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Technology, GDP per capita, economic growth, regression with breaks, unobserved components model

JEL Codes
O40, N70, C20, C32

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A reconstruction of the time series of global technology from 5500 BC to the 2000s*

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Abstract

The aim of this study is to reconstruct the millennial historical series of global technology level from 5000 BC to the twenty-first century, using the data collected by Lilley [*Men, machines and history*, Cobbett Press, London, 1948] and updating them. The resulting series reveals a similar dynamic to the millennial series of global real GDP per capita. This finding is supported by structural changes in the growth dynamics of both series during the period of proto-industrialization and by the results of estimations from an unobserved components model, which highlight the effect of technology on global output. This study contributes to understanding the link between technology and economic development over the course of millennia.

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1. Introduction

Technological advancements have been the cornerstone of human progress since the dawn of civilization. Despite this, the historical trajectory of global technology, spanning from the early Bronze Age in 5500 BC to the modern era, remains largely uncharted territory in scholarly research. This study aims to fill this significant gap by reconstructing a comprehensive historical series of global technology over this extensive period.

*Version 1.05. Any errors, if present, are the responsibility of the author.

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Understanding the long-term evolution of technology is of crucial importance for several reasons. First, it provides a deeper insight into the roots and dynamics of technological progress, which is fundamental to economic growth and societal development (see, for example, Schumpeter, 1942; Solow, 1956; Romer, 1986; Freeman and Louçã, 2001; Perez, 2004). Secondly, conducting such an analysis can shed light on the factors that have influenced the speed and direction of technological advancements throughout history. This contributes to a better understanding of the complex relationship between technology, culture, politics, and the economy (for further insights, see Bauchspies et al., 2006; Volti, 2017).
The reconstruction of the historical series of technology originates from the groundbreaking work of Samuel Lilley (1914-1987), a historian of science from Northern Ireland. In his monograph titled "Men, Machines and History" published in 1948 (Lilley, 1948), Lilley extensively examined numerous significant technological innovations spanning from 5500 BC to the 1940s. He meticulously ranked these inventions, assigning them numerical scores based on their overall impact on the development of various industries. Through the summation of these scores over different years, he successfully constructed a cumulative series that represents the technological advancements achieved by humanity up to that particular period.
Following the same approach, I continue the reconstruction of the series to include the major inventions realized globally from the 1930s to 2000. As explained in section 2, during the search for significant inventions after 1943, I discovered that some important innovations of the 1940s were actually developed a few years earlier. To ensure accuracy, I decided to update the dataset starting from the 1930s.
The upgrade process is not straightforward, as the number and significance of inventions, in terms of their overall impact on the economy, tend to increase significantly over the years, especially from the 1990s onwards. For this reason, I chose to conclude the series at the year 2000. Identifying the principal inventions became increasingly complex, and there was a risk of unintentionally omitting some truly significant ones.
To assess the accuracy of the reconstructed series depicting the historical level of global aggregate technology, I compare this series with the historical series of world GDP per capita in constant international dollars in the two versions produced by De Long (1998) and Maddison (2013). According to the neoclassical growth approach, one would expect the dynamics of the two series to be aligned.

To investigate this aspect, I follow two empirical approaches. The first approach simply involves using the methodology developed by Bai and Perron (1998, 2003) to examine whether the growth rates of the aforementioned historical series follow the same process and whether any changes or breaks occur in the same periods, as suggested by the economic theory of growth. The second approach entails estimating an unobserved component model (Harvey, 1989; Durbin and Koopman, 2001) to adequately model the process followed by all variables entering the growth equation of the theoretical model.

The empirical results of these econometric exercises reveal the following: (i) the structural breaks in the historical series of technology and GDP per capita align strongly, as expected; (ii) the estimated coefficients of the unobserved component models are statistically significant and in line with the predictions of the theoretical model; (iii) the reconstructed series of world GDP per capita and technology, based on the model estimates, virtually overlap with the original ones.

The remainder of this paper is structured as follows. Section 2 introduces and details both Lilley's original series and its subsequent revision. Following this, section 3 delves into the theoretical and econometric methodologies employed to evaluate the credibility of the updated technology series. Section 4 illustrate the results, and finally, section 5 provides a summary and concluding remarks.

2. Reconstruction of the historical series of global technology

The development of the historical series of technology began by amalgamating the more than 200 inventions compiled by (Lilley, 1948, p. 207–220), classified according to a scoring system to be explained shortly, in terms of importance in the years from 5000 BC to 1943. The inventions considered are those deemed most important by Lilley (1948) and are the result of an in-depth analysis conducted by the author himself, who examined and consulted hundreds of historical books, technical monographs, and journals. When identifying an invention, the author used a scoring system that ranged from 0.1 (indicating minimal impact on industry and economy) to 1 (representing the maximum impact on industry and economy) for each invention under consideration. The assignment of scores followed the guidance provided by scientific literature regarding the significance of each invention within the system. These scores were then associated with the specific years in which the invention was developed and/or introduced to the market. In some cases, the score was distributed across multiple years, reflecting the implementation of the invention occurring in various stages or spanning different time periods.

By summing the scores of multiple inventions for each year, Lilley constructed a historical series that captures the level of technological advancement achieved by humanity up to that specific point in time. Figure 50 in Lilley's work (Lilley, 1948) provides a visual representation of this series.

In pursuing this approach, several challenges arise regarding the potential risk of (i) omitting significant innovations, (ii) accurately determining the inception date of a particular invention, and (iii) appropriately assigning a score to each invention.

Regarding the first point, Lilley himself argued that for omissions to have a substantial impact on the dynamics of the reconstructed technology, they would need to be systematic and concentrated within specific historical periods. However, after an in-depth study, the author asserted that such omissions are highly unlikely. While there may be some omissions, they do not significantly alter the series' dynamics.

On the second point, it is worth noting that uncertainty regarding the exact date of a particular invention tends to decrease as we approach the present. The greatest uncertainty lies in inventions dating back to BC years up until approximately 1200-1400 AD. For some of these inventions, Lilley assigned dates based on common sense criteria. However, it is important to emphasize that the number of 'approximate dates' after 1000 AD is limited, and uncertain attribution involved a range of dates spanning a few decades. Therefore, any possible errors in date attribution do not affect the final dynamics of the historical technology series.

The third point presents the greatest complexity among the three. While it is relatively straightforward to assign a score to innovations like the steam engine or nuclear energy, determining a score for inventions such as the centrifugal pump or variable pitch propeller becomes more challenging. Scientific literature does not always reach a unanimous consensus regarding the extent of their impact on the evolution of the global industry. In such situations, Lilley chose to 'average' the more extreme positions, assigning a score that represents a balanced perspective among these viewpoints.

The update I conducted on the historical series of global technology levels, spanning from the 1930s to 2000, strictly follows the guidelines proposed by

Lilley (1948). While Lilley's database concludes in 1943, my research revealed that certain significant inventions emerging towards the end of the period were not adequately acknowledged by the author. This oversight likely occurred because the importance and impact of these inventions were not fully recognized until several decades after their creation. Various factors could contribute to this, such as the absence of supporting technologies, regulatory or social constraints, or a lack of clearly identifiable practical applications at the time of invention. Consider the example of the transistor, invented in 1947. It was not until many years later that transistors started replacing thermionic valves in electronic devices. Subsequently, they paved the way for the development of microprocessors, which revolutionized the field of computers. Similarly, let us consider the video game industry. Initially perceived as solely dedicated to entertainment since the 1970s, this industry has experienced exponential growth. Over time, it has become a significant catalyst for technological innovation, driving advancements in areas such as 3D graphics, virtual reality, and artificial intelligence.[1]

The construction of the global technology time series follows this rule:

$$A_t = A_{t-1} + \sum_{i=1}^{h} \gamma_{i,t}, \quad \gamma_{i,t} = \{0.1, 0.2, \ldots, 1\}, \tag{1}$$

where A_t represents the technology stock at the end of period t, A_{t-1} is the technology stock at the end of period $t-1$, and $\gamma_{i,t}$ are the h innovations (whose value, by definition, is included in the discrete range of 0.1 to 1) that contribute to the increase in the technology stock during period t. Of course, h varies from year to year.

The technology calculated in accordance with equation (1) offers two main

[1] To be precise, I have also made some minor adjustments to Lilley's original series (1948) in the period 1751-1929, using an alternative database collected by (Cole, 1960, p. 200–221). George D. H. Cole (1889-1959), an English historical economist, in his work "Introduction to Economic History: 1750-1950", conducted a similar study to Lilley (1948), focusing on the technological evolutionary process that occurred after the industrial revolution. However, unlike Lilley, Cole did not assign scores to the collected inventions; he simply listed them chronologically. Approximately 15% of the inventions originally considered by Lilley have been added to my technological series for completeness, after being appropriately classified by importance using the same approach as Lilley.

advantages: (i) to update the historical series, it is sufficient to start from the most recent value, eliminating the need to recalculate the entire series from the beginning; (ii) any corrections or adjustments over the years can be easily implemented by adding or subtracting values from the aggregate series. In this case, too, there is no need to retroactively recalculate the entire series.
The sources used to update the dataset (that is, to identify the $\gamma_{i,t}$ incresing the stock of technology in each period according to equation (1)) are numerous. However, providing an exhaustive list would occupy a considerable amount of space. The primary sources include: Bunch and Hellemans (1993), Bunch and Hellemans (2004), Pacey and Bray (2021), and Wikipedia. In particular, Wikipedia was used to gather additional information regarding the inventors' names and the dates of introduction and dissemination of new technologies.
The details of the inventions considered for this update, including the dates of their creation and/or dissemination, their respective inventors, their impact on global industry, and their assigned scores, are reported in tables A.12 and A.13. Specifically, table A.12 presents the inventions that serve to integrate the dataset developed by Lilley (1948). Table A.13, on the other hand, lists the inventions used to extend the historical series of technology over the years.
Certain aspects of the inventions listed in the tables require further clarification. One important aspect concerns the assigned dates for each invention, which may not always correspond to their actual date of creation due to various factors. For example, the impact of an invention on the industry might manifest at a different time, such as when it becomes commercially available. Whenever there is a discrepancy between the assigned date and the actual invention's date, this information is indicated in brackets alongside the respective date.
Furthermore, some inventions are associated with a range of dates instead of a single date, and it is necessary to provide an explanation for this. In certain cases, an initial realization date was followed by a subsequent development phase, resulting in a gradual rather than immediate impact on the industry. The Colossus, one of the earliest programmable electronic computers, serves as an example. The Mark I version was invented in late 1943, and within less than a year, a significant upgrade was made in 1944 with the Mark II version. In such progressive cases, where the effect on the industry spans multiple years, the assigned score is distributed evenly across the indicated years. For instance, both 1943 and 1944 would receive a score of 0.45 in the

case of the Colossus.
Additionally, it is important to note that the range of dates for certain inventions does not signify periods of realization or improvement but rather distinct phases, such as market diffusion or practical applications. In these instances, relevant information is always provided alongside the dates, and the assigned score is evenly distributed across the specified years.
Examining the inventions in table A.13, a notable observation emerges: there is a significant increase in the number of fundamental inventions starting from the 1980s. While the number of inventions identified in the decades 1960-1969 (26) and 1970-1979 (25) shows a balance, it is from the decade 1980-1989 onwards that the number of inventions starts to rise (37), and further accelerates in the period 1990-1999 (45). In essence, from 1980 to 1999, the number of introduced inventions increased by approximately 60% compared to the previous two decades. This growth is primarily driven by substantial innovations, particularly in the Information Technology sector, as highlighted by researchers such as Fernald and Ramnath (2004); Anderson et al. (2006); Brynjolfsson and McAfee (2014).
Figure 1 visually illustrates the historical evolution of the global technology stock, calculated using the methodology described earlier. The gray shaded area highlights the updates made to the original series by Lilley (1948), incorporating the innovations listed in tables A.12 and A.13. Notably, the latter part of the series shows a significant acceleration in technology dynamics. The key question is whether this reconstructed series accurately represents the technological advancements spanning centuries (or perhaps it would be more appropriate to say, millennia). To answer this question, it is essential to compare the dynamics of this series with that of the world's real per capita GDP.

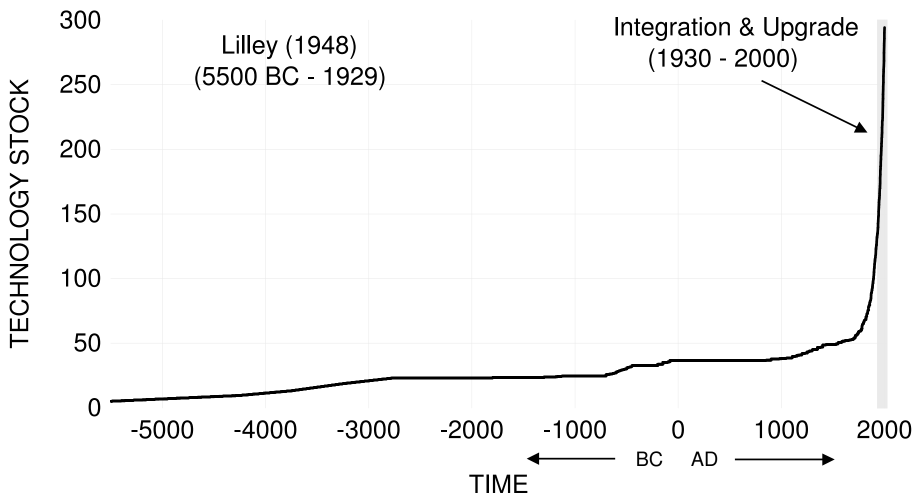
3. Theoretical Framework and Econometric Strategy

In this section, I outline the theoretical model (section 3.1) and empirical strategy (section 3.2) needed to analyze the validity of the constructed technology series.

