leq (P(t) - K)/\bar{P} < 0.75$ (75%) of the technological growth curve
- Recession, if 0.75 (75%) $\leq (P(t) - K)/\bar{P} < 1$ (100%) of the technological growth curve
- Potential ceiling of technology growth curve, if $(P(t) - K)/\bar{P} \approx 1$ (100%)

Besides the degree of synchronisation in time in terms of different cyclical points and phases of development, the diversity of technology dynamics is also characterised in relation to three of the most consulted properties relating to the structure of technological cycles: Cycle duration, technological opportunity of cycle, and technological socio-economic capability or impact of the cycle (see Sect. 2.2. concerning use of patent data as proxy measures for technological opportunity and socio-economic technological capability or impact).

- The potential duration of the cycles are calculated over the period in which the accumulated patent stock moves from 5% to 95% of the ceiling level, as we will only approach 0% when $t \to -\infty$ and 100% when $t \to \infty$.
- Overall potential technological opportunity of a cycle is expressed as the percentage growth in patent stock across the estimated cycle duration: $[P(t_{95\%}) - P(t_{5\%})] * 100\%/P(t_{5\%})$.
- Accumulated socio-economic capability or impact of a cycle at a given phase or time is expressed as the accumulated patent stock, P(t), at that time.

5.2 Cycle property results

The results of the timing and socio-economic capability or impact at the year of takeoff and for the four phases of the growth curves, as well as the cycle duration and technological opportunity of cycle are displayed in Tables 3–7.

The results shows absolutely no evidence of a fixed cycle duration, as the length of each cycle spans from just a few years up to several decades, and this is true for all broad groups: chemicals, electrical/electronics, mechanical, transport and non-industrial. Sorting the 106 identified cycles in Tables 3–7 by cycle duration, we have: 34 cycles < 10 years; 10 years ≥ 27 cycles < 20 years; 20 years ≥ 25 cycles < 30 years; 30 years ≥ 10 cycles < 40 years; 40 years ≥ 4 cycles 50 years; and finally, 6 cycles with a cycle duration ≥ 50 years. Hence, we see that, the longer the cycles the more rare they become. However, there is no evidence for innovation cycles to be longer or shorter depending on the historical period. Given no fixed periodicity of the time-span of each cycle, as well as no evidence for innovation cycles to be longer or shorter depending on the historical period, these results are in accordance with the findings of Schumpeter and Kuznets, who saw no need for such cycles to have a fixed length as the nature and impact of each new innovation is different[19]. That is, the length of the cycle depends on the nature and environment of the particular innovation (Schumpeter, 1939 p. 119).

The results also indicate cross technology differences in terms of the size of accumulated patent stocks at different stages of development, reflecting different socio-economic capability or historical impact, and in terms of change or growth in accumulated patent stock across the full cycle duration, reflecting different opportunities across technologies.

These results certainly confirm the diversity of technology dynamics in terms of cyclical phases, cycle duration, technological opportunity and level of socio-economic capability or impact.

As an empirical illustration, a few randomly selected full cycles from the broad categories – chemicals, electrical/electronics, mechanical, transport and non-industrial – have been plotted and are graphically presented in Figures 2–7. However, the plotted cycle for the transport patent class only reaches 81.58% of full potential, possibly due to a data constraint, as it ends in 1990.

5.3 Clustering of innovations: An exploration

As each cycle does not have the same time span, the cyclical phases are not appropriate to focus on when comparing the timing of innovation cycles. What is important is the point of technological takeoff. Synchronisation of such has often been used in tracing possible clusters of innovation. The year of technological takeoff for each growth cycle presented in Tables 3–7 has been plotted in Figure 8.

It is important to note that periods with no takeoff in technological patent groups are not indicative of a lack of inventive or innovative activity. The cycle might be on the inflection point with the most rapid rate of development, or may be well into the innovative prosperity phase. It may also be a period when radical (or basic) inventions are being patented, and individual patents are very significant for future exploitation, but are not important in numbers (i.e. the field as a whole has not reached the collective competence necessary for takeoff or revival).

