Breaking the waves: a Poisson regression approach to Schumpeterian clustering of basic innovations

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The Schumpeterian theory of long waves has given rise to an intense debate on the existence of clusters of basic innovations. Silverberg and Lehnert have criticised the empirical part of this literature on several methodological accounts. In this paper, we propose the methodology of Poisson regression as a logical way of incorporating this criticism. We construct a new time series for basic innovations (based on previously used time series), and use this to test the hypothesis that basic innovations cluster in time. We define the concept of clustering in various precise ways before undertaking the statistical tests. The evidence we find supports only the ‘weakest’ of our clustering hypotheses, i.e., that the data display overdispersion. We thus conclude that the authors who have argued that a long wave in economic life is driven by clusters of basic innovations have stretched the statistical evidence too far.

Key words: Radical technological change, Long waves, Innovation

JEL classifications: O3, O4, N10

1. Introduction

Schumpeter was the first economist to place the mechanism of basic innovation at the centre of the discussion about the long-run development pattern of global capitalism. His emphasis on the *clustering* of basic innovations¹ is the centrepiece of his theory of long-term economic development expounded at great length in his *Business Cycles* (Schumpeter, 1939). The introduction of *radical* innovations triggers a wave of economic activity involving investment-based diffusion driven by temporary monopoly profits and bandwagon-like imitation by other entrepreneurs known as the process of *creative destruction*. Schumpeter asserted that this process inexorably led to the type of long waves Kondratieff (1926/1935) had claimed to have discovered in the historical data. While his vision was challenged at the time by, for example, Kuznets (1940), Mensch (1975/1979) revived the discussion on

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¹ ‘[Innovations] are not evenly distributed in time, but that on the contrary they tend to cluster, to come about in bunches, simply because first some, and then most firms follow in the wake of successful innovation’ (Schumpeter, 1939, p. 75).

clustering of innovations and economic activity using new data and an original hypothesis about causality. This sparked an intensive empirical debate, partly in the pages of this Journal, in the 1980s. Thus the status of the clustering issue has remained a key concept in the debate about long waves and their explication.¹

The relationship between innovation and long waves is not just a matter of idle historical curiosity. The publicity surrounding the so-called 'new' economy (information and communication technology—ICT, the Internet) as an apparently golden era which seemingly repeals the constraints of the 'old' economy, is a case in point. Does ICT usher in an upswing in economic activity and productivity growth that suspends the orthodox wisdom about the relationship between, for example, employment and inflation, or the fair valuation of equities, or is it only a rerun of previous historical experience with revolutionary and pervasive innovations? Ten Raa and Wolff (2000), for example, find strong productivity effects related to ICT, while Gordon (2000) is much more sceptical after a comparison of the productivity gains of ICT with those of previous technological revolutions.

The perspective of long waves also raises the question as to whether the (supposed) productivity increases related to ICT represent a permanent increment in the long-term rate of technical change, or are simply a passing cyclical phenomenon. The long-wave view would hold that the current period of strong growth is the upswing of the fifth long wave and, hence, that a downswing will inevitably follow it.² The two views are not mutually exclusive. One may imagine the long-run rate of basic innovations as a process with both a positive trend and a cyclical component. In this case, the relevant question becomes whether a model can be formulated that identifies both elements simultaneously.

After a long period of quiescence, a new debate on Schumpeter's hypothesis arose in the 1970s and 1980s. In this debate, which is summarised in some detail below, much of the empirical argument centred around time series of basic innovations.³ These were collected by various authors (who obtained somewhat varying results) on the basis of a historical evaluation of the importance of innovations. The main research question for these authors was whether the number of basic innovations was higher in depression periods than in prosperity periods (a more specific hypothesis than Schumpeter put forward, since he did not relate clustering to specific phases of the economic cycle). The possibility of a (very) long-run trend in the rate of basic innovation did not play any explicit role in this debate.

As early as 1974, Sahal (1974) suggested using a statistical method based on the Poisson and negative binomial distributions to describe time series of incremental innovation. However, this was not taken up in subsequent studies by Kleinknecht (1990) and Solomou (1986), who relied instead on statistical methods based on the normal distribution. Silverberg and Lehnert (1993) highlighted this error and employed more appropriate non-parametric tests based on the Poisson process. In the mean time, Poisson regression has become a standard part of the econometric toolbox (see, e.g., Greene, 1995). Applying this method, the question of whether Schumpeter was right (i.e., basic innovations tend to cluster) can be analysed simultaneously with the question of whether the long-run rate of occurrence of basic innovations is rising. This is what this paper intends to do, working with

¹ However, Silverberg and Lehnert (1993), in a formal model, demonstrated that such clustering was not logically necessary to produce long-period quasi-cyclical behaviour of a Schumpeterian economy, even while their empirical analysis did point to non-uniform arrival rates of innovations.

² In his historical analysis, Schumpeter observed three long waves since the beginning of modern capitalism. Freeman and Soete (1997), in a similar vein, take note of five long waves, i.e., they argue that two new ones have occurred since the end of Schumpeter's analysis.

³ Schumpeter distinguished between inventions and innovations, the latter denoting the point in time at which the technology is successfully commercialised.

the same basic innovation databases used by authors such as Kleinknecht and Mensch in the 1970s and 1980s.

The rest of this paper is organised as follows. In Section 2, the empirical literature on basic innovation time series and long waves will be briefly reviewed and criticised. On the basis of these results, a number of explicit statistical hypotheses are formulated to capture the ideas that have only been implicit until now in the debate on Schumpeterian basic innovations. Section 3 implements this model in the context of several time series for basic innovations, estimating a model admitting both overdispersion (clustering) and trend components. Section 4 summarises the main findings and draws some conclusions. The two appendices present technical details of the econometric methods and our recompilation of the innovation data.

2. Innovation time series: review of the literature and shortcomings

The 1970s and 1980s witnessed a rekindling of the debate on the Schumpeterian hypothesis of clustering of innovations rooted in statistical analysis of real data. The first contribution to this debate was by Mensch (1975/1979), who argued strongly in favour of the Schumpeterian hypothesis that basic innovations tend to be clustered. Moreover, he claimed that this clustering occurs in the depression periods of the long wave. Mensch's theoretical explanation for such clustering was that only in the despair of the depression phase do firms resort to the highly risky strategy of introducing basic innovations (drawing on inventions that may have been made previously). During the upswing and upper turning phase, in contrast, firms focus on squeezing profits out of the dominant technologies, and search activities aimed at basic innovations are at a low level (whether this is perfectly rational or myopic behaviour with respect to the relative costs of the various technological opportunities over the cycle remains open). His approach was to construct a database of basic innovations, and to use a runs test on the resulting time series of the number of innovations occurring each year (using year of innovation rather than year of invention) to test whether the series clustered. A runs test is a test of independence on the assumption of identical distribution, and thus does not control for a trend. On the other hand, it does not require the researcher to impose a periodisation on the data, a defect which, as we shall see, mars the work of later researchers.