3.1. Theoretical Framework

In accordance with the principles of growth and development economics, technology is conceived as the means by which inputs to the production

Figure 1: The historical series of global technology from 5500 BC to 2000 AD



Notes: Data sources range from 5000 BC to 1929, as compiled by Lilley (1948); from 1930 to 2000, the data is derived from my own research using various sources including: Bunch and Hellemans (1993), Bunch and Hellemans (2004), Pacey and Bray (2021), and Wikipedia.

process are converted into output. If I consider a Cobb-Douglas production function with 'Hicks-neutral' technology, it can be written as follows:

$$Y_t = A_t K_t^{\alpha} L_t^{1-\alpha}, \quad 0 < \alpha < 1, \tag{2}$$

where A_t is the technology, K_t is the capital stock, L_t is the labor, and α $(1-\alpha)$ represent the capital (labor) share.

The dynamics of technology and per capita output are closely linked. To illustrate this, let me assume that the ratio of employment to population (N_t) is equal to ρ_t, namely:

$$\rho_t = \frac{L_t}{N_t}. \tag{3}$$

Then, equation (2) transforms into:

$$Y_t = A_t K_t^{\alpha} (\rho_t N_t)^{1-\alpha} = A_t \left(\frac{K_t}{\rho_t N_t} \right)^{\alpha} \rho_t N_t. \tag{4}$$

By dividing both terms by the population N_t, I derive:

$$\widehat{y}_t = A_t k_t^{\alpha} \rho_t, \tag{5}$$

where $\widehat{y}_t \equiv Y_t/N_t$ and $k_t \equiv K_t/L_t$, which means output is expressed in per capita terms, and capital is calculated per worker. By taking logs and time differences, I obtain:

$$\ln\widehat{y}_t - \ln\widehat{y}_{t-1} = [\ln\rho_t - \ln\rho_{t-1} + \alpha(\ln k_t - \ln k_{t-1})] + (\ln A_t - \ln A_{t-1}), \tag{6}$$

or employing the notation $g_t^X \equiv \ln X_t - \ln X_{t-1}$ for a generic variable X_t, I can write:

$$g_t^{\widehat{y}} = [g_t^{\rho} + \alpha g_t^{k}] + g_t^{A}. \tag{7}$$

This equation reveals that an increase in output per capita can originate from three sources: (i) changes in the worker-to-population ratio (g_t^{ρ}); (ii) shifts in the capital-to-worker ratio (g_t^{k}); (iii) variations in the level of technology (g_t^{A}). Based on these results, it is possible to implement two different econometric strategies that I discuss in section 3.2.

3.2. Econometric Strategy

The econometric strategy I apply is based on the result obtained in the previous section and follows two distinct levels. The first level involves verifying that the growth rate of per capita output and technology are indeed 'coordinated' over time, as suggested by equation (7). By 'coordinated', I mean that any shifts in the average growth of technology are aligned with shifts in the average growth of per capita output. To analyze this aspect, I will use the test proposed by Bai and Perron (1998, 2003), which aims to identify multiple breaks at unknown dates in the series of the growth rate of technology and per capita output, and I will compare the dates of these breaks.

The second level involves starting from equation (7) itself and modeling all variables that contribute to the determination of the per capita output growth rate. Since the factors in square brackets in (7) are not observable in reality, as the variables comprising them are not readily available, the method of unobservable components, also known as the state-space model, can be beneficial.

BP test for detecting mean shifts and comparison of identified break dates. The starting point of my analysis is the linear regression with m breaks ($m+1$ regimes):

$$g_t^i = \phi_j^i + u_t^i, \quad t = T_{j+1} + 1, \ldots, T_j. \tag{8}$$

Here, the index i corresponds to $\widehat{y}, A$, and $j = 1, \ldots, m+1$. In this equation, ϕ_j^i ($j = 1, \ldots, m+1$) represents the constant in the j-th regime, and u_t^i is the regression error at time t. The m-partition $(T_1, \ldots, T_m)$ delineates the break points for different regimes (conventionally, $T_0 = 0$ and $T_{m+1} = T$). These points, treated as unknown, are estimated following the methodology outlined by Bai and Perron (1998, 2003) (hereafter BP).

In my application of the BP procedure, I determine the optimal number of breaks by selecting the one that results in the lowest Bayesian information criterion (BIC) score. I set the trimming parameter to 0.15, which means that the minimum fraction of observations between two breaks must account for at least 15% of all observations. To ensure a robust analysis, the breaks cannot be positioned in the first or last 15% of the observations, allowing for a maximum of 5 breaks.

To calculate the test statistic and confidence intervals for the break dates and regression coefficients, I employ the Heteroscedasticity and Autocorrelation Consistent (HAC) Newey-West covariance matrix with an automatic band-

width method. This approach takes into account any autocorrelation and heteroscedasticity in the residuals of the regression model, providing reliable and robust results.
After identifying the break points for both the per capita output growth rate and the technology growth rate, I compare them to verify the alignment of dates. If the growth of per capita output indeed follows the process indicated in equation (7), I expect that a change in the growth of technology would have a corresponding effect on per capita output.

Unobserved component modelling. The equation (7) represents the measurement equation, which describes the relationship between observed and unobserved variables and serves as the starting point for modeling the state-space system. To complement this measurement equation, I can introduce another equation under the assumption that the technology growth rate is not purely determined by external factors. For instance, I can consider the technology growth rate as a function of an unobservable exogenous process and the growth of output. The assumption (to be empirically tested during estimation) is that the growth of per capita output may potentially stimulate the introduction of innovations into the economic system. This idea was initially proposed by Smith (Smith, 1982) and later explored by researchers such as Young (1928); Verdoorn (1949); Kaldor (1967).[2] Naturally, in the case of a pure neoclassical model of exogenous growth, this effect is expected to be statistically insignificant.
Once these two measurement equations are specified, I need to define the two state equations that capture the dynamics of the unobserved state variables involved in the per capita output equation and the technology equation. The state equation for the growth rate of per capita output is expressed as a function of its past values and the unobserved state variable representing technology. Including the unobserved technological component in the state equation of output is justified by examining its composition. According to the theoretical model (equation (7)), the unobserved output variable is influenced by the worker-to-population ratio and the capital-to-worker ratio, both expressed as growth rates. Changes in technology can impact employment and living standards, leading to shifts in the so-called organic composition

[2]These authors argued that higher output growth may have a positive impact on productivity trends due to various factors, including dynamic economies of scale linked to learning-by-doing, expanding markets, and increased division of labor.

of capital.[3] Lastly, the state equation for technology is simply a function of its past values.

Based on the above discussion, the unobserved component system can be expressed as follows:

$$g_t^{\widehat{y}i} = sv_t^{\widehat{y}i} + g_{t-1}^A + e_t^{\widehat{y}i}, \;\; e_t^{\widehat{y}i} \sim \mathsf{NID}(0, \sigma^2_{\widehat{y}i}) \tag{9.1}$$

$$g_t^A = sv_t^A + \psi^i \cdot g_{t-1}^{\widehat{y}i} + e_t^A, \;\; e_t^A \sim \mathsf{NID}(0, \sigma^2_A) \tag{9.2}$$

$$sv_t^{\widehat{y}i} = \theta^{1i} \cdot sv_{t-1}^{\widehat{y}i} + \theta^{2i} \cdot sv_{t-1}^A + e_t^{svi}, \;\; e_t^{svi} \sim \mathsf{NID}(0, \sigma^2_{svi}) \tag{9.3}$$

$$sv_t^A = \omega^A \cdot sv_{t-1}^A + e_t^{svA}, \;\; e_t^{svA} \sim \mathsf{NID}(0, \sigma^2_{svA}). \tag{9.4}$$

Equation (9.1) corresponds to equation (7) for $i = BD, AM$, where $\widehat{y}BD$ and $\widehat{y}AM$ represent per capita output estimates provided by De Long (1998) and Maddison (2013), respectively. $sv_t^{\widehat{y}i}$ and sv_t^A are the state variables associated with the terms inside the square brackets in equation (7) and technology, respectively. Equation (9.2) represents the equation for the technology growth rate, while equations (9.3) and (9.4) specify the unobserved components. The errors are assumed to follow a normal, independent, and identically distributed (NID) distribution with constant variance.

The estimation procedure for the systems described by equations (9.1)–(9.4) involves updating the parameter values iteratively to maximize the likelihood function. To accomplish this, I utilize the Broyden-Fletcher-Goldfarb-Shanno (BFGS) optimization method with the Marquardt step. This method is well-suited for adjusting the parameter estimates efficiently, aiming to find the optimal values that maximize the likelihood.

The iterative filter proposed by Kalman (1960) and Kalman and Bucy (1961) is employed to evaluate the likelihood. This filter consists of three phases: the filtering phase (one-step ahead prediction of state variables based on

[3]For example, (Council of Economic Advisers, 2007, p. 47–48) provides an illustrative example of increased agricultural productivity over the past two centuries: "In 1830, it took 250-300 hours for a farmer to produce 100 bushels of wheat. In 1890, with horse-drawn machines, it took only 40-50 hours to produce the same amount. By 1975, with large tractors and combines, a farmer could produce 100 bushels of wheat in only 3-4 hours." Technological innovation in agriculture led to a reduction in the required number of workers in the fields and an increased utilization of machinery. Simultaneously, it facilitated an expansion in available food resources, resulting in improved living standards and population conditions.

past and present observations), the smoothing phase (retrospective update of state variable estimates), and the forecasting phase (prediction of future state variables). The first two phases are crucial for obtaining parameter estimates in the model.

To obtain robust and efficient parameter estimates in the presence of heteroscedasticity violations, I calculate the covariances of coefficients using the Huber-White method, also known as robust White estimation.[4]

One way to evaluate whether the model adequately represents the data is by calculating the standardized residuals and conducting diagnostic tests to assess if they satisfy the distributional assumptions. According to Harvey (1989) and Durbin and Koopman (2001), three essential tests can be employed: normality (Jarque-Bera test), heteroscedasticity (Goldfeld-Quandt test), and serial correlation (Ljung-Box test). In our specific case, heteroscedasticity is not a concern since robust White covariance is utilized. However, the other two tests pose challenges due to the characteristics of the historical series under investigation.

Very long time series can present two primary difficulties: (i) the presence of outliers, especially for values corresponding to distant periods, and (ii) autocorrelation resulting from the interpolation necessary to ensure the continuity or constancy of the series across different time periods. Both the technology and per capita output series analyzed in our study suffer from outliers and autocorrelation, especially in the case of distant observations, although there is a slight difference regarding the source of autocorrelation. In the case of technology, autocorrelation arises solely because it remained nearly constant and flat for extended periods. On the other hand, for per capita output (in both 'BD' and 'AM' versions), autocorrelation is also a consequence of the necessity to the series continuous by interpolating very distant observations. These characteristics of the underlying data are likely to impact the residuals of the estimates.

When outliers are present in the series, affecting the normality tests of the residuals primarily through kurtosis, some researchers suggest paying attention to skewness (i.e., the asymmetry of the series) since an excess of kurtosis does not necessarily undermine the reliability of the estimates (see, for example, Juselius, 2006, p. 75–76). Alternatively, 'rule of thumb' guidelines are

[4]For further details on the estimation procedure, please refer to Anderson and Moore (1979), Harvey (1989) and Durbin and Koopman (2001).

provided by certain authors. For example, Field (2013) and Sheard (2018) propose that a range of ± 2 for both skewness and excess kurtosis can be considered acceptable.
The issue of serial correlation can be strategically addressed as follows. One can choose to estimate the model by excluding from the sample the portion (typically the most distant part) that contains data obtained through interpolation. By doing so, a substantial number of outliers is also likely to be excluded, and all the statistical tests (not just the test for autocorrelation of residuals) are expected to improve accordingly. Naturally, it is important that the parameter values of the model do not deviate significantly from those obtained previously using the entire sample, in order to ensure robustness and enhance the reliability of the results.