From Figure 8 it can be observed that although takeoffs do not move in any synchronised fashion, they do seem to follow a certain band-like (or epoch-like) character, with a clustering of takeoffs from 1920 (the beginning of the data set eligible for analysis) to 1934. Then there is a gap with no single takeoff up until 1946, followed by numerous takeoffs (especially in the upswing of the 1960s) up to about 1972. Hence, Figure 8 does suggest

[19] The 'cycle duration' issue (i.e. time span of each S-curve) discussed here ought not to be confused with the long 'wave' debate with is about 'clustering of innovations' (or synchronisation of cycle takeoffs).

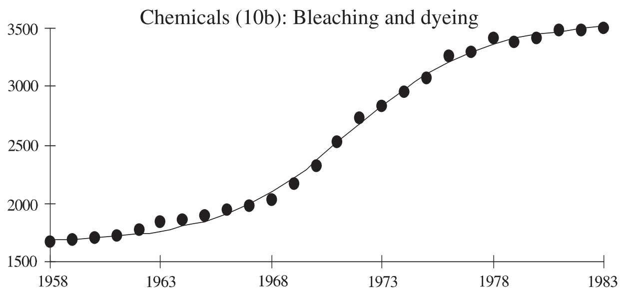


Fig. 2. Technological growth cycle [year; patent stock]

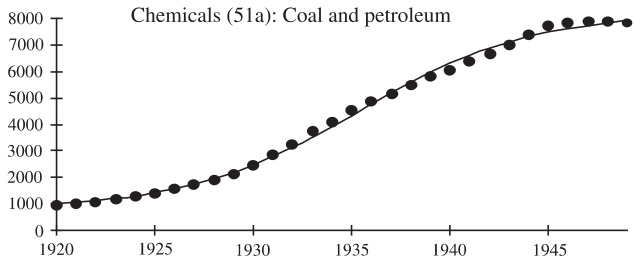


Fig. 3. Technological growth cycle [year; patent stock]

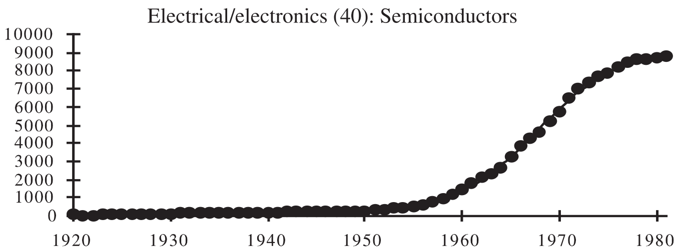


Fig. 4. Technological growth cycle [year; patent stock]

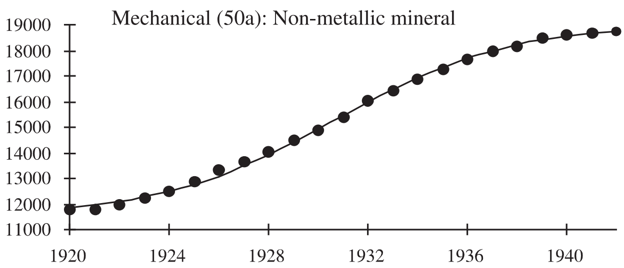


Fig. 5. Technological growth cycle [year; patent stock]

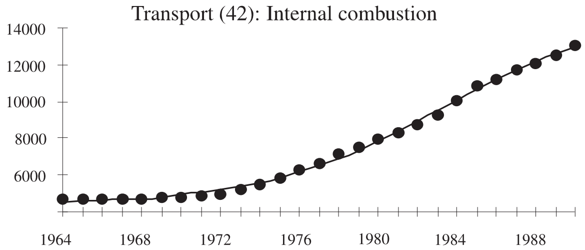


Fig. 6. Technological growth cycle [year; patent stock]