While Mensch drew on the work of Jewkes *et al.* (1958) for his time series, that work was not constructed to be representative, and in particular the datings used and choice of innovations were disputed by Freeman *et al.* (1982). All such innovation time series, including the ones used below, are naturally subject to limitations. The first limitation concerns the arbitrariness in the selection of innovations and their dates. Second, an end of sample bias may exist, since there is usually insufficient evidence to identify which innovations actually prove to be economically significant in the period close to the researcher's own epoch. Finally, a simple listing of innovations fails to capture their systemic and paradigmatic interrelatedness, the importance of which has been emphasised by Freeman and Perez (1988).

Haustein and Neuwirth (1982) compiled a different time series on basic innovations, and used spectral analysis to test for periodicity in this and other time series related to the long wave. They concluded that there are 'some doubts when looking at the regular patterns of inventions and innovations by Mensch and Marchetti' (p. 67). In other words, their results suggest a less strictly periodic pattern than was suggested by Mensch.

In the mean time, the interpretation of the innovation time series data by Mensch gained support from van Duijn (1983) and Kleinknecht (1981, 1987), who provided more extensive data sets. A further contribution that was critical of the clustering hypothesis was Solomou (1986). He applied a z -test to the null hypothesis that the mean number of basic innovations in adjacent periods were drawn from a normal distribution with the same mean, which could not be rejected.

Kleinknecht (1990) responded to this criticism by constructing a new time series of basic innovations that was a compilation of three different time series used earlier (Mensch, Haustein and Neuwirth, van Duijn). He used a similar null-hypothesis to Solomou's, but relied on a t -test rather than a z -test. His conclusions were strongly in favour of clustering of basic innovations in the depression periods of the long wave. An important element of the differences in the results between Kleinknecht and Solomou lies in the different periodisations they use (as admitted by Kleinknecht, 1990, p. 86). Both Solomou and Kleinknecht use a division of a full cycle into two periods (up and down). Solomou (1986) uses the periodisation proposed by Mensch (1975/1979), while Kleinknecht (1990) relies on two different periodisations (for different lead times of innovation to economic time series), which were both based on his own work (Kleinknecht, 1987).

The methodology of these studies was strongly criticised by Silverberg and Lehnert (1993). They argue that

z and *t* tests . . . are only applicable to a normally distributed random variable. On a priori grounds we have argued that the null hypothesis on innovations must be that they are homogeneous Poisson distributed, however, and a histogram of, for example, the Haustein and Neuwirth data (as well as any of the other series we have examined) confirms that they are anything but normally distributed . . . both authors apply their tests to sub samples they claim have been selected on a priori criteria . . . In general, the periodisations employed derive from previous authors such as Mensch, whose use of a runs test did not depend on it, or on the examination of growth rates and the addition of a time lag . . . growth rates and a moving average of the innovation data may be highly (cross) correlated, so that the selection of a proper lag against variations in the growth rate series may simply be a method to select sub periods of above- and below-average innovation activity even from a completely random series. This fact would further invalidate any means test (even one appropriate to a Poisson process, such as a binomial statistic). (p. 31)

Thus, the statistical methodology used by Solomou and Kleinknecht is flawed, both with regard to the assumed distribution underlying the test statistics, and the particular choice of a periodisation scheme. To overcome these difficulties, Silverberg and Lehnert apply a number of non-parametric tests to the null of a homogeneous Poisson process without imposing a periodisation on the time series. This is convincingly rejected for all series. They then test for the existence of an exponential trend, again using a non-parametric method appropriate for a Poisson process, and show such a trend to be highly significant for all series. The growth rate of the trend is estimated (on the assumption of a non-homogeneous Poisson process with exponentially growing arrival rate) and found to be in the range of 0.5–1% per annum, depending on the series examined. After eliminating the trend from the data by a process of exponential slowing down of the original time series, the resulting trendless series are still shown to deviate significantly (although less so than non-detrended data) from a time-homogeneous (i.e., non-clustering) Poisson distribution. They concluded that, while to a first approximation these count data appeared to be generated by a Poisson process with an exponentially growing trend, it cannot be determined by these methods whether the statistically significant remaining deviations were indeed periodic or were random clustering resulting from some point process other than Poisson (e.g., negative

binomial). They suggest further research using a more elaborate modelling strategy based on the Poisson distribution (p. 33) to carry this line of inquiry further.

This advance in the methodological discussion forces us to confront the question of what explicit statistical hypothesis actually corresponds to the Schumpeterian theory of basic innovation, since different variants are conceivable that necessitate different statistical tests. One particularly strong hypothesis, which we shall term the Schumpeter Mark I.0, seems to be implicit in most of the empirical work, although it is not necessarily attributable to Schumpeter himself. This hypothesis might be formulated as follows. Basic innovations are generated by a stochastic process, but one whose arrival rate fluctuates deterministically and strictly periodically with a period of 50–60 years.

A more involved version of this hypothesis, which we shall refer to as Schumpeter Mark I.1, also claims that the arrival rate varies deterministically, but as a function of macroeconomic variables such as the profit rate. The arrival rate will thus have time series properties similar to those of such variables and correlate with them, but not necessarily be strictly periodic. Which way causality runs will be difficult to determine (with Mensch arguing from macroeconomic variables to innovation back to macroeconomic variables, while Schumpeter, as near as we can make out, would only argue from innovation clusters to macroeconomic growth). If the macroeconomy is in fact more or less periodic, then the Schumpeter Mark I.0 and I.1 hypotheses will be almost impossible to distinguish.

Schumpeter (1939) himself appears to argue only that innovations cluster, without any reference to a specific deterministic structure determining when exactly clusters of innovations will occur in time (i.e., in which phase of the economic wave, or even in regularly spaced spells of high and low innovation activity). Such a ‘weak’ variant of clustering may be consistent with a random clustering pattern, i.e., periods of high and low innovation activity do occur in the data, but there is no regular and predictable mechanism governing their occurrence. We shall classify hypotheses of this kind as Schumpeter Mark II: the stochastic process generating innovations is more complicated than Poisson, and clusters arrive stochastically.¹ Two variants can be differentiated. Mark II.0 invokes purely random clustering from some additional distribution (such as a negative binomial process where the arrival rate fluctuates according to a Gamma distribution; see Appendix 1 and below). Mark II.1 calls for the clustering to be initiated by random events, but then obey some sort of causal mechanism that makes this random event ‘persist’ for some time. An example of such a process would be an autoregressive process, in which (with positive autocorrelation) a single random event tends to be followed by higher activity in the periods immediately following. To see how such a hypothesis might be consistent with at least part of Schumpeter’s arguments, recall the quotation from Schumpeter (1939) in fn. 1 on p. 671.