4. Empirical results

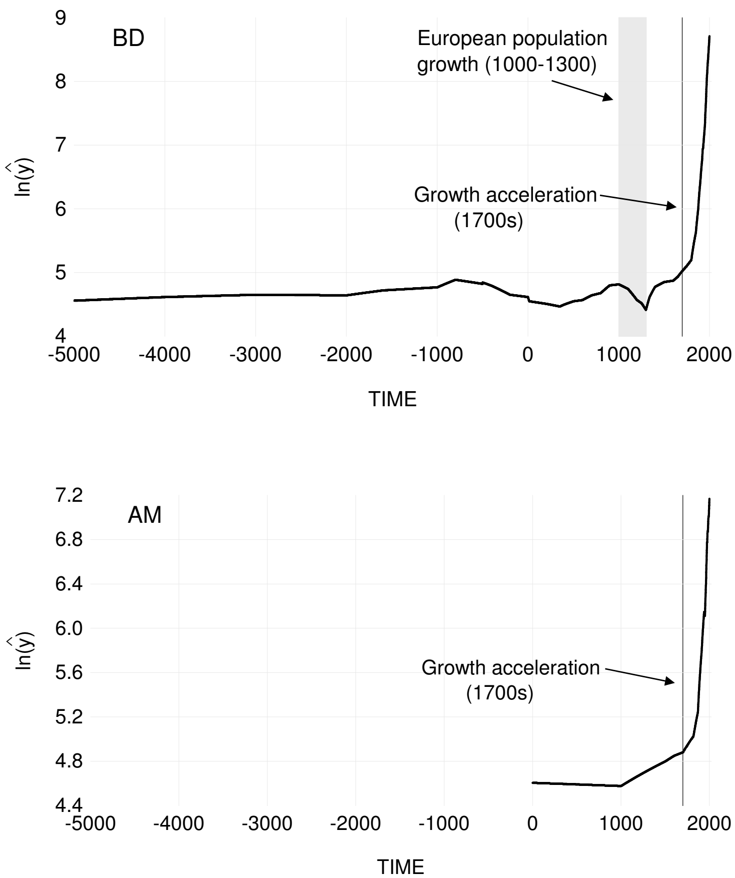
Before delving into the discussion of the empirical results obtained by applying the BP methodology (section 4.1) and the unobservable components model (section 4.2), it is essential to describe the per capita output series used in all statistical analyses.
I have used two historical series, likely the only two available on a millennial scale, of global per capita output. The first one is provided by De Long (1998) ($g^{\widehat{y}BD}$) and the second one by Maddison (2013) ($g^{\widehat{y}AM}$). Both series are expressed in constant international dollars. The main distinction lies in the start date: the historical series produced by De Long (1998) originates in 5000 BC, while the series published by Maddison (2013) begins in the year 1 AD. Despite this, both are available at time intervals that progressively shorten as we approach the present. For missing data between two dates, we resorted to linear interpolation to provide a complete time series. The two series, transformed into natural logarithms after setting the base year 1 AD = 100, are presented in figure 2.
Three significant aspects emerge from the graph. Firstly, by observing the 'BD' series from De Long (1998), it is evident that the growth rate of the per capita GDP in the period BC displays a substantially stable, almost flat, trend.
The second interesting aspect pertains to the period of economic growth between the eleventh and fourteenth centuries. During this period, the 'BD' series exhibits a 'V' dynamic (initial decline, followed by a low point, and

then a recovery), while the 'AM' series shows a more continuous trend. This difference can be explained by the approach adopted by De Long (1998), who designed his series to highlight the effects of the European population boom that occurred in High Middle Ages (see, for example, Russell, 1972; McEvedy and Jones, 1978; Herlihy, 1989). In that period, economic growth in Europe was outpaced by demographic growth. Around 1300, the population reached its peak, and output began to grow faster than the population. On the contrary, the 'AM' series from Maddison (2013) does not highlight this phenomenon, considering the impact of this European event on the global output as quite limited. According to his estimates, the contribution of the GDP of Western European countries to the world GDP fluctuated between 10 and 20% from year 1 to around 1700, with China and India together contributing over 50% (see Maddison, 2007, table A.6, p. 381).
The third aspect concerns the marked acceleration of per capita output that is evident in both historical series around the eighteenth century, that is, a few decades before the industrial revolution. This phenomenon, known as proto-industrialization, is considered by some scholars as the pivotal phase of change in the economic structure that led to significant shifts in productivity and economic growth (see, for example, Mendels, 1972; Kriedte et al., 1982).
For the empirical analysis, I will focus on the period from 1 AD to 2000 for two reasons: firstly, because growth in the pre-Christ era is virtually flat and exhibits little dynamics; secondly, because the 'AM' series by Maddison (2013) only begins from 1 AD. Therefore, in order to maintain homogeneity in the temporal range of analysis for comparative purposes, I will start from 1 AD.

4.1. BP test and breaks date comparison

The results of the BP test, carried out as explained in section 3.2, are detailed in table 1. For the period extending from 1 AD to 2000, the results show that the growth rate of technology exhibits a single break in 1698. The growth rate of per capita GDP in the version of De Long (1998) (BD) has three breaks: in 1001, 1301, and 1702. The growth rate of per capita GDP in the version of Maddison (2013) (AM) also shows a single break in 1702. This difference can be attributed to the fact that, as discussed in section 4 and apparent from figure 2, the series from De Long (1998) takes into account the effect of European population growth during the period 1000-1300 on global growth, unlike Maddison (2013).

Figure 2: The historical time series of real global per capita GDP (expressed in natural logarithms)



Notes: The data sources are referenced as follows: 'BD' pertains to De Long (1998) and 'AM' refers to Maddison (2013). The original data, expressed in 1990 US dollars, are not available at each temporal point. Missing data between two dates have been interpolated linearly for continuity. Both series have been normalized to 100 for the base year (1 AD) and then transformed into natural logarithms.

However, it is crucial to note that both measures of global per capita GDP highlight a significant surge in growth in 1702. This finding is also clearly visible when visually examining the series (see figure 2). Importantly, this shift aligns precisely with the change in the growth rate of technology, which actually precedes the shift in per capita output by several years. This pattern underscores the role of technology as the primary driver of economic development, consistent with economic theory.

Table 1: BP test of equation (8), 1–2000

Dep. variable	Dates of the regimes	$\phi_t^i \times 100$	St. Err.$\times$100
g_t^A			
	2–1697	0.022***	0.005
	1698–2000	0.566***	0.111
$g_t^{\widehat{y}BD}$			
	2–1000	0.021**	0.010
	1001–1300	-0.134***	0.017
	1301–1701	0.153***	0.039
	1702–2000	1.232***	0.302
$g_t^{\widehat{y}AM}$			
	2–1701	0.016***	0.003
	1702–2000	0.765***	0.216

Notes: The series of variable levels in logarithms start from the period 1 AD, so the first differences (i.e., growth rates) begin from the period 2 AD onwards. The test and the confidence intervals for the break dates and regression coefficients are carried out using the HAC Newey-West covariance matrix with an automatic bandwidth method. More details can be found in section 3.2.

4.2. Unobserved component model estimation

Tables 2 and 3 present the estimation of the system (9.1)–(9.4) over the entire sample (1–2000) using the output growth rate calculated by De Long (1998) and Maddison (2013), respectively. The parameter values have the expected signs and are statistically significant, except for ψ^i (with $i = BD, AM$), which measures the effect of per capita output on technology. This implies that the hypothesis of exogeneity of technology, as predicted by the neoclassical Solow model, is plausible. However, upon closer examination of the

results, issues arise regarding the diagnostic tests on the residuals, as they do not satisfy the conditions of normality and absence of autocorrelation.
Even when removing the dependence of per capita output on technology (by imposing $\psi^i = 0$, with $i = BD, AM$), the diagnostic tests yield unsatisfactory results (see tables 4 and 5). The unsatisfactory nature of the residuals can be attributed to the presence of outliers and autocorrelation in the time series, particularly in the more distant periods, for both technology and output gap variables, as discussed in section 3.2.
By focusing the estimation on the second half of the 1700s, corresponding to the beginning of industrial capitalism, similar parameter estimates are obtained, as shown in tables 6 and 7. Furthermore, it is once again observed that ψ^i is not statistically significant, indicating the robustness of the exogeneity hypothesis over time. Imposing $\psi^i = 0$ leads to similar results, as depicted in tables 8 and 9. In comparison to the more general case of estimation over the entire sample, the only difference is that the diagnostic tests on the residuals are greatly improved. The skewness values are in line with the values suggested by Field (2013) and Sheard (2018), and the Ljung-Box test is satisfactory.
As a final econometric exercise, an attempt is made to estimate the model starting from 1820, corresponding to the era of 'mature' industrial capitalism. As shown in tables 10 and 11, the parameter values are similar, and the tests on residuals yield satisfactory results.[5]
In conclusion, I present in figure 3 the historical series of the logarithm of technology and global per capita GDP (in both 'BD' and 'AM' versions) along with their estimated counterparts obtained from the smoothed component derived from the model presented in table 4 and 5. As seen in the graph, the

[5]Attentive readers may have noticed that in the estimates reported in tables 2–11, the coefficient ω^A is consistently equal to one. This implies that technology is an I(2) process, and consequently, so is the per capita output series. Theoretically, this implies that the neoclassical growth model still retains the structure described in section 3.1, with the clarification that both technology and per capita GDP are I(2), and naturally, their growth rates are I(1). Authors who explicitly model GDP as an I(2) process within the state space models class include Clark (1987), Harvey and Jaeger (1993), and Tóth (2021). Importantly, this result does not impact my discussion, which simply aims to identify a connection between the millennia-long technology series and the per capita output series to assess the adequacy of its reconstruction. Whether technology and per capita GDP are I(1) or I(2) is of little importance: what matters is that they are empirically 'linked', as suggested by growth theories.

estimates obtained over the entire period are highly accurate.

Table 2: Estimation results of system (9.1)–(9.4) with growth variable $g_t^{\widehat{y}BD}$. Period 1–2000.

Variable	Parameters							
	ψ^{BD}	θ^{1BD}	θ^{2BD}	ω_A	$\ln(\sigma^2_{\widehat{y}BD})$	$\ln(\sigma^2_A)$	$\ln(\sigma^2_{svBD})$	$\ln(\sigma^2_{svA})$
	0.008	0.855***	0.184**	1.000***	-11.945***	-11.900***	-13.303***	-18.084***
	(0.066)	(0.069)	(0.090)	(0.000)	(0.173)	(0.157)	(0.594)	(0.409)
(FS) $sv_t^{\widehat{y}BD}$	0.010***							
	[0.002]							
(FS) sv_t^A	0.012***							
	[0.000]							
		Diagnostic tests						
	JB	ske.	kur.	Q(2)	Q(4)			
$g_t^{\widehat{y}BD}$	11.701($\times 10^{-5}$)	-2.963	40.010	1.880	11.339			
				{0.391}	{0.023}			
g_t^A	18.867($\times 10^{-5}$)	5.626	49.248	8.903	11.794			
				{0.012}	{0.019}			
Log Lik.	17703							

Notes: The series of variable levels in logarithms starts from period 1 AD, so the first differences (i.e., growth rates) begin from period 2 AD onwards. The loglikelihood function is optimized using the BFGS algorithm with a Marquardt step. The starting values of the parameters are as follow: $\ln(\sigma^2_{\widehat{y}BD}) = 0$; $\psi^{BD} = 0.1$; $\ln(\sigma^2_A) = 0$; $\theta^{1BD} = 0.5$; $\theta^{2BD} = 0.2$; $\ln(\sigma^2_{svBD}) = 0$; $\omega^A = 0.5$; $\ln(\sigma^2_{svA}) = 0$. Statistical significance levels are denoted by *, **, and ***, indicating 10%, 5%, and 1% significance, respectively. Standard errors of the parameters (reported in parentheses beneath the coefficient values) are calculated using the Huber-White method. (FS) denotes the final state of the unobserved component, and the square brackets beneath (FS) estimates indicate the Root MSE. JB refers to the Jarque-Bera test for non-normality. The critical value of JB corresponding to a 5% significance level with a large number of observations ($n \to \infty$) is approximately 5.99. 'ske' and 'kur' represent skewness and kurtosis, respectively. Q(2) and Q(4) represent the Ljung–Box test based on serial correlation with 2 and 4 lags, respectively. The values in curly braces beneath the Ljung–Box test indicate the p-values of the statistics. 'Log. Lik.' indicates the log likelihood of the estimation.

Table 3: Estimation results of system (9.1)–(9.4) with growth variable $g_t^{\widehat{y}AM}$. Period 1–2000.