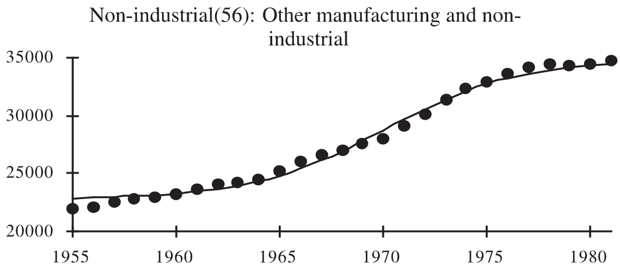


Fig. 7. Technological growth cycle [year; patent stock]

that something puzzling is happening with the takeoff bands. There is no single takeoff between 1934 and 1946, and relatively few takeoffs in the 1970s and the beginning of the1980s. However, the fact that takeoffs are not close to 1990, is a reflection on the constraints of the data (i.e. that the technological growth curve has to be at least 60% in 1990 to make sure that we are dealing with an S-curve).

There could be several explanations for this. For instance, a point which is commonly argued by historians is that takeoffs in technological innovations were held up by World War II and the (oil) crises of the 1970s. This would support an argument that takeoffs were otherwise randomly distributed. However, although external factors may account for much in innovative and economic fluctuations, it still leaves us without an understanding of whether and how the system by its own working produces clusters of innovation and booms or crises [issues addressed by Kuznets (1930a, 1940) and Schumpeter (1939)] and consequently, the most prominent discussions within evolutionary economics concern the possibility of clustering of innovations [if not merely a statistical observation due to random historical events] as a by-product of the internal dynamics of the economic system. There are several potential strings to the latter argument.

If the clustering of patent takeoffs in Figure 8 is treated as an indicator of clusters of innovations, they allow us to offer additional insight into the possible existence of long Kondratieff waves (Kondratieff, 1925). That is, one could well argue that there has been a Kondratieff upswing from the 1890s up to the late 1920s (there are only a few dots in Figure 8 in the

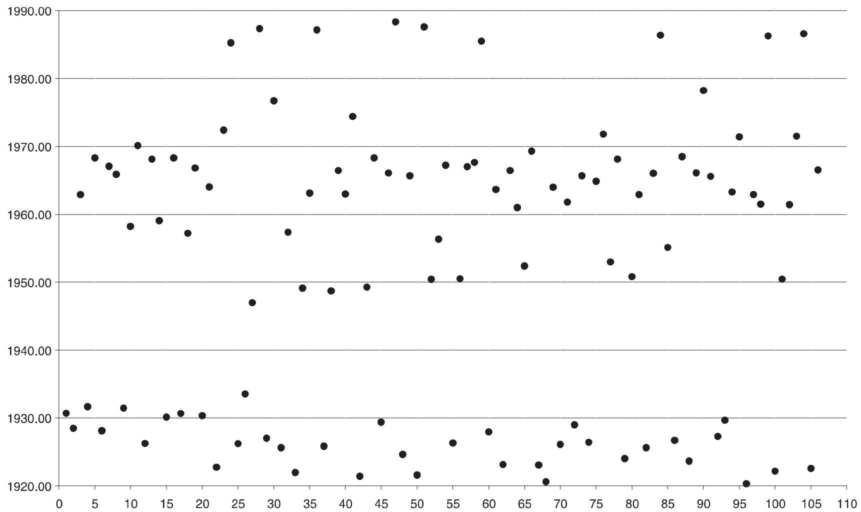


Fig. 8. Timing of technological cycle takeoff [technological group; year]. Technological groups are randomly numbered on the x-axis (i.e. they do not reflect the technological codes in Tables 3–7): Chemicals (1–21), Electrical/electronics (22–44), Mechanical (56–89), Transport (90–97) and Non-industrial (98–106)

period after) interrupted only by World War I, then a downswing of the third Kontradieff in the late interwar – World War II period (i.e. late 1930s – early 1940s), followed by an upswing of the forth Kontradieff in the 1950s and 1960s, and finally a downswing in the 1970s and 1980s. Such an argument would also be in line with the argument of Freeman et al. (1982) and Kleinknecht (1990). However, other could argue that this upswing ended in 1913, and subsequently interpret the boom of the 1920s in terms of a reconstruction boom. Mensch (1975) suggested that depressions induced clusters of innovations acted as the driving force for the next upswing, but his notion of ‘basic innovations’ is not really applicable in this context, as we are dealing with clusters of innovation takeoffs.