3. Empirical results

As we have argued above, innovations are intrinsically count data generated by a point process. Sahal (1974) proposed using the Poisson model to examine the characteristics of various time series of innovations in different industries. His conclusion was that ‘invention is properly characterised as a Poisson random process, but [. . .] its rate is a function of economic forces’ (p. 403). Although Sahal did provide some estimates of parameters related to these economic forces, these were based on ordinary least square methods. However, when the data contain many zero and small integer values, a maximum likelihood

¹ In particular: the stochastic process is overdispersed, a term to be explained below.

approach based explicitly on the Poisson distribution is more appropriate. Such a procedure was introduced into the literature on innovation by Hausman *et al.* (1984). They estimated a model in which the number of patents of a firm is related to the firm's R&D expenditure. Elaborations on this approach were presented by Crepon and Duguet (1997A, B) and Cincera (1997).

The methods used in this literature, commonly known as 'Poisson regression', are presented in Appendix 1. The Appendix also presents an extension of the methods of Poisson regression to time series analysis, which is of particular importance to the problem at hand. Our aim in this paper will be to apply these statistical tools to the investigation of the hypotheses formulated above.

Like Kleinknecht (1990), we shall use a time series for basic innovations that is created from several other time series introduced by other researchers. This new innovation time series was created by merging the two longest time series available in the literature, i.e., Haustein and Neuwirth's and van Duijn's. Kleinknecht's time series is too short compared to the two other basic innovation time series. Besides the innovations time series, we will also use the time series of important patents as identified by Baker (1976), which was also used by Kleinknecht (1987). The Baker data were not included in the merged innovation time series because they are based on patent data rather than innovation data, and hence are less compatible with the other two time series. Instead, the Baker time series will be treated separately in the statistical analysis.

The construction of our merged innovation time series differs substantially from the Kleinknecht approach. The main difference concerns the overlap, i.e., those innovations which are covered in both sources. Kleinknecht constructs a time series in which the innovations that occur more than once in the three time series he considers are double or triple counted. In other words, he simply adds up the numbers of innovations per year in the three innovation time series. Kleinknecht justifies this procedure by arguing that it provides some implicit weighting scheme, in which the important innovations (i.e., those on which all sources agree) are weighted more heavily.

It is clear that such an implicit weighting procedure introduces an element of extreme arbitrariness. We choose instead to count an innovation only once, even if it is covered by both samples. A complication in this procedure is that, as noted by Kleinknecht, the innovation dates of the same innovation often differ between the two sources. The majority of overlap cases are dated within a range of 10 years, but differences of up to 50 years exist. In all cases, the earliest date was used to assign the innovation to the merged sample. The merged sample contains 88 innovations that occur in both samples, 90 innovations that only occur in the Haustein and Neuwirth sample, and 70 cases that are only listed in the van Duijn sample. The merged series thus has 248 innovations, dating from 1764 to 1976. The complete listing of all innovations in the merged sample, as well as the original Haustein and Neuwirth and van Duijn sources, together with their assignment to the merged sample, are given in Appendix 2. Following Kleinknecht's terminology, we shall refer to this merged time series as the 'supersample time series'.

Figure 1 shows histograms for the Baker patent time series, the two time series we used to create the 'supersample time series' (Haustein and Neuwirth, and van Duijn), and the 'supersample time series'. The Baker time series runs from 1769 to 1970, and thus comprises 202 years. The Haustein and Neuwirth (1982) data run from 1764 to 1975 (212 years), while van Duijn (1983) covers the period 1811–1971 (161 years).

All three histograms show that the highest frequency is found for zero innovations. Also,

Fig. 1. Histograms of basic innovation time series data, on horizontal axis: number of innovations per year; on vertical axis: percentage share of total sample.

all histograms show mostly declining frequencies for larger numbers of innovations per year. No time series shows more than seven innovations per year (this occurs twice in the Haustein and Neuwirth series). The assumption of normally distributed data clearly must be rejected at face value.

As explained in Appendix 1 in more detail, Poisson regression is a technique aimed at estimating the arrival rate of a certain event. In the present context, the arrival rate can be thought of as the average number of basic innovations per year. It can be modelled either as a constant factor or as dependent on economic variables as well as time. We start by fitting a simple Poisson model with a constant arrival rate (i.e., a time-homogenous process), and then proceed to implement two departures from this simple model. The first generalises the Poisson model to allow the variance of the dependent variable to be larger than the mean (this phenomenon is known as overdispersion, and is discussed in Appendix 1). This is done by fitting a negative binomial model. The second is to estimate the arrival rates (in

both the Poisson and the negative binomial model) as following a time trend. The latter is specified by equating the log of the arrival rate to a polynomial function of time, where we experiment with polynomial degrees up to 3 (a log formulation is used to ensure that the arrival rate is always non-negative).¹ The results of these estimations are displayed in Table 1.

The hypothesis of a constant arrival rate (time-homogenous Poisson process, or all polynomial terms equal to zero) is obviously rejected. Both for the supersample innovations time series and the Baker patents time series, the exponential quadratic trend emerges as the 'best' model. Entering the third-order term only leaves the linear trend significant, while a second-order polynomial emerges with all coefficients significant. We thus proceed on the assumption that a quadratic trend captures the long-run growth rate of the number of basic innovations in a reasonable way.

Figure 2 displays the raw data and the fitted linear and quadratic exponential trends for the two models (Poisson and negative binomial). The monotonically increasing lines are the fitted linear trends, the lines levelling off towards the end of the period are the estimated quadratic trends. The estimated trends do not differ greatly between the pure Poisson and the negative binomial models. There is, however, a major difference between the linear and quadratic trends. The latter shows a higher level during the period (roughly) 1850 until 1900, and levels off around 1930 (supersample) or 1920 (Baker patents). This would seem to indicate that the rate of basic innovation is slowing down in the 20th century after a period of relatively rapid increase in the latter part of the 19th century. This phenomenon may, however, be caused by an end of sample bias in the time series caused by the fact that, at the time when the time series were constructed (during the 1970s), it was not yet clear which recent innovations would prove to be basic.

Overdispersion is measured by the significance of the parameter α in the negative binomial model (see Appendix 1 for details). The results differ somewhat between the two time series in this respect. In the case of the supersample of innovations, the negative binomial model is always preferred to the simple Poisson model, as is clear from the fact that the α parameter is always significant (at the 10% level). In the case of the Baker patent time series, the quadratic and cubic models both yield α s that are significant at a level just above 10%, while the linear exponential trend (10% level) model and the time-homogenous process (1% level) yield significant α s.

These results have implications for the hypotheses that were introduced above. Specifically, the fact that the negative binomial model is generally preferred over the simple Poisson model points to the fact that the data are in fact overdispersed. In other words, compared with a (time-homogenous) Poisson process, the data display clustering in the sense of random spells of high and low innovation activity. We interpret this as evidence in favour of the Schumpeter Mark II.0 hypothesis.

In order to get a first impression of the deviations from the long-run trend growth rate which bears on the three other hypotheses, an analysis of the autocorrelation of the residuals of the regressions was performed. To this end, the residuals were standardised by dividing them by the estimated standard deviation (square root of the variance). As explained in Appendix 1, in the case of a Poisson process, this implies dividing by the square root of the arrival rate itself (which varies over time when a trend is included). In the case of a negative binomial model, the variance is calculated as $\lambda(1 + \alpha\lambda)$, where λ is the estimated arrival

¹ In the notation of Appendix 1, we thus estimate $\ln \lambda = c + \beta_1 t + \beta_2 t^2 + \beta_3 t^3$ (where t is time, and we set some of the higher-order β s to zero in some estimations).