Variable	Parameters							
	ψ^{AM}	θ^{1AM}	θ^{2AM}	ω_A	$\ln(\sigma^2_{\widehat{y}AM})$	$\ln(\sigma^2_A)$	$\ln(\sigma^2_{svAM})$	$\ln(\sigma^2_{svA})$
	-0.007	0.838***	0.077	1.000***	-11.648***	-11.903***	-13.422***	-17.909***
	(0.059)	(0.084)	(0.048)	(0.000)	(0.172)	(0.156)	(0.514)	(0.392)
(FS) $sv_t^{\widehat{y}AM}$	0.008***							
	[0.002]							
(FS) sv_t^A	0.013***							
	[0.001]							
		Diagnostic tests						
	JB	ske.	kur.	Q(2)	Q(4)			
$g_t^{\widehat{y}AM}$	19.675($\times 10^{-5}$)	-0.492	51.592	4.223	14.681			
				{0.121}	{0.005}			
g_t^A	18.940($\times 10^{-5}$)	5.647	49.341	7.985	11.753			
				{0.018}	{0.019}			
Log Lik.	17508							

Notes: The series of variable levels in logarithms starts from period 1 AD, so the first differences (i.e., growth rates) begin from period 2 AD onwards. The loglikelihood function is optimized using the BFGS algorithm with a Marquardt step. The starting values of the parameters are as follow: $\ln(\sigma^2_{\widehat{y}AM}) = 0$; $\psi^{AM} = 0.1$; $\ln(\sigma^2_A) = 0$; $\theta^{1AM} = 0.5$; $\theta^{2AM} = 0.2$; $\ln(\sigma^2_{svAM}) = 0$; $\omega^A = 0.5$; $\ln(\sigma^2_{svA}) = 0$. Statistical significance levels are denoted by *, **, and ***, indicating 10%, 5%, and 1% significance, respectively. Standard errors of the parameters (reported in parentheses beneath the coefficient values) are calculated using the Huber-White method. (FS) denotes the final state of the unobserved component, and the square brackets beneath (FS) estimates indicate the Root MSE. JB refers to the Jarque-Bera test for non-normality. The critical value of JB corresponding to a 5% significance level with a large number of observations ($n \to \infty$) is approximately 5.99. 'ske' and 'kur' represent skewness and kurtosis, respectively. Q(2) and Q(4) represent the Ljung–Box test based on serial correlation with 2 and 4 lags, respectively. The values in curly braces beneath the Ljung–Box test indicate the p-values of the statistics. 'Log. Lik.' indicates the log likelihood of the estimation.

Table 4: Estimation results of system (9.1)–(9.4) with growth variable $g_t^{\widehat{y}BD}$ under the restriction $\psi^{BD} = 0$. Period 1–2000.

Variable	Parameters							
	ψ^{BD}	θ^{1BD}	θ^{2BD}	ω_A	$\ln(\sigma^2_{\widehat{y}BD})$	$\ln(\sigma^2_A)$	$\ln(\sigma^2_{svBD})$	$\ln(\sigma^2_{svA})$
	= 0	0.853***	0.182**	1.000***	-11.946***	-11.900***	-13.298***	-18.053***
		(0.069)	(0.088)	(0.000)	(0.172)	(0.157)	(0.593)	(0.341)
(FS) $sv_t^{\widehat{y}BD}$	0.010***							
	[0.002]							
(FS) sv_t^A	0.012***							
	[0.000]							
		Diagnostic tests						
	JB	ske.	kur.	Q(2)	Q(4)			
$g_t^{\widehat{y}BD}$	11.685($\times 10^{-5}$)	-2.966	39.983	1.922	11.201			
				{0.382}	{0.024}			
g_t^A	18.887($\times 10^{-5}$)	5.630	49.256	9.065	12.113			
				{0.011}	{0.017}			
Log Lik.	17708							

Notes: The series of variable levels in logarithms starts from period 1 AD, so the first differences (i.e., growth rates) begin from period 2 AD onwards. The loglikelihood function is optimized using the BFGS algorithm with a Marquardt step. The starting values of the parameters are as follow: $\ln(\sigma^2_{\widehat{y}BD}) = 0$; $\ln(\sigma^2_A) = 0$; $\theta^{1BD} = 0.5$; $\theta^{2BD} = 0.2$; $\ln(\sigma^2_{svBD}) = 0$; $\omega^A = 0.5$; $\ln(\sigma^2_{svA}) = 0$. Statistical significance levels are denoted by *, **, and ***, indicating 10%, 5%, and 1% significance, respectively. Standard errors of the parameters (reported in parentheses beneath the coefficient values) are calculated using the Huber-White method. (FS) denotes the final state of the unobserved component, and the square brackets beneath (FS) estimates indicate the Root MSE. JB refers to the Jarque-Bera test for non-normality. The critical value of JB corresponding to a 5% significance level with a large number of observations ($n \to \infty$) is approximately 5.99. 'ske' and 'kur' represent skewness and kurtosis, respectively. Q(2) and Q(4) represent the Ljung–Box test based on serial correlation with 2 and 4 lags, respectively. The values in curly braces beneath the Ljung–Box test indicate the p-values of the statistics. 'Log. Lik.' indicates the log likelihood of the estimation.

Table 5: Estimation results of system (9.1)–(9.4) with growth variable $g_t^{\widehat{y}AM}$ under the restriction $\psi^{AM} = 0$. Period 1–2000.

Variable	Parameters							
	ψ^{AM}	θ^{1AM}	θ^{2AM}	ω_A	$\ln(\sigma^2_{\widehat{y}AM})$	$\ln(\sigma^2_A)$	$\ln(\sigma^2_{svAM})$	$\ln(\sigma^2_{svA})$
	$= 0$	0.835***	0.079**	1.000***	-11.651***	-11.905***	-13.401***	-21.146***
		(0.067)	(0.035)	(0.001)	(0.180)	(0.153)	(0.459)	(0.658)
(FS) $sv_t^{\widehat{y}AM}$	0.009***							
	[0.002]							
(FS) sv_t^A	0.014***							
	[0.000]							
		Diagnostic tests						
	JB	ske.	kur.	Q(2)	Q(4)			
$g_t^{\widehat{y}AM}$	19.330($\times 10^{-5}$)	-0.579	51.161	4.318	14.810			
				{0.115}	{0.005}			
g_t^A	18.746($\times 10^{-5}$)	5.366	49.200	7.329	11.418			
				{0.026}	{0.022}			
Log Lik.	17524							

Notes: The series of variable levels in logarithms starts from period 1 AD, so the first differences (i.e., growth rates) begin from period 2 AD onwards. The loglikelihood function is optimized using the BFGS algorithm with a Marquardt step. The starting values of the parameters are as follow: $\ln(\sigma^2_{\widehat{y}AM}) = 0$; $\ln(\sigma^2_A) = 0$; $\theta^{1AM} = 0.5$; $\theta^{2AM} = 0.2$; $\ln(\sigma^2_{svAM}) = 0$; $\omega^A = 0.5$; $\ln(\sigma^2_{svA}) = 0$. Statistical significance levels are denoted by *, **, and ***, indicating 10%, 5%, and 1% significance, respectively. Standard errors of the parameters (reported in parentheses beneath the coefficient values) are calculated using the Huber-White method. (FS) denotes the final state of the unobserved component, and the square brackets beneath (FS) estimates indicate the Root MSE. JB refers to the Jarque-Bera test for non-normality. The critical value of JB corresponding to a 5% significance level with $n \approx 200$ is approximately 5.728. 'ske' and 'kur' represent skewness and kurtosis, respectively. Q(2) and Q(4) represent the Ljung–Box test based on serial correlation with 2 and 4 lags, respectively. The values in curly braces beneath the Ljung–Box test indicate the p-values of the statistics. 'Log. Lik.' indicates the log likelihood of the estimation.

Table 6: Estimation results of system (9.1)–(9.4) with growth variable $g_t^{\widehat{y}BD}$. Period 1770–2000.

Variable	Parameters							
	ψ^{BD}	θ^{1BD}	θ^{2BD}	ω_A	$\ln(\sigma^2_{\widehat{y}BD})$	$\ln(\sigma^2_A)$	$\ln(\sigma^2_{svBD})$	$\ln(\sigma^2_{svA})$
	0.030	0.763***	0.319***	1.000***	-10.649***	-10.406***	-10.936***	-16.242***
	(0.072)	(0.079)	(0.122)	(0.001)	(0.225)	(0.100)	(0.341)	(0.671)
(FS) $sv_t^{\widehat{y}BD}$	0.010**							
	[0.005]							
(FS) sv_t^A	0.011***							
	[0.001]							
		Diagnostic tests						
	JB	ske.	kur.	Q(2)	Q(4)			
$g_t^{\widehat{y}BD}$	65.260	-0.489	5.413	1.236	2.892			
				{0.539}	{0.576}			
g_t^A	84.289	1.238	4.620	2.717	4.054			
				{0.257}	{0.399}			
Log Lik.	1685							

Notes: The series of variable levels in logarithms starts from period 1 AD, so the first differences (i.e., growth rates) begin from period 2 AD onwards. The loglikelihood function is optimized using the BFGS algorithm with a Marquardt step. The starting values of the parameters are as follow: $\ln(\sigma^2_{\widehat{y}BD}) = 0$; $\psi^{BD} = 0.1$; $\ln(\sigma^2_A) = 0$; $\theta^{1BD} = 0.5$; $\theta^{2BD} = 0.2$; $\ln(\sigma^2_{svBD}) = 0$; $\omega^A = 0.5$; $\ln(\sigma^2_{svA}) = 0$. Statistical significance levels are denoted by *, **, and ***, indicating 10%, 5%, and 1% significance, respectively. Standard errors of the parameters (reported in parentheses beneath the coefficient values) are calculated using the Huber-White method. (FS) denotes the final state of the unobserved component, and the square brackets beneath (FS) estimates indicate the Root MSE. JB refers to the Jarque-Bera test for non-normality. The critical value of JB corresponding to a 5% significance level with $n \approx 200$ is approximately 5.728. 'ske' and 'kur' represent skewness and kurtosis, respectively. Q(2) and Q(4) represent the Ljung–Box test based on serial correlation with 2 and 4 lags, respectively. The values in curly braces beneath the Ljung–Box test indicate the p-values of the statistics. 'Log. Lik.' indicates the log likelihood of the estimation.

Table 7: Estimation results of system (9.1)–(9.4) with growth variable $g_t^{\widehat{y}AM}$. Period 1770–2000.

Variable	Parameters							
	ψ^{AM}	θ^{1AM}	θ^{2AM}	ω_A	$\ln(\sigma^2_{\widehat{y}AM})$	$\ln(\sigma^2_A)$	$\ln(\sigma^2_{svAM})$	$\ln(\sigma^2_{svA})$
	-0.012	0.835***	0.081	1.000***	-9.970***	-10.414***	-11.271***	-15.929***
	(0.059)	(0.095)	(0.057)	(0.000)	(0.221)	(0.134)	(0.569)	(0.462)
(FS) $sv_t^{\widehat{y}AM}$	0.010*							
	[0.005]							
(FS) sv_t^A	0.013***							
	[0.001]							
		Diagnostic tests						
	JB	ske.	kur.	Q(2)	Q(4)			
$g_t^{\widehat{y}AM}$	388.508	0.747	9.175	0.966	3.915			
				{0.617}	{0.418}			
g_t^A	83.938	1.247	4.580	2.616	4.670			
				{0.270}	{0.346}			
Log Lik.	1642							

Notes: The series of variable levels in logarithms starts from period 1 AD, so the first differences (i.e., growth rates) begin from period 2 AD onwards. The loglikelihood function is optimized using the BFGS algorithm with a Marquardt step. The starting values of the parameters are as follow: $\ln(\sigma^2_{\widehat{y}AM}) = 0$; $\psi^{AM} = 0.1$; $\ln(\sigma^2_A) = 0$; $\theta^{1AM} = 0.5$; $\theta^{2AM} = 0.2$; $\ln(\sigma^2_{svAM}) = 0$; $\omega^A = 0.5$; $\ln(\sigma^2_{svA}) = 0$. Statistical significance levels are denoted by *, **, and ***, indicating 10%, 5%, and 1% significance, respectively. Standard errors of the parameters (reported in parentheses beneath the coefficient values) are calculated using the Huber-White method. (FS) denotes the final state of the unobserved component, and the square brackets beneath (FS) estimates indicate the Root MSE. JB refers to the Jarque-Bera test for non-normality. The critical value of JB corresponding to a 5% significance level with $n \approx 200$ is approximately 5.728. 'ske' and 'kur' represent skewness and kurtosis, respectively. Q(2) and Q(4) represent the Ljung–Box test based on serial correlation with 2 and 4 lags, respectively. The values in curly braces beneath the Ljung–Box test indicate the p-values of the statistics. 'Log. Lik.' indicates the log likelihood of the estimation.

Table 8: Estimation results of system (9.1)–(9.4) with growth variable $g_t^{\widehat{y}BD}$ under the restriction $\psi^{BD}=0$. Period 1770–2000.