Freeman, Clark and Soete (1982) argued that upswings are not to be related to the *appearance* of basic innovations so much as to their *diffusion*, and that there would be a clustering of related product, process, and applications innovations making up the new technology and associated with the ‘entrepreneurial swarming’ process (rather than a clustering of unrelated innovations). This is supported by Coombs, Saviotti and Walsh (1987), who highlight the fact that technological acceleration and diffusion in an upswing are very much related to institutional factors (i.e. no war, no financial crises, stable business environment etc.) rather than the extent to which the technologies are new or old (basic or not). In this perspective, innovation clusters are driven by a series of new ‘technology systems’, despite a more random distribution of basic innovations or innovation activity in general. Hence, it might be argued that the clusters in Figure 8 are ‘Schmooklerian’ or ‘band-wagon’ effect patent takeoffs, or clusters of technological trajectories [using Dosi's (1982) terminology], rather than (basic) radical inventions, in which case it neither contradicts nor supports Mensch's argument. In order to investigate whether there is a clustering of radical innovation in the downswing (Mensch's argument), it would be necessary to investigate in detail the content of every patent within every technological field to identify which are the patents representing radical innovation. This is outside the scope of this paper.

From the literature we have also learned that innovation clusters may be a sectoral phenomena with macroeconomic manifestations (Schmookler, 1966; Schumpeter, 1939), which derives their character from innovations in the industry where they begin; or, alternatively, they may be a 'real' phenomenon of long waves, associated with related induced innovations that gives rise to expansionary effects in the economy as a whole, in which clustering of innovations cannot be linked to a particular type of innovation as against other types carried out during the same epoch (Kondratieff, 1925; Rosenberg and Frischtak, 1984). However, the evidence presented here is much too tenuous to be worth stating any such conclusion. A validation of whether the documented periods of takeoff are due to 'sectoral phenomena with macroeconomic manifestations' or 'long waves' in economic life, would require further investigation into the relationship between invention, innovation and the economic effects and externalities of such, as well as require further investigation into a qualitative interpretation of history. Such analysis is indeed interesting, but outside the scope of this paper.

From a technology system perspective (following up on Freeman et al., 1982), grouping the technological growth cycles with respect to their two band of takeoffs within this century (as identified in the text above and in Fig. 8), and sorting those technologies within each band by cycle opportunity (cycle growth rates) and historical impact or socio-economic capability (accumulated patent stocks), (see Tables 2–6), it can be observed that epochs differ radically with respect to (i) the technologies involved, including (ii) their scope (i.e. socio-economic capability (or accumulated patent stock) and opportunity (or cycle growth rate)) and (iii) overall 'technological configuration' (i.e. the combined structure of i and ii).

Assuming that the overall configuration of technologies within a certain band of takeoff can be associated with an overall system takeoff (as suggested in Andersen, 1999; Andersen and Walsh, 2000), this suggests how we might start to measure and understand evolving technological systems of innovation clusters.

The notion of 'uneven system development', in terms of the timing of takeoffs (i.e. they seems to follow a certain band- (or epoch-) like character, although they are not totally synchronized), and in terms of the periodicity of the time-span of each cycle (i.e. cycle duration), combined with cross technology differences in socio-economic collective capability or historical impact, and differences in opportunities of different technological fields, also suggests that the formation of technology systems might evolve in the way suggested by Hughes (1992), who refers to salients (or reverse salients) in the technology development phase and to the solving of critical problems. The salient metaphor and the notion of uneven technology development can also be related to Dahmen's (1989) concept of development blocks and Dosi's (Dosi, 1982; Dosi et al., 1988) concept of technological paradigms and technological trajectories. Rosenberg (1982) writes of bottlenecks in technological development to capture a similar idea to Hughes' 'reverse-salients'. Rosenberg also uses the notion of 'focusing devices' in arguing that technological change historically moves in 'patches'. Although a qualification of such arguments in relation to this study also seems of have great potentials, it is outside of the scope of the paper.