Table 1. Regression results, Poisson and negative binomial models, arrival rate function of time

Innovation data source	N	Start year	c	β_1	β_2	β_3	α	$\log l$	SQ	Q
Innovations	213	1764	0.1521 (0.000)					-331.654	***	***
Innovations	213	1764	0.1521 (0.069)				0.6087 (0.000)	-316.186	***	***
Innovations	213	1764	-1.0568 (0.000)	0.9692 ^a (0.000)				-291.823	**	**
Innovations	213	1764	-1.1420 (0.000)	0.0104 (0.000)			0.2662 (0.023)	-286.994	**	**
Innovations	213	1764	-2.5467 (0.000)	0.0389 (0.000)	-0.1168 ^b (0.000)			-279.317		
Innovations	213	1764	-2.5702 (0.000)	0.0393 (0.000)	-0.1186 ^b (0.000)		0.1744 (0.077)	-276.876		
Innovations	213	1764	-2.6012 (0.000)	0.0408 (0.028)	-0.1347 ^b (0.0410)	0.4946 ^c (0.912)		-279.311		
Innovations	213	1764	-2.6159 (0.000)	0.0410 (0.044)	-0.1351 ^b (0.465)	0.4669 ^c (0.928)	0.1742 (0.077)	-276.872		***
Baker patents	202	1769	0.1123 (0.041)					-299.213	***	***
Baker patents	202	1769	0.1123 (0.166)				0.4254 (0.005)	-291.537	***	***
Baker patents	202	1769	-0.7487 (0.000)	0.7256 ^a (0.000)				-279.997	***	***
Baker patents	202	1769	-0.7867 (0.000)	0.7577 ^a (0.000)			0.2422 (0.059)	-276.740	***	**
Baker patents	202	1769	-1.6670 (0.000)	0.0269 (0.000)	-0.8347 ^c (0.000)			-274.230	**	*
Baker patents	202	1769	-1.6616 (0.000)	0.0268 (0.000)	-0.8268 ^c (0.001)		0.1876 (0.110)	-272.086	**	*
Baker patents	202	1769	-1.7662 (0.000)	0.0308 (0.029)	-0.1225 ^b (0.366)	0.1133 ^d (0.769)		-274.204	**	*
Baker patents	202	1769	-1.7267 (0.000)	0.0294 (0.068)	-0.1093 ^b (0.491)	0.7774 ^d (0.866)	0.1870 (0.112)	-272.076	**	*

Notes: β_1 , β_2 and β_3 are the coefficients on the polynomials of time (1st, 2nd and 3rd degree, respectively). α is the parameter for overdispersion in the negative binomial model. Estimated coefficients are equal to documented coefficients divided by the following factors (absence of a note indicates estimated coefficient is equal to documented coefficient): ^a 100, ^b 1,000, ^c 1,000,000, ^d 10,000,000. N is the number of observations. Numbers between brackets are p -values associated with the t -statistics. One, two and three stars point to rejection at the 10, 5 or 1% level, respectively, for a χ^2 test of the null-hypothesis 'all autocorrelations of the residuals up to this order are zero'. Column SQ gives the statistic suggested by Cameron and Trivedi (1998, p. 229). Column Q gives the Box-Ljung statistic. All residuals used in these tests are standardised.

rate, which again varies over time in the event of a time trend. We test for the null-hypothesis that all autocorrelations up to (and including) order $k = (1 \dots 20)$ are zero using two tests. The first is suggested by Cameron and Trivedi (p. 229), and 'guards against incorrect standardisation' of the residuals. The second is the standard Box–Ljung statistic. Both tests apply a statistic that is χ^2 distributed with k degrees of freedom (the maximum order of the autocorrelation process).

The last column in Table 1 gives the significance level at which (if at all) we reject the null-hypothesis of no autocorrelation in the residuals. We used orders up to 20 to test for this. In the case of a time-homogenous process, there is clearly very significant autocorrelation, for both time series (patents and innovations) and both statistical models (Poisson model and negative binomial). When time trends are included, this diminishes, although the extent to which this happens differs greatly between the two time series. With the innovation data, a linear time trend still leaves significant autocorrelation at the 5% level; for the Baker patent time series at the 1% level for three of four cases. For higher-order polynomial

Fig. 2. Raw data and fitted linear and quadratic trends (details of estimation are in Table 1).

trends, however, autocorrelation vanishes completely in the case of the innovation data. For the patent data, the second-order and third-order polynomial trends leave significant autocorrelation in the residuals at the 10% or 5% level. These results suggest that, for the Baker patent time series, the models in Table 1 leave at least some aspects of the long-run dynamics of the time series unexplained, and hence that there is scope for investigating the three other Schumpeterian hypotheses. We now proceed in two ways.

First, we estimate a set of autoregressive models specified in the way explained in Appendix 1. These models take, besides the variables already used, lagged values of the dependent variable itself as explanatory variables. One problem in estimating these models is in determining the exact order of the autoregressive process, i.e., deciding how many lagged terms to include. This is in fact common to all autoregressive models, and the approach most commonly found in the literature is an empirical procedure employing information criteria. These are simple statistics based on the log likelihood value of the models for different autoregressive orders. The simplest is the Aikake Information Criterion (AIC), which we shall use here. The procedure is to find the minimum value of the AIC for a range of autoregressive orders, which in the present case we select as 0–20.

We estimated (and calculated the AIC for) a model with a quadratic exponential time trend plus autoregressive terms. Both a Poisson model and a negative binomial model were estimated for both time series and all autoregressive orders in the range 0–20. For the innovation supersample, the Poisson model has minimum AIC at order 1, while the negative binomial model has minimum AIC at order 12. When the AIC is plotted against the autoregressive order, the Poisson model also has a local minimum that does not differ much in value from the global minimum at order 1, at order 12, while the negative binomial model has a local minimum (again not so much different from the global minimum) at order 1. We therefore document the full set of results for the model at both orders 1 and 12. When the negative binomial term α is significant, we only document this model, while if it is not significant, we only document the Poisson model.

For the Baker patent time series, the minimum value of the AIC was found at orders 19 (Poisson) and 12 (negative binomial). The Poisson model has a local minimum of the AIC at order 3, which is also documented. In this case, the negative binomial term α is not significant for either the autoregressive order 19 or 3, which is why we document only pure Poisson models. The results for the autoregressive model are documented in Table 2. The autoregressive terms are indicated by the symbol ρ .

We note from the table that the significance of the time-parameters β is largely unaffected, i.e., that the time trends estimated in Table 1 are robust against the inclusion of autoregressive terms. This does not hold for the negative binomial term α . When autoregressive terms are included in the model, this term becomes insignificant in three of the four cases in Table 2 (and, in fact, in most of the undocumented autoregressive models that were run; these results are available on request). The general loss of significance of the negative binomial model points to the fact that the clustering effects that we have attributed above (in our Schumpeter Mark II.0 hypothesis and the discussion of Table 1) to overdispersion may in fact also (and statistically more satisfactorily) be captured by an autoregressive model.