Variable	Parameters							
	ψ^{BD}	θ^{1BD}	θ^{2BD}	ω_A	$\ln(\sigma^2_{\widehat{y}BD})$	$\ln(\sigma^2_A)$	$\ln(\sigma^2_{svBD})$	$\ln(\sigma^2_{svA})$
	$=0$	0.760***	0.302***	1.000***	-10.652***	-10.407***	-10.931***	-16.123***
		(0.076)	(0.106)	(0.001)	(0.226)	(0.096)	(0.340)	(0.587)
(FS) $sv_t^{\widehat{y}BD}$	0.010**							
	[0.005]							
(FS) sv_t^A	0.012***							
	[0.001]							
		Diagnostic tests						
	JB	ske.	kur.	Q(2)	Q(4)			
$g_t^{\widehat{y}BD}$	65.714	-0.491	5.421	1.258	2.900			
				{0.533}	{0.575}			
g_t^A	83.176	1.237	4.586	2.917	4.479			
				{0.233}	{0.345}			
Log Lik.	1685							

Notes: The series of variable levels in logarithms starts from period 1 AD, so the first differences (i.e., growth rates) begin from period 2 AD onwards. The loglikelihood function is optimized using the BFGS algorithm with a Marquardt step. The starting values of the parameters are as follow: $\ln(\sigma^2_{\widehat{y}BD})=0$; $\ln(\sigma^2_A)=0$; $\theta^{1BD}=0.5$; $\theta^{2BD}=0.2$; $\ln(\sigma^2_{svBD})=0$; $\omega^A=0.5$; $\ln(\sigma^2_{svA})=0$. Statistical significance levels are denoted by *, **, and ***, indicating 10%, 5%, and 1% significance, respectively. Standard errors of the parameters (reported in parentheses beneath the coefficient values) are calculated using the Huber-White method. (FS) denotes the final state of the unobserved component, and the square brackets beneath (FS) estimates indicate the Root MSE. JB refers to the Jarque-Bera test for non-normality. The critical value of JB corresponding to a 5% significance level with $n \approx 200$ is approximately 5.728. 'ske' and 'kur' represent skewness and kurtosis, respectively. Q(2) and Q(4) represent the Ljung–Box test based on serial correlation with 2 and 4 lags, respectively. The values in curly braces beneath the Ljung–Box test indicate the p-values of the statistics. 'Log. Lik.' indicates the log likelihood of the estimation.

Table 9: Estimation results of system (9.1)–(9.4) with growth variable $g_t^{\widehat{y}AM}$ under the restriction $\psi^{AM} = 0$. Period 1770–2000.

Variable	Parameters							
	ψ^{AM}	θ^{1AM}	θ^{2AM}	ω_A	$\ln(\sigma^2_{\widehat{y}AM})$	$\ln(\sigma^2_A)$	$\ln(\sigma^2_{svAM})$	$\ln(\sigma^2_{svA})$
	$= 0$	0.836***	0.082	1.000***	-9.970***	-10.413***	-11.272***	-15.960***
		(0.095)	(0.058)	(0.001)	(0.222)	(0.135)	(0.568)	(0.443)
(FS) $sv_t^{\widehat{y}AM}$	0.009*							
	[0.005]							
(FS) sv_t^A	0.013***							
	[0.001]							
		Diagnostic tests						
	JB	ske.	kur.	Q(2)	Q(4)			
$g_t^{\widehat{y}AM}$	388.638	0.748	9.176	0.964	3.915			
				{0.618}	{0.418}			
g_t^A	85.312	1.252	4.611	2.557	4.341			
				{0.278}	{0.362}			
Log Lik.	1642							

Notes: The series of variable levels in logarithms starts from period 1 AD, so the first differences (i.e., growth rates) begin from period 2 AD onwards. The loglikelihood function is optimized using the BFGS algorithm with a Marquardt step. The starting values of the parameters are as follow: $\ln(\sigma^2_{\widehat{y}AM}) = 0$; $\ln(\sigma^2_A) = 0$; $\theta^{1AM} = 0.5$; $\theta^{2AM} = 0.2$; $\ln(\sigma^2_{svAM}) = 0$; $\omega^A = 0.5$; $\ln(\sigma^2_{svA}) = 0$. Statistical significance levels are denoted by *, **, and ***, indicating 10%, 5%, and 1% significance, respectively. Standard errors of the parameters (reported in parentheses beneath the coefficient values) are calculated using the Huber-White method. (FS) denotes the final state of the unobserved component, and the square brackets beneath (FS) estimates indicate the Root MSE. JB refers to the Jarque-Bera test for non-normality. The critical value of JB corresponding to a 5% significance level with $n \approx 200$ is approximately 5.728. 'ske' and 'kur' represent skewness and kurtosis, respectively. Q(2) and Q(4) represent the Ljung–Box test based on serial correlation with 2 and 4 lags, respectively. The values in curly braces beneath the Ljung–Box test indicate the p-values of the statistics. 'Log. Lik.' indicates the log likelihood of the estimation.

Table 10: Estimation results of system (9.1)–(9.4) with growth variable $g_t^{\widehat{y}BD}$ under the restriction $\psi^{BD} = 0$. Period 1820–2000.

Variable	Parameters						
	ψ^{BD}	θ^{1BD}	θ^{2BD}	ω_A	$\ln(\sigma^2_{\widehat{y}BD})$	$\ln(\sigma^2_A)$	$\ln(\sigma^2_{svBD})$	$\ln(\sigma^2_{svA})$
	$= 0$	0.719***	0.359***	1.000***	-10.556***	-10.282***	-10.683***	-16.020***
		(0.096)	(0.133)	(0.001)	(0.286)	(0.109)	(0.386)	(0.671)
(FS) $sv_t^{\widehat{y}BD}$	0.011*							
	[0.006]							
(FS) sv_t^A	0.012***							
	[0.001]							
		Diagnostic tests						
	JB	ske.	kur.	Q(2)	Q(4)			
$g_t^{\widehat{y}BD}$	34.234	-0.477	4.904	1.109	4.154			
				{0.714}	{0.722}			
g_t^A	47.162	1.109	4.154	2.510	3.422			
				{0.285}	{0.490}			
Log Lik.	1295							

Notes: The series of variable levels in logarithms starts from period 1 AD, so the first differences (i.e., growth rates) begin from period 2 AD onwards. The loglikelihood function is optimized using the BFGS algorithm with a Marquardt step. The starting values of the parameters are as follow: $\ln(\sigma^2_{\widehat{y}BD}) = 0$; $\ln(\sigma^2_A) = 0$; $\theta^{1BD} = 0.5$; $\theta^{2BD} = 0.2$; $\ln(\sigma^2_{svBD}) = 0$; $\omega^A = 0.5$; $\ln(\sigma^2_{svA}) = 0$. Statistical significance levels are denoted by *, **, and ***, indicating 10%, 5%, and 1% significance, respectively. Standard errors of the parameters (reported in parentheses beneath the coefficient values) are calculated using the Huber-White method. (FS) denotes the final state of the unobserved component, and the square brackets beneath (FS) estimates indicate the Root MSE. JB refers to the Jarque-Bera test for non-normality. The critical value of JB corresponding to a 5% significance level with $n \approx 200$ is approximately 5.728. 'ske' and 'kur' represent skewness and kurtosis, respectively. Q(2) and Q(4) represent the Ljung–Box test based on serial correlation with 2 and 4 lags, respectively. The values in curly braces beneath the Ljung–Box test indicate the p-values of the statistics. 'Log. Lik.' indicates the log likelihood of the estimation.

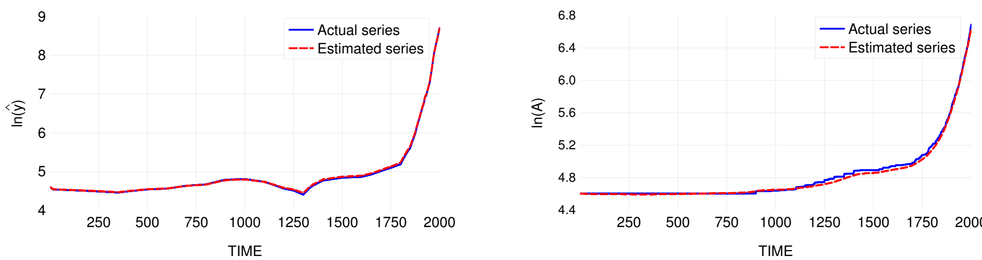
Table 11: Estimation results of system (9.1)–(9.4) with growth variable $g_t^{\widehat{y}AM}$ under the restriction $\psi^{AM} = 0$. Period 1820–2000.

Variable	Parameters							
	ψ^{AM}	θ^{1AM}	θ^{2AM}	ω_A	$\ln(\sigma^2_{\widehat{y}AM})$	$\ln(\sigma^2_A)$	$\ln(\sigma^2_{svAM})$	$\ln(\sigma^2_{svA})$
	$= 0$	0.826***	0.092	1.000***	-9.784***	-10.287***	-11.053***	-15.847***
		(0.103)	(0.065)	(0.001)	(0.232)	(0.144)	(0.588)	(0.468)
(FS) $sv_t^{\widehat{y}AM}$	0.010*							
	[0.005]							
(FS) sv_t^A	0.013***							
	[0.001]							
		Diagnostic tests						
	JB	ske.	kur.	Q(2)	Q(4)			
$g_t^{\widehat{y}AM}$	184.758	0.676	7.761	0.532	2.901			
				{0.767}	{0.574}			
g_t^A	47.103	1.107	4.157	2.276	3.359			
				{0.321}	{0.500}			
Log Lik.	1258							

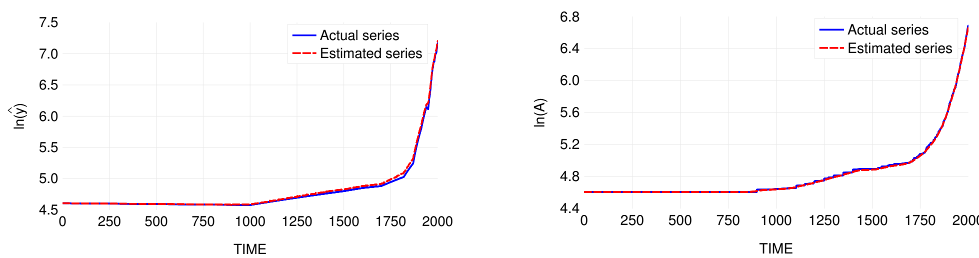
Notes: The series of variable levels in logarithms starts from period 1 AD, so the first differences (i.e., growth rates) begin from period 2 AD onwards. The loglikelihood function is optimized using the BFGS algorithm with a Marquardt step. The starting values of the parameters are as follow: $\ln(\sigma^2_{\widehat{y}AM}) = 0$; $\ln(\sigma^2_A) = 0$; $\theta^{1AM} = 0.5$; $\theta^{2AM} = 0.2$; $\ln(\sigma^2_{svAM}) = 0$; $\omega^A = 0.5$; $\ln(\sigma^2_{svA}) = 0$. Statistical significance levels are denoted by *, **, and ***, indicating 10%, 5%, and 1% significance, respectively. Standard errors of the parameters (reported in parentheses beneath the coefficient values) are calculated using the Huber-White method. (FS) denotes the final state of the unobserved component, and the square brackets beneath (FS) estimates indicate the Root MSE. JB refers to the Jarque-Bera test for non-normality. The critical value of JB corresponding to a 5% significance level with $n \approx 200$ is approximately 5.728. 'ske' and 'kur' represent skewness and kurtosis, respectively. Q(2) and Q(4) represent the Ljung–Box test based on serial correlation with 2 and 4 lags, respectively. The values in curly braces beneath the Ljung–Box test indicate the p-values of the statistics. 'Log. Lik.' indicates the log likelihood of the estimation.

Figure 3: Actual vs estimated series

(a) Growth variable: $g_t^{\widehat{y}BD}$



(b) Growth variable: $g_t^{\widehat{y}AM}$



Notes: Variables are expressed in natural log. Estimates are obtained from table 4 (for the 'BD' version) and 5 (for the 'AM' version).

5. Concluding remarks

In this study, I reconstructed the historical series of technology stocks at an aggregate level. To accomplish this, I used a database provided by Lilley (1948) and updated the series from the 1930s to the year 2000. This updated historical series is unique as it covers a thousand-year period, spanning from 5000 BC to the present day. The approach followed Lilley (1948)'s methodology, which collected the major inventions that had an impact on global industry and its growth, assigning a representative score reflecting their importance.
The resulting historical series exhibits a robust statistical relationship with

the historical series of global real per capita GDP. Notably, periods of significant technology growth, corresponding to the proto-industrialization era, precede the 'leap' in per capita output growth by only a few years, consistent with growth theory. By employing a bivariate model with unobserved components and leveraging the theoretical connections between per capita output and technology, I ascertain that technology serves as the exogenous component influencing the underlying process of output, as expected according to theory. These econometric exercises strengthen the validity of the millennium-long technology series reconstruction.

I conclude by noting that the approach followed in reconstructing the millennium-long technology series can potentially be extended at the country level or to a group of countries. A notable example is Joseph Needham, an English biochemist and scholar of science, who embarked on an extensive project starting in 1954. His monumental work aimed to document the major technological discoveries in China, dating back to the earliest days of its civilization. Specifically, volumes 4 to 6 of Needham's comprehensive series were dedicated to describing the significant inventions introduced in various scientific and technological fields throughout China's history. Drawing upon this valuable resource, it would be feasible to undertake the reconstruction of a millennium-long technology series focused specifically on China.

References

Anderson, B. D. and Moore, J. B. (1979). *Optimal filtering.* Englewood Cliffs: Prentice-Hall, New York.

Anderson, R. G., Kliesen, K. L., et al. (2006). The 1990s acceleration in labor productivity: Causes and measurement. *Review*, 88(May):181–202.