Hence, the results certainly confirm clustering of innovation, and suggests how we might start to understand evolving waves of innovation or technology systems.

6 Conclusion

Using Kuznets' cyclical units of troughs and peaks as representing the growth cycle of a technology, and applying them to Schumpeter's four phases of development (depression, revival, prosperity and recession), it can be concluded that technological growth tends to follow an *S*-shaped growth curve, and that the biological growth model in logistic form is an appropriate approximation to describe the paths of evolution.

When identifying the technology cycles of sustained growth (as opposed to periods of random fluctuations), we saw how we often have periods of punctuated equilibrium in which one growth curve follows another with no period of absolute decline. However, periods of sustained decline (i.e. crisis), when they occur, tend to be of very short duration in comparison to the growth cycle. This suggest that the *S*-shaped growth curve does not reflect only half of a technology's 'life', as has sometimes been argued.

The results also indicate that, although the timing of takeoffs tends to be clustered within certain time bands (normally associated with upswing periods), the technologies vary in terms of the timing of operation (i.e. no synchronisation in the timing of phases of depression, revival, prosperity and recession) due to the great diversity in cycle duration. The results also indicate cross-technology differences in terms of collective experience and opportunity (identified from the accumulated patent stock and change or growth in stock over the life cycle, respectively). This confirms the variety of technology dynamics, as well as a scope for how we might start to understand evolving waves of innovations within clusters or technology systems.

The results also show that most of the *S*-shaped growth cycles are not subject to significant external shocks, but are carried through or survive almost all the way to their potential long run ceiling level. This reinforces the relevance of Schumpeter's point that development proceeds not in a smooth line but in cycles, and that although external factors have a large influence on change and growth, it is still very important to understand the mechanics and dynamics internal to the system.

Appendix

Table a. Parameter results: Chemicals

Code*	Technological group	Period used for model fitting t_0 = first obs.	$P(t_{initial})$ K	Ceiling $\bar{P}$	$P(t_{ceiling})$ $\bar{P} + K$	$\hat{a}$	$\hat{b}$	R^2**
2	Distillation processes	1920–83	3.80	1808.84	1812.64	−1.74	0.06	0.9928
3a	Inorganic chemicals	1920–40	2661.59	1982.33	4643.93	−4.41	0.39	0.9819**
3b	Inorganic chemicals	1955–85	3609.53	5811.04	9420.58	−2.76	0.21	0.9948
4a	Agricultural chemicals	1930–42	310.13	163.30	473.43	−2.56	0.89	0.9825
4b	Agricultural chemicals	1950–90	396.37	4459.79	4856.16	−3.43	0.13	0.9947**
5a	Chemical processes	1920–44	4120.37	7124.13	11244.50	−3.15	0.25	0.9972*
5b	Chemical processes	1949–90	10361.33	29360.8	39722.11	−4.21	0.17	0.9954**
6	Photographic chemistry	1920–90	385.17	14614.7	14999.83	−5.51	0.10	0.9816**
7a	Cleaning agents and other compositions	1920–46	3154.13	6875.61	10029.74	−3.24	0.19	0.9978*
7b	Cleaning agents and other compositions	1955–62	8900.00	1604.89	10504.89	−19.91	0.49	0.9907
7c	Cleaning agents and other compositions	1964–90	9904.47	7118.70	17023.17	−2.63	0.25	0.9847
8a	Disinfecting and preserving	1920–40	36.63	72.36	109.00	−2.17	0.17	0.9656
8b	Disinfecting and preserving	1955–90	99.60	452.99	552.59	−2.91	0.14	0.9856
9	Synthetic resins and fibres	1920–90	537.47	43804.80	44342.27	−4.72	0.09	0.9950**
10a	Bleaching and dyeing	1920–42	632.77	1849.94	2482.70	−4.00	0.29	0.9974**
10b	Bleaching and dyeing	1958–83	1664.13	1885.04	3549.18	−4.58	0.34	0.9972**
51a	Coal and petroleum products	1920–49	815.77	7412.66	8228.43	−3.56	0.23	0.9972*
51b	Coal and petroleum products	1956–60	7637.95	973.09	8611.04	−3.53	2.02	0.9993*
51c	Coal and petroleum products	1964–77	8466.17	1883.87	10350.04	−2.51	0.50	0.9722*
55a	Explosive compositions and charges	1928–34	408.58	73.28	481.86	−3.48	1.02	0.9946*
55b	Explosive compositions and charges	1959–78	359.97	1101.06	1461.03	−1.11	0.26	0.9756