This raises the question as to what pattern of clustering is implied by the estimated autoregressive structure, and whether this pattern is consistent with, for example, our Schumpeter Mark II.1 hypothesis. The answer to this question obviously depends on the value of the estimated ρ parameters. As in a conventional autoregressive model, the values of these parameters have implications for the speed at which ‘errors’ leave their trace

Table 2. *Regression results, Poisson and negative binomial models, arrival rate function of time and lagged dependent variable*

Coefficient	Innovations		Baker patents	
	(1)	(2)	(3)	(4)
c	-2.7656 (0.000)	-2.6037 (0.000)	-1.6902 (0.000)	-3.3500 (0.001)
β_1	0.0424 (0.000)	0.0395 (0.000)	0.0271 (0.000)	0.0526 (0.001)
β_2	-0.1290 ^b (0.000)	-0.1207 ^b (0.000)	-0.8646 ^c (0.001)	-0.1711 ^b (0.003)
α	0.1762 (0.078)			
ρ_1	-0.0184 (0.871)	0.0431 (0.675)	0.2651 (0.010)	0.2342 (0.056)
ρ_2		0.6907 ^a (0.947)	0.0933 (0.302)	0.0748 (0.527)
ρ_3		-0.0809 (0.422)	-0.1776 (0.056)	-0.1914 (0.122)
ρ_4		0.1680 (0.065)		0.0622 (0.617)
ρ_5		0.0516 (0.578)		-0.1807 (0.145)
ρ_6		-0.1155 (0.234)		-0.0612 (0.647)
ρ_7		-0.0417 (0.692)		-0.0209 (0.866)
ρ_8		0.0447 (0.646)		0.0767 (0.497)
ρ_9		-0.2083 (0.040)		-0.1685 (0.143)
ρ_{10}		0.2489 (0.010)		-0.1302 (0.323)
ρ_{11}		-0.2508 ^a (0.983)		-0.1335 (0.337)
ρ_{12}		-0.0263 (0.801)		-0.1832 (0.123)
ρ_{13}				0.1076 (0.350)
ρ_{14}				-0.1912 (0.125)
ρ_{15}				-0.2145 ^a (0.987)
ρ_{16}				0.0867 (0.480)
ρ_{17}				-0.1436 (0.233)
ρ_{18}				-0.0891 (0.479)
ρ_{19}				-0.0843 (0.474)
log likelihood	-274.108	-264.790	-263.916	-240.489

Notes: β_1 and β_2 are the coefficients on the polynomials of time (1st and 2nd degree, respectively). α is the parameter for overdispersion in the negative binomial model. ρ indicates the autoregressive terms, the subscript to ρ the order of the autoregressive term. Estimated coefficients are equal to documented coefficients divided by the following factors (absence of a note indicates estimated coefficient is equal to documented coefficient): ^a 100, ^b 1,000, ^c 10,000, ^d 1,000,000, ^e 10,000,000. Numbers between brackets are p -values associated with the t -statistics.

in the fitted time series. This speed can be visualised by plotting the impulse response function, which, because of the model we have specified in Section 3, must be a multiplicative function rather than the commonly used additive function (see, e.g., Hamilton, 1994, ch. 1).

Figure 3 shows the impulse response function for columns (2)–(4) in Table 2. The function for column (1) is almost completely flat and is therefore not documented. These graphs display the net multiplicative effect of a random innovation in period 0 on the arrival rate in the subsequent periods. For example, the figure for the Baker patent time series at autoregressive order 19 shows that the effect of one ‘random extra’ innovation in period 0 is to raise the arrival rate in period 19 by slightly more than 10% compared with a situation without such a random extra innovation (value of 1.1 at the peak is indicated by the arrow). Note that the fact that all three graphs converge to one implies that the effect of a random extra innovation ultimately dies out, i.e., that the process is (trend) stationary. Thus, there will be no persistent long-term effect of a rise in the innovation rate

Fig. 3. Impulse-response functions for the autoregressive processes in Table 2.

All three graphs show oscillatory behaviour following a 'random extra' innovation. This is caused by the negative autoregressive parameters (ρ_s), and leads us to reject the Schumpeter Mark II.1 hypothesis introduced above. This hypothesis argues that a random extra innovation leaves a slowly dying trace of (relatively) high innovation activity. Such a pattern would result if (most of) the estimated ρ_s had high positive values. With the large number of negative values for the autoregressive parameters we obtain in Table 2, the result is the highly irregular and random-looking pattern observed in Figure 3. This is consistent to some extent with the Schumpeter Mark II.0 hypothesis of random clustering, but not with the Schumpeter Mark II.1 hypothesis.

This still leaves both Schumpeter Mark I hypotheses to be investigated. As a preliminary remark, note that if a strictly periodic pattern (possibly surrounding a trend of some form) existed in the data, one would expect the autoregressive specification to pick this up in some form. In other words, the irregular patterns observed in Figure 3 also have implications for the Schumpeter Mark I hypotheses, in particular, they cast doubt on them. To clarify this further, we employ an additional test to reach a final verdict on Schumpeter Mark I.

This test does not involve data on economic variables, as called for in the Mark I.1 hypothesis. Instead, we investigate the residuals from the regressions in Table 1 to see whether any strictly periodic movements can be detected. To this end, we perform spectral analysis on the standardised residuals (defined above). If the Schumpeter Mark I hypotheses are valid, one would expect clear peaks in the spectral density plot for these residuals, as a result of strictly periodic movements around the estimated trend arrival rate.

Figure 4 displays the spectral density plots for residuals from the Poisson and negative binomial regressions in Table 1. Although there clearly are some peaks in the plots, these are consistent with white-noise data. The overall impression is one of a relatively flat spectrum, which indicates the absence of clear periodic components in the residuals. This holds

Fig. 4. *Spectral density plots for the residuals of the quadratic trend regressions in Table 1.*

especially for the supersample innovation time series, and to a somewhat lesser extent for the Baker patent time series.

We thus conclude that the evidence in favour of strictly periodic movements around the (exponential) quadratic trend in the arrival rate is weak. The finding that is closest to our Schumpeter Mark I hypotheses is the ‘weak’ peak at a cycle length of 20 years in the Baker patent time series.

4. Summary and conclusions

This paper pursues a suggestion made by Silverberg and Lehnert (1993) in their discussion of the empirical evidence on the ‘Schumpeterian hypothesis’ that basic innovations tend to

cluster. They proposed, in order to overcome the methodological shortcoming of previous work, modelling and estimating a stochastic Poisson process describing the occurrence of basic innovations. We formulate four alternative hypotheses bearing on the Schumpeterian clustering hypothesis that are amenable to statistical testing. We then estimated a model of the trend in the arrival rate of basic innovations, and found that a quadratic exponential trend fits the data best (compared with a linear or third-degree trend). Investigating the residuals of this regression for periodic cycles around the trend, we found essentially no evidence in favour of such strong periodic clustering.