Bai, J. and Perron, P. (1998). Estimating and testing linear models with multiple structural changes. *Econometrica*, 66(1):47–78.

Bai, J. and Perron, P. (2003). Computation and analysis of multiple structural change models. *Journal of Applied Econometrics*, 18(1):1–22.

Bauchspies, W. K., Croissant, J., and Restivo, S. (2006). *Science, technology and society: A sociological approach.* Blackwell Publishing, Malden, MA.

Brynjolfsson, E. and McAfee, A. (2014). *The second machine age: Work, progress, and prosperity in a time of brilliant technologies.* WW Norton & Company.

Bunch, B. H. and Hellemans, A. (1993). *The timetables of technology. A cronology of the most important people and events in the history of technology.* Simon & Schuster, New York.

Bunch, B. H. and Hellemans, A. (2004). *The history of science and technology.* Houghton Mifflin Company, New York.

Clark, P. K. (1987). The cyclical component of US economic activity. *The Quarterly Journal of Economics*, 102(4):797–814.

Cole, G. D. H. (1960). *Introduction to economic history: 1750–1950.* Macmillan, London.

Council of Economic Advisers (2007). Economic Report of the President. H. Doc. 2.

De Long, B. J. (1998). Estimates of World GDP, one million BC–present. Mimeo, UC Berkeley.

Durbin, J. and Koopman, S. J. (2001). *Time series analysis by state space methods.* Oxford University Press, Oxford.

Fernald, J. G. and Ramnath, S. (2004). The acceleration in US total productivity after 1995: the role of information technology. *Economic Perspectives*, 28(QI):52–67.

Field, A. (2013). *Discovering statistics using SPSS*. Sage Publications, London.

Freeman, C. and Louçã, F. (2001). *As time goes by: From the industrial revolutions to the information revolution*. Oxford University Press, Oxford.

Harvey, A. C. (1989). *Forecasting, structural time series models and the Kalman filter*. Cambridge University Press, Cambridge.

Harvey, A. C. and Jaeger, A. (1993). Detrending, stylized facts and the business cycle. *Journal of Applied Econometrics*, 8(3):231–247.

Herlihy, D. (1989). *Medieval demography*, volume 4. Charles Scribner's Sons, New York.

Juselius, K. (2006). *The cointegrated VAR model: Methodology and applications*. Oxford University Press, Oxford.

Kaldor, N. (1967). *Strategic factors in economic development*. Cornell University Press, New York: Ithaca.

Kalman, R. E. (1960). A new approach to linear filtering and prediction problems. *Journal of Basic Engineering, Transactions ASMA, Series D*, 82(1):35–45.

Kalman, R. E. and Bucy, R. S. (1961). New results in linear filtering and prediction theory. *Journal of Basic Engineering, Transactions ASMA, Series D*, 83(1):95–107.

Kriedte, P., Medick, H., and Schlumbohm, J. (1982). *Industiarlization before Industiarlization*. Cambridge University Press, Cambridge.

Lilley, S. (1948). *Men, machines and history*. Cobbett Press, London.

Maddison, A. (2007). *Countors of the World economy, 1–2030 AD*. Oxford University Press, Oxford.

Maddison, A. (2013). Statistics on World population, GDP and per capita GDP, 1—2010 AD. Data retrieved from Groningen Growth and Development Centre, http://www.rug.nl/ggdc/historicaldevelopment/maddison/releases/maddison-project-database-2013.

McEvedy, C. and Jones, R. (1978). *Atlas of world population history*. Penguin Books, Harmondsworth, Middlesex.

Mendels, F. F. (1972). Proto-industrialization: The first phase of the industrialization process. *The Journal of Economic History*, 32(1):241–261.

Pacey, A. and Bray, F. (2021). *Technology in world civilization: A thousand–year history. Revised and expanded edition*. Mit Press, Cambridge, MA.

Perez, C. (2004). Technological revolutions, paradigm shifts and socio-institutional change. In Reinert, E. S., editor, *Globalization, economic development and inequality*, pages 217–242. Edward Elgar, Cheltenham.

Romer, P. M. (1986). Increasing returns and long-run growth. *Journal of Political Economy*, 94(5):1002–1037.

Russell, J. (1972). Population in Europe: 500–1500. In Cipolla, C. M., editor, *The Fontana Economic History of Europe, Vol. 1*, pages 25–71. Collins, Glasgow.

Schumpeter, J. A. (1942). *Capitalism, socialism and democracy*. Allen & Unwin, London.

Sheard, J. (2018). Quantitative data analysis. In Williamson, K. and Johanson, G., editors, *Research methods: Information, systems, and contexts*, pages 429–452. Chandos Publishing, Cambridge.

Smith, A. (1982). *The wealth of nations [1776]*. Penguin Classics, London.

Solow, R. M. (1956). A contribution to the theory of economic growth. *The Quarterly Journal of Economics*, 70(1):65–94.

Tóth, M. (2021). A multivariate unobserved components model to estimate potential output in the Euro Area: A production function based approach. Working Paper 2523.

Verdoorn, P. J. (1949). Fattori che regolano lo sviluppo della produttivita' del lavoro. *L'Industria*, 1:3–10.

Volti, R. (2017). *Society and technological change.* Worth Publishers, New York.

Young, A. A. (1928). Increasing returns and economic progress. *The Economic Journal*, 38(152):527–542.

Appendix A. Timeline of Innovations 1930–2000

Table A.12: Integration of the dataset from Lilley (1948) for the period 1930–1943

Fiberglass (1930–1940, mass production) Inventors: Various contributors Industry Use: Construction, aerospace industry, automotive, naval Importance for the Industry: 0.8
Walkie–Talkie (1940, widely used from 1943) Inventors: Donald L. Hings, Alfred J. Gross, and their team Industry Use: Military communications, security, teamwork in industrial environments Importance for the Industry: 0.7
Nuclear reactor (Chicago Pile-1, 1942–1943) Inventors: Enrico Fermi and his team Industry Use: Nuclear power, research Importance for the Industry: 0.8
Inertial Navigation Device (1942–1945) Inventors: Charles Stark Draper and his team Industry Use: Air, space and marine navigation, missile guidance systems Importance for the Industry: 0.8
Penicillin synthesis (1943, industrial-level production) Inventors: Howard Florey, Ernst Boris Chain and their team Industry Use: Antibiotic production, medicine Importance for the Industry: 0.9
Colossus (1943–1944) Inventors: Tommy Flowers and his team Industry Use: Decryption, data processing and communication systems Importance for the Industry: 0.9

Table A.13: Inventions 1944–2000. Upgrade of the original dataset by Lilley (1948)

Jet airplane (1944, year of mass production) Inventors: Various engineers and scientists, including Frank Whittle and Hans von Ohain Industry Use: Air transport, defense, aerospace industry Importance for the Industry: 0.9

Radioactive Nucleic Acid (1944)
Inventors: George Beadle and Edward Tatum
Industry Use: Genetic research, biotechnology, medicine
Importance for the Industry: 0.8

Solar cell (1945–1946)
Inventors: Russell Ohl and other scientists at Bell Labs
Industry Use: Light sensors, light measurement, solar panels, telecommunications
Importance for the Industry: 0.8

ENIAC (1946)
Inventors: John Mauchly and J. Presper Eckert
Industry Use: Electronic calculation, data processing, software development
Importance for the Industry: 1.0

Tupperware (1946)
Inventor: Earl Silas Tupper
Industry Use: Food preservation, household products
Importance for the Industry: 0.6

Transistor (1947)
Inventors: John Bardeen, Walter Brattain, and William Shockley
Industry Use: lectronics, telecommunications, computers
Importance for the Industry: 1.0

Holography (1947)
Inventor: Dennis Gabor
Industry Use: Three-dimensional display, art, medicine, scientific research
Importance for the Industry: 0.7

Manchester Mark 1 (1948)
Inventors: Frederic C. Williams, Tom Kilburn, and Geoff Tootill
Industry Use: Electronic calculation, data processing, software development
Importance for the Industry: 0.9

Velcro (1948)
Inventor: Georges de Mestral
Industry Use: Textile, fashion, aerospace sector, medical devices
Importance for the Industry: 0.7

Jet Aircraft (1944, series production year)
Inventors: Various engineers and scientists, including Frank Whittle and Hans von Ohain
Industry Use: Air transportation, defense, aerospace industry

Importance for the Industry: 0.9

Radioactive Nucleic Acid (1944)
Inventors: George Beadle and Edward Tatum
Industry Use: Genetic research, biotechnology, medicine
Importance for the Industry: 0.8

Solar Cell (1946)
Inventors: Russell Ohl and other scientists at Bell Labs
Industry Use: Light sensors, light measurement, solar panels, telecommunications
Importance for the Industry: 0.8

Tupperware (1946)
Inventor: Earl Silas Tupper
Industry Use: Food storage, household products
Importance for the Industry: 0.6

ENIAC (1946)
Inventors: John Mauchly and J. Presper Eckert
Industry Use: Electronic computing, data processing, software development
Importance for the Industry: 1.0

Holography (1947)
Inventor: Dennis Gabor
Industry Use: Three-dimensional visualization, art, medicine, scientific research
Importance for the Industry: 0.7

Transistor (1947)
Inventors: John Bardeen, Walter Brattain, and William Shockley
Industry Use: Electronics, telecommunications, computers
Importance for the Industry: 1.0

Velcro (1948)
Inventor: Georges de Mestral
Industry Use: Textile, fashion, aerospace sector, medical devices
Importance for the Industry: 0.7

Manchester Mark 1 (1948)
Inventors: Frederic C. Williams, Tom Kilburn, and Geoff Tootill
Industry Use: Electronic computing, data processing, software development
Importance for the Industry: 0.9

Instant Polaroid Camera (1948, widely commercialized in 1950)
Inventor: Edwin Land
Industry Use: Photography, entertainment, professional applications

Importance for the Industry: 0.6

Inertial Navigation Systems (1950–1960)
Inventors: Charles Stark Draper and his team at MIT
Industry Use: Aviation, space, military vehicles
Importance for the Industry: 0.7

Bipolar Junction Transistor (1951)
Inventors: John Bardeen, Walter Brattain, and William Shockley
Industry Use: Electronics, communications, computing
Importance for the Industry: 1.0

IBM 701 (1952)
Inventor: IBM
Industry Use: Electronic computing, data processing, software development
Importance for the Industry: 0.7

Optical Fibers (1952, first light transmission experiment)
Inventor: Narinder Singh Kapany
Industry Use: Telecommunications, high-speed data transmission, medical and industrial applications
Importance for the Industry: 0.9

Magnetic Core Memory (1953)
Inventor: Jay Forrester
Industry Use: Computer memory, data processing
Importance for the Industry: 0.8

Frequency Modulation Multiplexing (1953)
Inventor: Edwin Armstrong
Industry Use: Radio broadcasting, communications
Importance for the Industry: 0.6

Doppler Radar (1954)
Inventor: Bernard Gordon
Industry Use: Aviation, meteorology, security
Importance for the Industry: 0.7

Teflon (1954, household applications)
Inventor: Roy Plunkett
Industry Use: Non-stick coatings, corrosion-resistant components, engineering and aerospace applications
Importance for the Industry: 0.7

Photovoltaic Cell (1954, first silicon solar cell)
Inventors: Daryl Chapin, Calvin Fuller, and Gerald Pearson
Industry Use: Solar energy production, electronics and communications applications

Importance for the Industry: 0.8

Polypropylene (1954)
Inventors: Giulio Natta and Karl Ziegler
Industry Use: Plastics, packaging, textiles, automotive components
Importance for the Industry: 0.8

20-High Rolling Mill (1954, widespread adoption)
Inventor: Tadeusz Sendzimir (invented in 1933)
Industry Use: Steel production, cost reduction, and improved steel quality
Importance for the Industry: 0.7

Videotape Recorder (1956)
Inventors: Charles Ginsburg and his team at Ampex Corporation
Industry Use: Television broadcasting, video recording, film production
Importance for the Industry: 0.7

Hard Disk Drive (1956)
Inventors: Reynold B. Johnson and his team at IBM
Industry Use: Computer memory, data processing
Importance for the Industry: 0.9

FORTRAN Programming Language (1957, compiler released)
Inventors: John Backus and his team at IBM
Industry Use: Computer programming, engineering, scientific research
Importance for the Industry: 0.8

Pulse Code Modulation (PCM) for Telephone Transmission (1957, first commercial system)
Inventors: Paul M. Rainey (conceived in 1921), Alec Reeves (further developed in 1937)
Industry Use: Telecommunications, digital data transmission
Importance for the Industry: 0.8

Electronic Fuel Injection (1957–1959)
Inventor: Bosch (company)
Industry Use: Automotive, improved efficiency of internal combustion engines
Importance for the Industry: 0.7

Microchip (1958)
Inventors: Jack Kilby and Robert Noyce (independently)
Industry Use: Electronics, computers, telecommunications
Importance for the Industry: 1.0

Super Glue (1958)
Inventor: Harry Coover
Industry Use: Industrial and household adhesives