* a, b, and c, after the technological group code number, denote different cycles of same technological group across different periods in time.
** The first empirical observation is below 2% (**) or 5% (*) of the growth cycle's ceiling level. Otherwise it is between 5% and 10% (or perhaps between 5% and 25% if t_0 is 1920).

Table b. Parameter results: Electrical/Electronics

Code*	Technological groups	Period used for model fitting t_0 = first obs.	$P(t_{initial})$ K	Ceiling $\bar{P}$	$P(t_{ceiling})$ $\bar{P}+K$	$\hat{a}$	$\hat{b}$	R^2**
30a	Mechanical calculators and typewriters	1921–26	4695.47	312.48	5007.95	−2.97	1.06	0.9999*
30b	Mechanical calculators and typewriters	1971–77	2563.80	168.14	2731.94	−2.93	1.29	0.9923
30c	Mechanical calculators and typewriters	1979–90	2616.14	1163.62	3779.76	−3.37	0.36	0.9981*
33	Telecommunications	1920–42	4909.50	4969.50	9879.00	−2.74	0.27	0.9797
34	Other electrical communication systems	1923–44	2047.57	914.66	2962.23	−4.41	0.31	0.9933**
35a	Special radio systems	1920–78	108.20	7101.51	7209.71	−3.75	0.10	0.9952*
35b	Special radio systems	1986–90	5703.64	308.46	6012.10	−2.51	1.02	0.9587
36a	Image and sound equipment	1924–32	5375.97	1863.73	7239.70	−2.99	0.63	0.9944*
36b	Image and sound equipment	1955–90	5239.47	21263.4	26502.84	−3.73	0.12	0.9858*
37a	Illumination devices	1920–42	6834.53	5709.23	12543.76	−2.47	0.24	0.9855
37b	Illumination devices	1955–62	10641.78	1340.80	11982.58	−4.76	1.54	0.9931**
38a	Electrical devices and systems	1920–42	6834.53	26126.6	32961.12	−1.40	0.15	0.9917
38b	Electrical devices and systems	1948–53	27918.80	2215.08	30133.88	−2.80	1.51	0.9990
38c	Electrical devices and systems	1955–77	29653.98	26242.8	55896.79	−3.09	0.24	0.9920*
38d	Electrical devices and systems	1983–90	50040.57	4444.32	54484.89	−5.19	0.98	0.9912**
39a	Other general electrical equipment	1920–42	12389.33	10018.10	22407.43	−2.70	0.28	0.9923
39b	Other general electrical equipment	1948–52	20540.03	1441.48	21981.51	−2.90	2.54	0.9932
39c	Other general electrical equipment	1955–90	21717.03	21185.1	42902.12	−3.30	0.19	0.9818*
40	Semiconductors	1920–81	43.13	9347.36	9390.49	−10.92	0.23	0.9988**
41	Office equipment and data processing systems	1948–90	2699.03	49971.50	52670.53	−3.86	0.10	0.9784*
52a	Photographic equipment	1920–26	2017.10	110.06	2127.16	−2.02	0.66	0.9491
52b	Photographic equipment	1948–52	2535.03	231.69	2766.72	−3.74	2.11	0.9992*
52c	Photographic equipment	1955–90	1855.05	11622.20	13477.25	−2.96	0.14	0.9958*

*, ** See Table a.