A weaker version of the clustering theory interprets clusters as themselves randomly distributed. Evidence for this interpretation is presented in the form of estimates of the negative binomial parameter, which is found to be significantly different from zero.

A different version of random clustering occurs when random events tend to 'persist' in time, for example owing to an autoregressive process. We have estimated autoregressive Poisson and negative binomial models (again based on a quadratic exponential trend), and found that these models may indeed improve the fit. However, by plotting the impulse response functions, we showed that innovation impulses do not lead to long periods of above-normal innovative activity. Rather, such impulses die out in an oscillatory way, and leave a rather irregular and random-looking trace. We interpret this as evidence against a knock-on effect being the source of clustering.

We are thus left with the conclusion that the only form of clustering of basic innovations that is consistent with the data is 'random clustering' superimposed on a second-degree trend. Basic innovations, while they arrive in clusters, do not engender higher rates of basic innovative activity (although they may initiate periods of higher incremental innovation not picked up in our data), nor are these clusters in any way periodic. Thus even if we have just come through a period of exceptionally high innovation in the 1990s (the purported 'new economy'), this is no guarantee that innovation rates will remain at historically high levels in the future. To what extent these rates are influenced by the macroeconomic context is a subject we hope to study further.

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Appendix 1: Poisson regression

The starting point for all statistical analysis in this paper is the (time-homogeneous) Poisson process, which makes the simplifying assumption that the probability of occurrence of an innovation within a given interval of time is independent of previous innovations and independent of time. The probability of y innovations during an interval of time T is given by

$$\text{Prob}(y) = \frac{e^{-\lambda T} (\lambda T)^y}{y!}$$

where $y \in \mathbb{N}$, and λ is a parameter, often referred to as the arrival rate of the Poisson process. Note that λ is not necessarily an integer number. It is easily shown that the expected number of events per unit time is λ , which also happens to be the variance of the distribution. Note that time series generated from a time-homogeneous Poisson process will not display a completely uniform pattern of occurrences of the random event. In other words, to the naïve eye, some clustering will characterise even this simplest point process.

The parameter λ may also be specified endogenously, for example as $\ln \lambda = \beta' \mathbf{x}$, where $\mathbf{x}$ is a vector of independent variables, and β is a parameter vector. Other specifications for λ are possible, but the example above is often used because it is convenient for estimation purposes (using $\ln \lambda$ as the independent variable ensures non-negative arrival rates). In this case, the parameter vector β can be interpreted as a vector of elasticities of the arrival rate with respect to the independent variables. Such an approach allows us to test the assumption that the Poisson process is time-homogeneous by setting up the null hypothesis that all elements of β , including one corresponding to time itself, are equal to zero.

One problem with the Poisson model is its peculiarity that the mean and variance of the distribution are equal. Empirical data often show a larger variance than mean for the dependent variable, a phenomenon termed ‘overdispersion’. Hausman *et al.* (1984), for example, observed overdispersion in their firm-level patent database. A model that can account for overdispersion may be obtained by adding an unobserved random effect to the mean of the Poisson distribution (Hausman *et al.*, 1984). This leads to a modified probability distribution of the type:

$$\text{Prob}(Y = y | u) = \frac{e^{-\lambda u} (\lambda u)^y}{y!}$$

where u is a random variable for which some distribution must be assumed (see Greene, 1995, p. 939). The variable u may, for example, reflect random noise, or cross-sectional heterogeneity (when the model is estimated in the cross-sectional dimension). Assuming that u is gamma distributed, one obtains the following unconditional distribution (Cameron and Trivedi, 1998, p. 71):

$$\text{Prob}(Y = y | \mathbf{x}) = \frac{\Gamma(\alpha^{-1} + y)}{\Gamma(y + 1) \Gamma(\alpha^{-1})} r^y (1 - r)^{\alpha^{-1}}, \text{ where } r = \frac{\lambda}{\lambda + \alpha^{-1}}.$$

This distribution is known as the negative binomial distribution and has mean λ and variance $\lambda(1 + \lambda)$ for $\alpha > 0$. When λ approaches 0, the model reduces to a standard Poisson model, and the variance becomes equal to λ again. The negative binomial model can also be estimated using a maximum likelihood method. A test of the Poisson against the negative binomial distribution can be implemented by means of a Likelihood Ratio test, Wald test or t -test (Green, 1995) of the null hypothesis $\alpha = 0$.

In the context of time series and the hypothesis of clustering of events (innovations) in specific time periods, the correlation structure of the residuals becomes of interest. Cameron and Trivedi (1998) suggest investigating the standardised residual $z_t = (y_t - m_t)/\sqrt{\sigma_t}$, where y_t is the observed (integer) value, m_t is the sample mean value and σ_t is the sample variance. When a Poisson model is fitted, $m_t = \sigma_t$ is equal to the estimated arrival rate. Cameron and Trivedi (1998) then suggest applying the Box–Pierce portmanteau, the Box–Ljung statistic (which has better small sample properties) or a slightly modified statistic that guards against incorrect standardisation, to test for the null-hypothesis that all autocorrelations of the residuals up to lag k are zero.

In case such a null-hypothesis is rejected, various ways are suggested (Cameron and Trivedi, 1998, Section 7.5) of specifying a model to deal with the autocorrelated residuals. The method closest to our original Poisson regression approach is to estimate an autoregressive model, i.e., to include lagged values of the dependent variable in the regression as independent variables. The simplest model is called exponential feedback, and assumes $\ln \lambda_t = \beta' \mathbf{x}_t + \rho y_{t-1}$. This, however, implies explosive behaviour for $\rho > 0$. In order to rule out this undesirable property, Cameron and Trivedi suggest using $\lambda_t = \exp(\beta' \mathbf{x}_t) \sum_k (y_{t-k}^*)^{\rho_{t-k}}$ where y^* is a transformation of y to ensure positive values, $y^* = \max(1/2, y)$, or $y^* = y + 1/2$.