Importance for the Industry: 0.6

LISP Language (1958)
Inventor: John McCarthy
Industry Use: Programming language for artificial intelligence and research
Importance for the Industry: 0.7

ALGOL Language (1958)
Inventors: International group of researchers, including John Backus and Peter Naur
Industry Use: Programming language, foundation for many other programming languages
Importance for the Industry: 0.7

First Commercial Nuclear Power Plant (1958)
Inventors: Various scientists and engineers involved in the design and construction of the plant
Industry Use: Electricity production
Importance for the Industry: 0.8

Alkaline Batteries (1959, widespread distribution)
Inventor: Lewis Urry
Industry Use: Electronics, portable devices, toys
Importance for the Industry: 0.7

Hovercraft (1959, application)
Inventor: Sir Christopher Cockerell
Industry Use: People and cargo transportation, military vehicles, research and rescue vehicles
Importance for the Industry: 0.6

COBOL Language (1959)
Inventors: Grace Hopper and her team (CODASYL)
Industry Use: Computer programming, business and government applications
Importance for the Industry: 0.8

Laser (1960)
Inventor: Theodore H. Maiman
Industry Use: Communications, medicine, research, industry
Importance for the Industry: 0.9

First Oral Contraceptive Pill (1960, widespread use)
Inventors: Gregory Pincus, Min Chueh Chang, and John Rock
Industry Use: Birth control, pharmaceuticals
Importance for the Industry: 0.7

Transit Satellite Navigation System (1960, first satellite launched)

Inventors: Research team from the Johns Hopkins University Applied Physics Laboratory
Industry Use: Navigation, telecommunications, weather and climate monitoring
Importance for the Industry: 0.7

Artificial Heart Valves (1960)
Inventors: Dr. Albert Starr and Lowell Edwards
Industry Use: Cardiovascular surgery, medical devices, treatment of heart diseases
Importance for the Industry: 0.7

COBOL programming language (1961)
Inventors: Grace Hopper and her team (CODASYL)
Industry Use: Computer programming, database management, business applications
Importance for the Industry: 0.8

Videodisc (1961)
Inventors: David Paul Gregg and his team at MCA/Philips
Industry Use: Video playback, home entertainment, data storage
Importance for the Industry: 0.6

LED (Light Emitting Diode) (1962)
Inventor: Nick Holonyak Jr.
Industry Use: Lighting, displays, electronic signaling
Importance for the Industry: 0.9

Quartz clock (1962)
Inventors: Warren Marrison (initial development in 1927), Seiko (first quartz wristwatch in 1969)
Industry Use: Watchmaking, precision equipment, timing systems
Importance for the Industry: 0.8

Semiconductor laser (1962, first prototype) (1966, first commercial model)
Inventors: Robert N. Hall (prototype), Nick Holonyak Jr. (commercial)
Industry Use: Telecommunications, barcode readers, laser surgery
Importance for the Industry: 0.8

BASIC programming language (1964)
Inventors: John Kemeny and Thomas Kurtz
Industry Use: Computer programming, educational and scientific applications
Importance for the Industry: 0.7

Geostationary satellite navigation system (1964, first satellite launched)

Inventors: NASA and MIT research team
Industry Use: Navigation, telecommunications, weather and climate monitoring
Importance for the Industry: 0.8

Integrated Circuit Computer (1964, first commercial model)
Inventors: Robert Noyce and Jack Kilby
Industry Use: Computers, electronics, telecommunications
Importance for the Industry: 1.0

PL/I programming language (1964)
Inventors: IBM and SHARE (a consortium of IBM users)
Industry Use: Computer programming, business and scientific applications
Importance for the Industry: 0.6

Mouse (1964, first prototype) (1968, public demonstration)
Inventor: Douglas Engelbart
Industry Use: Computers, input devices, human-computer interaction
Importance for the Industry: 0.8

Portable Video Camera (1965)
Inventors: Charles Ginsburg and his team at Ampex Corporation
Industry Use: Film production, television broadcasting, video recording
Importance for the Industry: 0.7

Kevlar Synthetic Fiber (1965)
Inventor: Stephanie Kwolek
Industry Use: Strong material for bulletproof vests, helmets, cables, tires
Importance for the Industry: 0.9

SRAM (Static Random Access Memory) (1965)
Inventor: John Schmidt
Industry Use: Computer memory, electronic devices, microcontrollers
Importance for the Industry: 0.7

Fiber optic cable (1966)
Inventors: Charles K. Kao and George Hockham
Industry Use: Telecommunications, data transmission, communication networks
Importance for the Industry: 0.9

DRAM (Dynamic Random Access Memory) (1966, first prototype) (1968, first commercial model)
Inventor: Robert H. Dennard at IBM
Industry Use: Computer memory, electronic devices, storage devices
Importance for the Industry: 0.9

ATM (Automated Teller Machine) (1967, first installed model)
Inventor: John Shepherd-Barron

Industry Use: Banking services, electronic payments, retail commerce
Importance for the Industry: 0.8

ALGOL 68 programming language (1968)
Inventors: ALGOL Committee (international group of computer science experts)
Industry Use: Computer programming, scientific research, academic applications
Importance for the Industry: 0.6

QWERTY keyboard (1968, electronic version)
Inventors: Christopher Latham Sholes (mechanical version in 1868), IBM (electronic version)
Industry Use: Computers, input devices, typewriters
Importance for the Industry: 0.8

Liquid Crystal Display (LCD) (1968, first prototype) (1972, first commercial model)
Inventors: George H. Heilmeier and his team at RCA Laboratories
Industry Use: Computer screens, TVs, mobile devices, clocks
Importance for the Industry: 0.9

Laptop computer (1968)
Inventor: Alan Kay (concept)
Industry Use: Computers, mobile devices, business and personal applications
Importance for the Industry: 0.8

Magnetic stripe credit card (1969)
Inventor: IBM
Industry Use: Electronic payments, banking services, retail commerce
Importance for the Industry: 0.8

UNIX operating system (1969)
Inventors: Ken Thompson, Dennis Ritchie and their team at Bell Labs
Industry Use: Computer operating systems, server applications, research and development
Importance for the Industry: 0.9

Excimer laser (1970)
Inventors: Nikolai Basov and Yuri Popov
Industry Use: Eye surgery, microfabrication, scientific research
Importance for the Industry: 0.7

Pascal programming language (1970)
Inventor: Niklaus Wirth
Industry Use: Computer programming, computer education, software applications

Importance for the Industry: 0.7

E-mail (1971)
Inventor: Ray Tomlinson
Industry Use: Communications, collaboration, internet services
Importance for the Industry: 0.9

Microprocessor (1971, invention of the Intel 4004 processor)
Inventors: Ted Hoff, Federico Faggin, Stanley Mazor, and Masatoshi Shima at Intel
Industry Use: Computers, electronics, telecommunications, industrial automation
Importance for the Industry: 1.0

Magnetic resonance imaging (MRI) (1971, first prototype) (1973, first experiment on a human)
Inventors: Raymond Damadian and Paul Lauterbur
Industry Use: Medical imaging diagnostics, biomedical research, neuroscience
Importance for the Industry: 0.9

C programming language (1972)
Inventor: Dennis Ritchie at Bell Labs
Industry Use: Computer programming, operating systems, software applications
Importance for the Industry: 0.9

Ethernet (1973)
Inventors: Robert Metcalfe and his team at Xerox PARC
Industry Use: Computer networks, communications, data transmission
Importance for the Industry: 0.9

PET bottle (1973)
Inventor: Nathan Weith, Du Pont employee
Industry Use: Beverage and liquid storage
Importance for the Industry: 0.8

Three-way automotive catalyst (1973)
Inventor: Engelhard Corporation
Industry Use: Reduction of pollutant emissions in internal combustion engines, environmental protection
Importance for the Industry: 0.8

SQL programming language (1974, developed) (1979, standardized)
Inventors: Donald D. Chamberlin e Raymond F. Boyce at IBM
Industry Use: Database managing, enterprises applications, computer programming

Importance for the Industry: 0.9

PostScript (1975, developed)
Inventors: John Warnock and Charles Geschke at Adobe Systems
Industry Use: Vector graphics, digital printing, electronic publishing
Importance for the Industry: 0.8

DNA sequencing (1975)
Inventors: Frederick Sanger and his team
Industry Use: Genetic research, medical diagnostics, biotechnology
Importance for the Industry: 0.9

Apple I computer (1976)
Inventors: Steve Wozniak and Steve Jobs
Industry Use: Personal computer, productivity, software development
Importance for the Industry: 0.8

Photovoltaic technology (1976, first large-scale installation)
Inventors: Various, based on semiconductor technology
Industry Use: Renewable energy, electricity generation, CO2 emissions reduction
Importance for the Industry: 0.9

Fuel cell technology (1977, first commercial prototype)
Inventors: Various, based on previous research
Industry Use: Energy production, transportation, CO2 emissions reduction
Importance for the Industry: 0.8

Commodore PET computer (1977)
Inventors: Chuck Peddle and his team at Commodore International
Industry Use: Personal computer, productivity, software development
Importance for the Industry: 0.7

TRS-80 computer (1977)
Inventors: Don French and Steve Leininger at Tandy Corporation
Industry Use: Personal computer, productivity, software development
Importance for the Industry: 0.7

Apple II computer (1977)
Inventors: Steve Wozniak and Steve Jobs
Industry Use: Personal computer, productivity, software development
Importance for the Industry: 0.8

Atari 2600 computer (1977)
Inventors: Joe Decuir, Jay Miner, and the Atari team
Industry Use: Video game console, entertainment, video game industry
Importance for the Industry: 0.6

Free-electron laser (1977)

Inventors: John Madey and his team at Stanford University
Industry Use: Scientific research, medicine, industry
Importance for the Industry: 0.6

In vitro fertilization (IVF) (1978, first application)
Inventors: Patrick Steptoe, Robert Edwards, and Jean Purdy
Industry Use: Reproductive medicine, fertility therapies, genetic research
Importance for the Industry: 0.9

Recombinant DNA technology (1978)
Inventors: Herbert Boyer and Stanley Cohen
Industry Use: Biotechnology, medicine, genetic research
Importance for the Industry: 1

Walkman (1979)
Inventor: Sony Corporation
Industry Use: Portable audio devices, personal entertainment, music industry
Importance for the Industry: 0.8

High Electron Mobility Transistor (HEMT) (1979, initial development)
Inventors: Takashi Mimura
Industry Use: Electronics, telecommunications, radar
Importance for the Industry: 0.8

VisiCalc (1979, release date)
Inventors: Dan Bricklin and Bob Frankston
Industry Use: Spreadsheet software, productivity, financial analysis
Importance for the Industry: 0.8

C++ programming language (1980, developed) (1983, published)
Inventor: Bjarne Stroustrup
Industry Use: Computer programming, operating systems, software applications, video games
Importance for the Industry: 0.9

Scanning Tunneling Microscope (STM) (1981)
Inventors: Gerd Binnig and Heinrich Rohrer
Industry Use: Scientific research, nanotechnology, materials research
Importance for the Industry: 0.8

IBM PC (1981)
Inventors: IBM development team
Industry Use: Personal computers, productivity, software development
Importance for the Industry: 0.9

Osborne 1 Portable Computer (1981)
Inventor: Adam Osborne

Industry Use: Portable personal computers, productivity, software development
Importance for the Industry: 0.7

Compact Disc (CD) (1982)
Inventors: Philips and Sony
Industry Use: Data storage, video playback, home entertainment
Importance for the Industry: 0.7

Grid Compass 1101 Laptop (1982)
Inventor: Bill Moggridge
Industry Use: Portable personal computers, productivity, software development
Importance for the Industry: 0.4

ARPANET (1982, TCP/IP protocol definition)
Inventors: Vint Cerf, Bob Kahn, and their team
Industry Use: Computer network, communications, data transmission
Importance for the Industry: 0.9

Musical Instrument Digital Interface (MIDI) (1983)
Inventors: Dave Smith and Ikutaro Kakehashi
Industry Use: Communication between electronic musical instruments, music production, performance
Importance for the Industry: 0.8

C programming language (ANSI C Standard) (1983, standardized)
Inventor: Dennis Ritchie
Industry Use: Computer programming, operating systems, software applications
Importance for the Industry: 0.9

3.5-inch Hard Disk Drive (1983)
Inventors: IBM development team
Industry Use: Data storage, productivity, software development
Importance for the Industry: 0.8

Cellular Phones (1983, first commercial mobile phone, Motorola DynaTAC 8000X)
Inventors: Martin Cooper and the Motorola team
Industry Use: Telecommunications, mobile communication, mobile internet
Importance for the Industry: 1

Microsoft Word (1983)
Inventors: Microsoft development team
Industry Use: Word processing, productivity, documentation

Importance for the Industry: 0.8

Polymerase Chain Reaction (PCR) (1983)
Inventor: Kary Mullis
Industry Use: Genetic research, medical diagnostics, biotechnology
Importance for the Industry: 0.9