Table c. Parameter results: Mechanical

Code*	Technological groups	Period used for model fitting t_0 = first obs.	$P(t_{initial})$ K	Ceiling $\bar{P}$	$P(t_{ceiling})$ $\bar{P}+K$	$\hat{a}$	$\hat{b}$	R^2**
1a	Food and tobacco products	1920–43	3111.25	2632.33	5743.59	−3.47	0.25	0.9900*
1b	Food and tobacco products	1955–81	5125.55	4277.08	9402.63	−3.81	0.24	0.9906*
1c	Food and tobacco products	1985–90	9086.93	739.27	9826.20	−8.60	2.25	0.9992**
13a	Metallurgical processes	1920–42	5217.92	7917.37	13135.29	−2.07	0.21	0.9972
13b	Metallurgical processes	1955–90	9627.47	14655.3	24282.78	−12.36	0.25	0.9982**
14a	Miscellaneous metal products	1920–33	75247.94	16684.7	91932.60	−1.52	0.27	0.9919
14b	Miscellaneous metal products	1985–90	64260.19	8302.06	72562.25	−3.51	0.93	0.9925*
15a	Food, drink and tobacco equipment	1949–53	2896.34	187.00	3083.34	−4.07	2.10	0.9998**
15b	Food, drink and tobacco equipment	1955–59	1954.86	4.83	1959.69	−2.56	1.10	0.9865
15c	Food, drink and tobacco equipment	1964–76	2866.39	706.00	3572.39	−2.74	0.51	0.9866
16a	Chemical and allied equipment	1920–35	24714.62	8024.67	32739.29	−3.26	0.34	0.9906*
16b	Chemical and allied equipment	1949–53	26788.41	625.00	27413.41	−4.26	2.07	0.9993**
16c	Chemical and allied equipment	1955–90	27045.61	15079.5	42125.12	−4.65	0.30	0.9967**
17a	Metal working equipment	1961–77	25045.09	10200.00	35245.09	−3.80	0.41	0.9851*
17b	Metal working equipment	1984–90	31963.00	840.90	32803.90	−2.93	1.23	0.9450
18a	Paper making apparatus	1920–40	6081.30	3521.21	9602.52	−4.24	0.39	0.9956**
18b	Paper making apparatus	1957–76	7467.71	5424.02	12891.73	−2.83	0.26	0.9919
19a	Building material processing equipment	1920–33	4160.86	859.03	5019.89	−2.71	0.51	0.9703
19b	Building material processing equipment	1963–77	2839.45	861.20	3700.65	−2.60	0.44	0.9686
20	Assembly and material handling equipment	1949–77	18339.14	20703.6	39042.77	−3.19	0.17	0.9969*
21a	Agricultural equipment	1949–65	5657.00	971.04	6628.04	−2.29	0.35	0.9812
21b	Agricultural equipment	1968–73	6571.15	648.48	7219.64	−3.14	1.55	0.9928*
22a	Other construction and excavating equipment	1920–26	2507.08	268.54	2775.62	−5.10	1.30	0.9844**
22b	Other construction and excavating equipment	1928–32	2711.00	220.42	2931.42	−2.75	1.03	0.9786
22c	Other construction and excavating equipment	1957–77	1771.94	649.18	2421.12	−3.22	0.30	0.9868*
23a	Mining equipment	1920–44	1789.84	3256.59	5046.43	−2.60	0.25	0.9919
23b	Mining equipment	1951–90	3910.53	5512.91	9423.44	−3.62	0.23	0.9936*

Table c (Continued)