Appendix 2: Data on basic innovations

Table A1. *The supersample of basic innovations*

Item number	Innovation	Year	Item number	Innovation	Year
89	Spinning machine	1764	192	Siemens–Martin steel	1864
90	Steam engine	1775	112	Paper from wood	1865
91	Automatic band loom	1780	4	Deep-sea cable	1866
92	Sliding carriage	1794	50	Dynamite	1867
81	Blast furnace	1796	75	Dynamo	1867
48	Steam ship	1809	113	Commutator	1869
95	Whitney's method	1810	60	Typewriter	1870
80	Crucible steel	1811	193	Celluloid	1870
183	Street lighting (gas)	1814	194	Combine harvester	1870
184	Mechanical printing press	1814	85	Margarine	1871
78	Lead chamber process	1819	6	Thomas steel	1872
77	Quinine	1820	46	Reinforced concrete	1872
98	Isolated conduction	1820	114	Drum rotor	1872
99	Rolled wire	1820	115	Preservatives	1873
100	Cartwright's loom	1820	51	Sulphuric acid	1875
3	Steam locomotive	1824	195	Four-stroke engine	1876
61	Cement	1824	5	Telephone	1877
66	Puddling furnace	1824	116	Nickel	1878
101	Pharma fabrication	1827	53	Electric railway	1879
102	Calcium chlorate	1831	12	Incandescent lamp	1880
79	Telegraphy	1833	47	Water turbine	1880
103	Urban gas	1833	117	Jodoforme	1880
104	Rolled rails	1835	196	Half-tone process	1880
87	Electric motor	1837	197	Electric power station	1881
67	Photography	1838	118	Veronal	1882
9	Bicycle	1839	119	Cable	1882
88	Vulcanised rubber	1840	120	Antipyrin	1883
7	Arc lamp	1841	121	Coals whisks	1883
105	Jacquard loom	1844	10	Steam turbine	1884
106	Lathe	1845	122	Chloroform	1884
107	Inductor	1846	198	Punched card	1884
108	Electrodynamic measuring	1846	199	Cash register	1884
185	Rotary press	1846	38	Syntethic fertilisers	1885
186	Anaesthetics	1846	52	Transformer	1885
187	Steel (puddling process)	1849	123	Synthetic alkaloids	1885
188	Sewing machine	1851	124	Magnesium	1886
109	Plaster of paris	1852	125	Electric welding	1886
14	Aluminium	1854	200	Linotype	1886
40	Safety match	1855	72	Phonographe	1887
189	Bunsen burner	1855	126	Electrolyse	1887
36	Refined steel/Bessemer steel	1856	28	Motor car	1888
84	Steel pen/Fountain pen	1856	59	Pneumatic tyre	1888
110	Tare colours industry	1856	127	Electric counter	1888
111	Baking powder	1856	201	Portable camera	1888
190	Elevator	1857	202	Alternating-current generator	1888
76	Lead battery	1859	86	Man-made fibres	1890
191	Drilling for oil	1859	128	Chemical fibres	1890
54	Internal combustion engine	1860	129	Melting by induction	1891
39	Soda works	1861	83	Acetylene welding	1892
19	Anilin dyes	1863	130	Accounting machine	1892

Table A1. *(continued)*

Item number	Innovation	Year	Item number	Innovation	Year
41	Cinematography	1894	223	Freon refrigerants	1931
131	Antitoxines	1894	34	Crease-resistant fabrics	1932
203	Motor cycle	1894	224	Gas turbine	1932
204	Monotype	1894	225	Polyvinylchloride	1932
8	Diesel engine	1895	226	Antimalaria drugs	1932
132	Drilling machine for mining	1895	227	Sulfa drugs	1932
205	Electric automobile	1895	56	Fluor lamp	1934
206	X-rays	1896	146	Diesel locomotive	1934
37	Aspirin	1898	147	Fischer–Tropsch procedure	1934
133	Arc welding	1898	11	Radar	1935
134	Air ship	1900	13	Ballpoint pen	1935
135	Synthesis of indigo	1900	30	Rockets/guided missiles	1935
207	Submarine	1900	31	Plexiglas	1935
136	Holing machine	1901	62	Magnetophone	1935
137	Electric steel making	1902	70	Catalytic cracking	1935
208	Safety razor	1903	82	Colour photo	1935
209	Viscose rayon	1905	148	Gasoline	1935
210	Vacuum cleaner	1905	16	Television	1936
138	Acetylene	1906	149	Photoelectric cell	1936
211	Chemical accelerator for rubber vulcanisation	1906	228	FM radio	1936
212	Electric washing machine	1907	150	Vitamins	1937
15	Gyro compass	1909	229	Electron microscope	1937
2	Aeroplane	1910	20	Helicopter	1938
69	Bakelite (Phenol plastics)	1910	230	Nylon	1938
139	High-voltage isolation	1910	21	Polethylene	1939
65	Vacuum tube	1913	55	Automatic gears	1939
71	Assembly line	1913	151	Hydraulic gear	1939
213	Thermal cracking	1913	27	Antibiotics (penicillin)	1940
214	Domestic refrigerator	1913	152	Cotton picker	1941
140	Ammonia synthesis	1914	43	Jet engine/plane	1942
141	Tractor	1914	45	DDT	1942
215	Stainless steel	1914	153	Heavy water	1942
142	Tank	1915	231	Continuous catalytic cracking	1942
32	Synthetic rubber	1916	24	Silicones	1943
42	Cellophane	1917	232	Aerosol spray	1943
1	Zip fastener	1918	233	High-energy accelerators	1943
29	AM radio	1920	44	Streptomycin	1944
216	Acetate rayon	1920	154	Titan reduction	1944
217	Continuous thermal cracking	1920	22	Sulzer loom	1945
26	Synthetic detergents	1922	68	Oxygen steelmaking	1946
57	Insulin	1922	234	Phototype	1946
143	Synthesis of methanol	1922	49	Numerically controlled machine tools	1948
35	Continuous rolling	1923	58	Continuous steel making	1948
218	Dynamic loudspeaker	1924	235	Orlon	1948
219	Leica camera	1924	236	Cortisone	1948
144	Deep-frozen food	1925	237	Long-playing record	1948
220	Electric record player	1925	238	Polaroid land camera	1948
145	Coal hydrogenation	1927	155	Thonet furniture	1949
17	Power steering	1930	156	Polyester	1949
221	Polystyrene	1930	18	Computer	1950
222	Rapid freezing	1930	23	Transistor	1950

Table A1. (*continued*)

Item number	Innovation	Year	Item number	Innovation	Year
25	Xerography	1950	248	Polycarbonates	1960
239	Terylene	1950	249	Contraceptive pill	1960
240	Radial tyre	1950	250	Hovercraft	1960
157	Double-floor railway	1951	64	Integrated circuit	1961
158	Cinerama	1953	169	Planar process	1961
241	Colour television	1953	73	Laser	1962
33	Nuclear energy	1954	251	Communication satellite	1962
242	Gas chromatograph	1954	170	Implementation of ions	1963
243	Remote control	1954	171	Epitaxy	1963
244	Silicon transistor	1954	172	Synthetic leather	1964
159	Air-compressed building	1956	173	Transistor laser	1964
160	Atomic ice breaker	1957	174	Optoelectronic diodes	1966
161	Space travel	1957	252	Wankel-motor	1967
162	Stitching bond	1958	74	Video	1968
163	Holography	1958	175	Light-emitting fluor display	1968
164	Transistor radio	1958	176	Minicomputers	1968
165	Diffusion process	1958	177	Quartz watches	1970
245	Fuel cell	1958	63	Microprocessor	1971
166	Quartz clocks	1959	178	Electronic calculator	1971
246	Polyacetates	1959	179	Light-tunnel technology	1972
247	Float glass	1959	180	16-bit microprocessor	1975
167	Maser	1960	181	16384 bit RAM	1976
168	Micro modules	1960	182	Microcomputer	1976

Note: Items 1–88 occur in both databases, items 89–182 occur only in Haustein and Neuwirth data, items 183–252 occur only in van Duijn data.