Ethernet (IEEE 802.3 Standard) (1983, standardized)
Inventors: Robert Metcalfe, David Boggs, and the Xerox PARC team
Industry Use: Computer networks, data transmission, IT infrastructure
Importance for the Industry: 0.9

Nintendo Entertainment System (NES) (1983, launch in Japan; 1985, launch in the United States)
Inventors: Masayuki Uemura and the Nintendo development team
Industry Use: Video game console, entertainment, video game industry
Importance for the Industry: 0.6

Apple Macintosh (1984)
Inventors: Jef Raskin, Burrell Smith, Bill Atkinson, Andy Hertzfeld, and the Apple development team
Industry Use: Personal computer, productivity, software development
Importance for the Industry: 0.8

Adobe PostScript (1984)
Inventors: John Warnock and Charles Geschke
Industry Use: Vector graphics, printing, desktop publishing
Importance for the Industry: 0.9

3D printing (1984)
Inventor: Charles Hull
Industry Use: Rapid prototyping, additive manufacturing, 3D modeling
Importance for the Industry: 0.8

Microsoft Windows operating system (1985)
Inventors: Microsoft development team
Industry Use: Operating systems, productivity, software development
Importance for the Industry: 0.9

Amiga 1000 (1985)
Inventors: Commodore development team
Industry Use: Personal computer, music and video production, video game development
Importance for the Industry: 0.4

Cray-2 Supercomputer (1985)
Inventors: Seymour Cray and the Cray development team
Industry Use: Scientific research, weather forecasting, nuclear weapons simulation

Importance for the Industry: 0.8

DNA Fingerprinting (1985, first application)
Inventor: Sir Alec Jeffreys
Industry Use: Law, forensic medicine, genetic research
Importance for the Industry: 0.8

High Definition Television (HDTV) (1986, Japanese standard)
Inventors: NHK Science & Technology Research Laboratories
Industry Use: Television broadcasting, entertainment, advertising
Importance for the Industry: 0.9

High-Speed DNA Sequencing (1986)
Inventors: Leroy Hood and Lloyd Smith
Industry Use: Genetic research, medicine, biotechnology
Importance for the Industry: 0.9

Mammalian Cloning from Embryonic Cells (1986, first successful in a sheep)
Inventor: Steen Willadsen
Industry Use: Genetic research, medicine, agriculture
Importance for the Industry: 0.8

Atomic Force Microscope (1986)
Inventors: Gerd Binnig, Calvin Quate, Christoph Gerber
Industry Use: Scientific research, nanotechnology, medicine
Importance for the Industry: 0.8

MP3 (1987, initial development; released 1994)
Inventors: Fraunhofer Institute development team
Industry Use: Digital audio, music, entertainment
Importance for the Industry: 0.9

Antivirus Software (1987, first antivirus software for PC)
Inventor: Bernd Fix
Industry Use: Cybersecurity, data protection, IT infrastructure
Importance for the Industry: 0.9

Prozac (1987)
Inventors: Eli Lilly development team
Industry Use: Pharmaceuticals, mental health, depression treatment
Importance for the Industry: 0.9

Statins (1987, FDA approval for lovastatin)
Inventors: Akira Endo and his team
Industry Use: Pharmaceutical, hypercholesterolemia treatment
Importance for the Industry: 0.9

High-Field Magnetic Resonance Imaging (MRI) (1987, market diffusion)

Inventors: Paul C. Lauterbur, Peter Mansfield, and others
Industry Use: Medical diagnostics, medical research
Importance for the Industry: 0.9

Digital Cellular Technology (GSM) (1988, finalized specification)
Inventors: Groupe Spécial Mobile
Industry Use: Mobile communications, telecommunications
Importance for the Industry: 1

Humanized Monoclonal Antibody (1988)
Inventors: Greg Winter and his team at the MRC Laboratory of Molecular Biology
Industry Use: Medicine, immunotherapy, medical research
Importance for the Industry: 0.9

Macintosh Portable Laptop (1989)
Inventors: Apple development team
Industry Use: Portable personal computers, productivity, software development
Importance for the Industry: 0.7

World Wide Web (1989, proposed)
Inventor: Tim Berners-Lee
Industry Use: Communication, e-commerce, entertainment
Importance for the Industry: 1

Game Boy (1989)
Inventors: Gunpei Yokoi and the Nintendo development team
Industry Use: Portable video game console, entertainment, video game industry
Importance for the Industry: 0.6

Global Positioning System (GPS) (1989, full operational capability)
Inventors: U.S. Department of Defense
Industry Use: Navigation, transportation, geolocation
Importance for the Industry: 1

Microsoft Windows 3.0 (1990)
Inventors: Microsoft development team
Industry Use: Operating systems, productivity, software development
Importance for the Industry: 0.9

Microsoft Office (1990, first version)
Inventors: Microsoft development team
Industry Use: Productivity, word processing, presentations
Importance for the Industry: 0.9

Functional Magnetic Resonance Imaging (fMRI) (1990, initial development)

Inventor: Seiji Ogawa
Industry Use: Neuroscience, medical diagnosis, research
Importance for the Industry: 0.8

Python Programming Language (1990)
Inventor: Guido van Rossum
Industry Use: Software development, artificial intelligence, web development
Importance for the Industry: 0.9

Sega Mega Drive (Genesis in North America) (1990, launch in Europe and diffusion)
Inventors: Sega
Industry Use: Entertainment, video games
Importance for the Industry: 0.5

HTML (HyperText Markup Language) (1990, proposed; first publication 1993)
Inventor: Tim Berners-Lee
Industry Use: Web development, e-commerce, communication
Importance for the Industry: 1

Linux (1991)
Inventor: Linus Torvalds
Industry Use: Operating systems, servers, supercomputers
Importance for the Industry: 0.9

Wi-Fi (1991, initial development)
Inventors: NCR Corporation/AT&T
Industry Use: Communication, internet, wireless technology
Importance for the Industry: 1

GSM (Global System for Mobile Communications) Network (1991, first operational system)
Inventors: Mobile Standards Group of the European Telecommunications Standards Institute
Industry Use: Communication, mobile telephony, mobile data
Importance for the Industry: 1

SIM Card (GSM) (1991, first commercial introduction) (widespread global adoption starting from 1998)
Inventors: Giesecke & Devrient for the GSM consortium
Industry Use: Mobile telephony, user identification, security
Importance for the Industry: 1

SMS (Short Message Service) (1992, first message sent)
Inventors: Friedhelm Hillebrand and Bernard Ghillebaert
Industry Use: Communication, marketing, social media

Importance for the Industry: 0.9

Super Nintendo Entertainment System (SNES) (1992, global distribution)
Inventors: Nintendo
Industry Use: Entertainment, video games
Importance for the Industry: 0.6

PDF (Portable Document Format) (1993)
Inventors: Adobe development team
Industry Use: Document sharing, printing, publishing
Importance for the Industry: 0.9

Windows NT 3.1 (1993)
Inventors: Microsoft development team
Industry Use: Operating systems, productivity, software development
Importance for the Industry: 0.9

Mosaic Web Browser (1993)
Inventors: Marc Andreessen and Eric Bina
Industry Use: Web browsing, e-commerce, communication
Importance for the Industry: 0.9

Yahoo! (1994)
Inventors: Jerry Yang and David Filo
Industry Use: Internet search, advertising, information
Importance for the Industry: 0.9

Amazon (1994)
Inventor: Jeff Bezos
Industry Use: E-commerce, distribution, cloud computing
Importance for the Industry: 0.9

QR Code (1994)
Inventors: Masahiro Hara at Denso Wave
Industry Use: Marketing, product traceability, mobile connectivity
Importance for the Industry: 0.8

SSL (Secure Sockets Layer) (1994–1995)
Inventors: Netscape Communications
Industry Use: Internet security, e-commerce, data protection
Importance for the Industry: 1

DVD (Digital Versatile Disc) (1995, initial development)
Inventors: Philips, Sony, Toshiba, Panasonic
Industry Use: Entertainment, data storage, computer
Importance for the Industry: 0.9

Java (programming language) (1995)
Inventor: James Gosling at Sun Microsystems

Industry Use: Software development, web applications, embedded systems
Importance for the Industry: 0.9

Apache HTTP Server (1995)
Inventors: Robert McCool and the Apache development team
Industry Use: Web hosting, web development, e-commerce
Importance for the Industry: 0.9

PlayStation (1995, Europe and US launch)
Inventors: Sony Computer Entertainment
Industry Use: Entertainment, video games, multimedia
Importance for the Industry: 0.6

Sega Saturn (1995, global release)
Inventors: Sega
Industry Use: Entertainment, video games, multimedia
Importance for the Industry: 0.5

RealAudio (1995)
Inventors: RealNetworks
Industry Use: Audio streaming, entertainment, communication
Importance for the Industry: 0.6

JavaScript (1995)
Inventor: Brendan Eich at Netscape Communications
Industry Use: Web development, web interactivity, web applications
Importance for the Industry: 0.9

Cloning of mammals from adult cells (1996, first success in a sheep)
Inventors: Team led by Ian Wilmut at the Roslin Institute
Industry Use: Genetic research, medicine, agriculture
Importance for the Industry: 0.8

USB (Universal Serial Bus) (1996)
Inventors: Ajay Bhatt, Bala Cadambi, Shaun Knoll, Shelagh Callahan
Industry Use: Hardware connectivity, data transfer, device charging
Importance for the Industry: 1

Palm Pilot (1996, realization)
Inventors: Palm, Inc.
Industry Use: Productivity, personal digital assistants (PDAs), organization
Importance for the Industry: 0.6

Flash Memory (1996, standardization)
Inventors: Fujio Masuoka at Toshiba, with significant contributions from Samsung and others
Industry Use: Data storage, consumer electronics, mobile devices

Importance for the Industry: 0.9

Nokia 9000 Communicator (1996)
Inventors: Nokia
Industry Use: Communication, productivity, mobile telephony
Importance for the Industry: 0.7

XML (eXtensible Markup Language) (1996, initial development)
Inventors: W3C
Industry Use: Data transfer, web development, system integration
Importance for the Industry: 0.9

Adobe Flash (originally FutureSplash Animator, 1996)
Inventors: Jonathan Gay, Robert Tatsumi, Michelle Welsh, Charlie Jackson
Industry Use: Web development, animation, online games
Importance for the Industry: 0.8

Wi-Fi (802.11 Standard) (1997)
Inventor: IEEE
Industry Use: Communication, internet, wireless technology
Importance for the Industry: 0.6

Six Degrees (1997, first social networking site)
Inventor: Andrew Weinreich
Industry Use: Social media, communication, marketing
Importance for the Industry: 0.7

Google Search Engine (1998)
Inventors: Larry Page and Sergey Brin
Industry Use: Internet search, advertising, information
Importance for the Industry: 1

MP3 Player (1998, first commercial player)
Inventor: Tomislav Uzelac at Advanced Media Products
Industry Use: Entertainment, digital music
Importance for the Industry: 0.8

PayPal (1998)
Inventors: Peter Thiel, Max Levchin, Luke Nosek, Elon Musk
Industry Use: Finance, online payments, e-commerce
Importance for the Industry: 0.9

Hypersonic Sound Technology (1998)
Inventor: Elwood "Woody" Norris
Industry Use: Audio, advertising, defense technology
Importance for the Industry: 0.7

Apple iMac G3 (1998)
Inventor: Apple Inc.

Industry Use: Computing, design, multimedia
Importance for the Industry: 0.6

Wi-Fi (802.11b Standard) (1999)
Inventor: IEEE
Industry Use: Communication, internet, wireless technology
Importance for the Industry: 0.6

Bluetooth (1999, standard release)
Inventor: Ericsson
Industry Use: Communication, device connectivity, Internet of Things (IoT)
Importance for the Industry: 1

TiVo (1999)
Inventors: Jim Barton and Mike Ramsay
Industry Use: Entertainment, digital television, digital video recording
Importance for the Industry: 0.8

Blogging (1999, opening of Blogger)
Inventor: Pyra Labs
Industry Use: Communication, social media, marketing
Importance for the Industry: 0.8

File Sharing (Napster) (1999)
Inventors: Shawn Fanning, Sean Parker, John Fanning
Industry Use: Entertainment, music, digital distribution
Importance for the Industry: 0.7

BlackBerry (2000)
Inventor: Research in Motion
Industry Use: Communication, mobile email, productivity
Importance for the Industry: 0.7

PlayStation 2 (2000, global release)
Inventors: Sony Computer Entertainment
Industry Use: Entertainment, video games, multimedia
Importance for the Industry: 0.7

Windows 2000 (2000)
Inventor: Microsoft
Industry Use: Operating systems, productivity, software development
Importance for the Industry: 0.8

Human Genome Project (2000, complete sequencing)
Inventors: International collaboration of scientists led by the National Institutes of Health and the Wellcome Trust
Industry Use: Biomedical research, genetics, personalized medicine

Importance for the Industry: 1

GPS (Global Positioning System) for Civilian Use (2000)
Inventor: United States Department of Defense
Industry Use: Navigation, geolocation, mapping, telecommunications
Importance for the Industry: 1