24a	Electrical lamp manufacturing	1920–43	73.00	212.29	285.29	−4.39	0.37	0.9935**
24b	Electrical lamp manufacturing	1955–78	339.38	382.97	722.35	−4.24	0.30	0.9755**
25	Textile and clothing machinery	1920–41	17799.48	3957.37	21756.86	−3.32	0.35	0.9955*
26a	Printing and publishing machinery	1963–67	4942.48	293.00	5235.48	−5.90	2.57	0.9997**
26b	Printing and publishing machinery	1970–77	5116.00	518.00	5634.00	−2.37	0.71	0.9768
27a	Woodworking tools and machinery	1950–62	926.00	350.78	1276.78	−2.48	0.46	0.9519
27b	Woodworking tools and machinery	1964–78	1245.08	322.70	1567.78	−2.60	0.36	0.9747
28a	Other specialised machinery	1920–34	31784.30	8481.04	40265.34	−2.57	0.37	0.9876
28b	Other specialised machinery	1949–53	28878.00	672.08	29550.08	−4.62	1.95	0.9947**
28c	Other specialised machinery	1955–76	28567.90	13057	41624.94	−3.14	0.26	0.9902*
29a	Other general industrial equipment	1920–34	57029.79	12984.4	70014.21	−3.24	0.38	0.9860*
29b	Other general industrial equipment	1959–81	47653.12	14575.1	62228.18	−3.81	0.39	0.9897*
29c	Other general industrial equipment	1984–90	60720.76	2299.09	63019.86	−2.85	0.73	0.9617
31	Power plants	1930–80	2064.27	6271.58	8335.85	−5.35	0.17	0.9965**
50a	Non-metallic mineral products	1920–42	11461.65	7604.41	19066.06	−2.98	0.28	0.9990*
50b	Non-metallic mineral products	1957–90	12509.80	22886.4	35396.22	−3.11	0.17	0.9807*
53a	Other instruments and controls	1920–36	34504.57	10234.3	44738.91	−2.26	0.32	0.9860
53b	Other instruments and controls	1948–90	33240.02	92818.1	126058.15	−2.79	0.09	0.9840

*, ** See Table a.

Table d. Parameter results: Transport

Code*	Technological groups	Period used for model fitting t_0 = first obs.	$P(t_{initial})$ K	Ceiling $\bar{P}$	$P(t_{ceiling})$ $\bar{P} + K$	$\hat{a}$	$\hat{b}$	R^{2}**
42	Internal combustion engines	1964–90	4390.01	10488.00	14878.03	−4.23	0.22	0.9976**
43	Motor vehicles	1955–90	2869.91	4747.34	7617.25	−2.79	0.16	0.9777
44	Aircraft	1920–33	2552.51	2750.00	5302.51	−3.94	0.39	0.9693**
45a	Ships and marine propulsion	1928–32	3714.16	251.56	3965.72	−3.98	1.75	0.9881**
45b	Ships and marine propulsion	1954–78	2040.62	3583.40	5624.01	−3.51	0.26	0.9887*
46	Railways and railway equipment	1965–75	4465.58	815.00	5280.58	−6.79	0.89	0.9831**
49a	Rubber and plastic products	1920–26	7050.05	1305.94	8355.98	−1.46	1.12	0.9968
49b	Rubber and plastic products	1955–85	3813.27	7211.58	11024.85	−2.43	0.17	0.9982

*, ** See Table a.

Table e. Parameter results: Non-industrial

Code*	Technological groups	Period used for model fitting t_0 = first obs.	$P(t_{initial})$ K	Ceiling $\bar{P}$	$P(t_{ceiling})$ $\bar{P} + K$	$\hat{a}$	$\hat{b}$	R^2**
32a	Nuclear reactors	1938–78	0.00	2546.15	2546.15	−8.99	0.34	0.9955**
32b	Nuclear reactors	1985–90	2749.84	472.16	3222.01	−3.86	2.17	0.9928*
48	Textiles, clothing and leather	1920–32	7679.46	1757.30	9436.77	−1.86	0.35	0.9921
54a	Wood products	1949–53	4602.93	663.00	5265.93	−3.02	1.33	0.9909*
54b	Wood products	1955–67	5254.16	891.46	6145.63	−3.89	0.44	0.9593*
54c	Wood products	1970–75	5908.96	310.00	6218.96	−2.81	1.13	0.9631
54d	Wood products	1984–90	5370.49	980.58	6351.07	−3.33	0.86	0.9933*
56a	Other manufacturing and non-industrial	1920–32	27733.43	4232.82	31966.25	−2.82	0.67	0.9805
56b	Other manufacturing and non-industrial	1955–81	22750.70	12153.3	34903.98	−4.68	0.31	0.9906**

*, ** See Table a.

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