Table A2. *Innovations in the Haustein and Neuwirth time series that were matched to innovations in the van Duijn time series*

Innovation	Year	To which item in merged series?	Innovation	Year	To which item in merged series?
Blast furnace	1796	to 81	Aspirin	1898	to 37
Steamer	1809	to 48	Steel concrete	1902	to 46
Crucible cast steel	1811	to 80	Gyro compass	1909	to 15
Lead-chamber process	1819	to 78	Pheno plastics	1910	to 69
Chinin fabrication	1820	to 77	Airplane	1911	to 2
Locomotive	1824	to 3	Conveyor belt production	1913	to 71
Puddling furnace	1824	to 66	Synthetic rubber	1916	to 32
Telegraphy	1833	to 79	Electronic tubes	1920	to 65
Photography	1838	to 67	Detergents/synthetic	1922	to 26
Bicycle (pedal)	1839	to 9	Radio	1922	to 29
Cement	1844	to 61	Insulin	1922	to 57
Arc lamp	1844	to 7	Zip fastener	1923	to 1
Generator of current	1849	to 87	Continuous rolling	1923	to 35
Hard rubber	1852	to 88	Cellophane	1926	to 42
Aluminium	1854	to 14	Power steering	1930	to 17
Refined steel	1856	to 36	Crease-resistant fabrics	1932	to 34
Steel pen	1856	to 84	Fluorescent lamp	1934	to 56
Lead accumulator	1859	to 76	Ball-point pen	1935	to 13
Soda works	1861	to 39	Rockets	1935	to 30
Production of analin	1863	to 19	Plexiglass	1935	to 31
Deep sea cable	1866	to 4	Magnetophone	1935	to 62
Safety matches	1866	to 40	Catalytic cracking	1935	to 70
Dynamite	1867	to 50	Colour film	1935	to 82
Dynamo	1867	to 75	TV	1936	to 16
Thomas steel	1872	to 6	Radar	1939	to 11
Typewriter	1873	to 60	Helicopter	1939	to 20
Sulphuric acid production	1875	to 51	Automatic gears	1939	to 55
Telephone	1878	to 5	Synthetic fibres	1939	to 86
Electric locomotive	1879	to 53	Antibiotics	1940	to 27
Incandescent lamp	1880	to 12	DDT	1942	to 45
Cooking fat	1882	to 85	Jet engine	1943	to 43
Electricity	1882	to 87	Streptomycine	1944	to 44
Electric heating	1882	to 87	Sulzer loom	1945	to 22
Long-distance conduction	1882	to 87	Silicons	1946	to 24
Synthetic fertilisers	1885	to 38	Oxygen-process	1946	to 68
Transformers	1885	to 52	NC machines	1948	to 49
Combustion engine	1886	to 54	Continuous steelmaking	1948	to 58
Phonograph	1887	to 72	Computer	1950	to 18
Tyres with air compression	1888	to 59	Transistor	1950	to 23
Water turbine	1890	to 47	Xerographie	1950	to 50
Welding by acetylene	1892	to 83	Polyethylene	1953	to 21
Steam turbine	1895	to 10	Nuclear power station	1954	to 33
Automobile	1895	to 28	Integrated circuits	1961	to 64
Cinematography	1895	to 41	Laser	1962	to 73
Electric railway	1895	to 53	Video-tape recorder	1968	to 74
Diesel engine	1897	to 8	Microprocessor	1971	to 63

Table A3. *Innovations in the van Duijn time series that were matched to innovations in the Haustein and Neuwirth time series*

Innovation	Year	To which item in merged series?
Crucible steel	1811	to 80
Sulphuric acid (lead chamber process)	1819	to 78
Quinine	1820	to 77
Portland cement	1824	to 61
Coke blast furnace	1829	to 81
Steam locomotive	1830	to 3
Puddling furnace	1832	to 66
Electric motor	1837	to 87
Steamship (Atlantic crossing)	1838	to 48
Photography	1839	to 67
Electric telegraph	1839	to 79
Vulcanised rubber	1840	to 88
Arc lamp	1841	to 7
Safety match	1855	to 40
Bessemer steel	1856	to 36
Lead battery	1859	to 76
Internal combustion engine	1860	to 54
Sodium carbonate	1861	to 39
Aniline dyes	1865	to 19
Atlantic telegraph cable	1866	to 4
Dynamite	1867	to 50
Dynamo	1867	to 75
Typewriter	1870	to 60
Margarine	1871	to 85
Reinforced concrete	1872	to 46
Sulphuric acid	1875	to 51
Telephone	1877	to 5
Electric railway	1879	to 53
Thomas oven	1879	to 6
Incandescent lamp	1880	to 12
Water turbine	1880	to 47
Steam turbine	1884	to 10
Fountain pen	1884	to 84
Transformer	1885	to 52
Bicycle	1885	to 9
Aluminium	1887	to 14
Motor car	1888	to 28
Cylindrical record player	1888	to 72
Pneumatic tyre	1889	to 59
Mechanical record player	1889	to 72
Rayon (nitro-cellulose pr.)	1892	to 86
Motion picture film	1894	to 41
Diesel engine	1895	to 8
Rayon (cuprammonium pr.)	1898	to 86
Aspirin	1899	to 37
Oxy-acetylene welding	1903	to 83
Airplane	1910	to 2
Bakelite	1910	to 69
Gyro compass	1911	to 15
Synthetic fertiliser (nitrogen)	1913	to 38

Table A3. *(continued)*

Innovation	Year	To which item in merged series?
Vacuum tube	1913	to 65
Assembly line	1913	to 71
Cellophane	1917	to 42
Zip fastener	1918	to 1
AM radio	1920	to 29
Continuous hot strip rolling	1923	to 35
Insulin	1923	to 57
Synthetic detergents	1930	to 26
Synthetic rubber	1932	to 32
Crease-resisting fabrics	1932	to 34
Radar	1935	to 11
Plexiglas	1935	to 31
Magnetic tape recorder	1935	to 62
Colour photography	1935	to 82
Television	1936	to 16
Catalytic cracking	1937	to 70
Helicopter	1938	to 20
Fluorescent lamp	1938	to 56
Polyethylene	1939	to 21
Penicillin	1942	to 27
Guided missiles	1942	to 30
Jet airplane	1942	to 43
DDT	1942	to 45
Silicones	1943	to 24
Ball-point pen	1945	to 13
Streptomycin	1946	to 44
Automatic transmission (passenger cars)	1948	to 55
Sulzer loom	1950	to 22
Xerography	1950	to 25
Power steering (passenger cars)	1951	to 17
Electronic computer	1951	to 18
Transistor	1951	to 23
Continuous casting of steel	1952	to 58
Oxygen steel making	1953	to 68
Numerically controlled machine tools	1955	to 49
Nuclear energy	1956	to 33
Integrated circuit	1961	to 64
Laser	1967	to 73
Video cassette recorder	1970	to 74
Micro-processor	1971	to 63