Technological Forecasting & Social Change 78 (2011) 303–318

Contents lists available at ScienceDirect

Technological Forecasting & Social Change

New relationships between production and patent activity during the high-growth life cycle stage for materials

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A R T I C L E I N F O

Article history:
Received 4 November 2009
Received in revised form 8 September 2010
Accepted 14 October 2010

Keywords:
Patents
Innovation
Invention
Life cycle
Life-stage
Correlation
Innovation constant
Innovation-modified resources

A B S T R A C T

A comparison of the life cycle plots for the production and patent activity for several materials indicates that the two life cycle plots may be correlated to such an extent that they may be superimposed to a large degree, for all growth-stages, simply by an origin shift. Over fifty metallic and non-metallic materials have been studied. This origin shift may be indicative of the presence of Stage III (high-growth stage). The drive force ratio for innovation-enhanced supply also scales with the origin shift. When the drive force ratio is equal to one, the materials in their Stage III life, are balanced in the amount of resources which impact production and patents. One of the key findings is that materials may be grouped into two groups depending on their drive ratio and the lag ratio in the data sets of the production and patent activity. In the first group, innovation is unable to influence the production activity and consequently materials tend to slide towards Stage IV (i.e. the stage of low average growth with high oscillation) regardless of the fact that patents may impact unit production significantly in this group. The existence of a Stage V (final death stage) is also discussed. It appears that materials that have been recognized to be highly toxic are particularly prone to a Stage V type behavior.

1. Introduction

This article expands our previously published research [1–3] on the long-term life cycle pattern, best-fit analysis, to over fifty materials. The selected materials are listed in Table 1 and are not only chosen for the availability of complete sets of production and patent data between the years of 1900 and 2007, but also as representatives of a wide variety of materials, their production processes and their applications.

The primary goal of this work is to discover relationships between patents (technical inventions) and how such relationships affect, or are affected by, global material production (innovation stages) [1–3]. During the 21st Century, which is a period of knowledge driven economies, it has been demonstrated that intellectual property could be a dominant force providing the capital that will continue to drive future worldwide economic growth [1,4–54]. However, there is no clear quantitative connection that has been established between patents and products excepted in recent articles [1–3]. Sekhar et al. [2,3] have clearly demarcated the difference between invention and innovation based on the overall long-term life cycle. In this article, further correlations are made between the production innovation activity i.e. Stage III and patent activity in a similar Stage III or beyond for the overall life cycle for both quantities. Several other methods have been employed to measure and define inventions and innovation starting with the work of Joseph Schumpeter [55–57]. The literature is divided as to whether or not patents (inventions) are the best way to describe innovation, but a majority of this opinion seems to favor the use of patents as measurable indicators of innovation [58–77]. A certain amount of quality seems to be inferred into all patents issued due to the cost and expectation of profit in obtaining patent protection. Although there are some applications of the *quality* of patents, such as, applying a "patent success ratio" [75] or

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doi:10.1016/j.techfore.2010.10.004

Table 1
Materials studied.

Aluminum	Antimony	Arsenic	Asbestos	Barite
Bauxite/alumina	Beryllium	Bismuth	Boron	Cadmium
Chromium	Cobalt	Copper	Feldspar	Fluorspar
Gold	Graphite	Gypsum	Helium	Hydraulic cement
Iodine	Iron	Kyanite	Lead	Lithium
Magnesite	Magnesium	Manganese	Mercury	Molybdenum
Nickel	Niobium	Nitrogen	Phosphate	Platinum
Potash	Rare earths	Salt	Selenium	Silicon
Silver	Sulfur	Talc	Tantalum	Tin
Titanium	Tungsten	Vanadium	Zinc	Zirconium

counting the number of citations in other patents as an indication of innovativeness [76,77] the *quantity* of patents published was chosen here as the measure of innovation (particularly technical innovation) since, generally speaking, the costs in money and time associated with obtaining patent protection for inventions are expected to provide benefits that outweigh such investments [64]. Later in this article we infer that patenting itself may have constructive and destructive features for overall production.

The production data for the materials is taken from the United States Geologic Survey (USGS) mineral historical statistics compilations section from the USGS web site [78]. The data is based on yearly worldwide production and is reported in metric tons in all cases. The patent data is collected from patent searches on the European Patent Office (EPO) search engine found on the EPO web site [79]. The United States Patent and Trademark Office (USPTO) patent data base is not chosen as its on-line patent data only goes back to the 1970s. Patent searches were performed using keywords in the patent title and abstract that is descriptive of the specific material, to find yearly counts of patents. The date of publication of the patent is used to match the patent data to its corresponding production data. The USGS and EPO sites are each chosen due to their worldwide scope and completeness of their data.

Correlation theory is applied to these materials to determine if a relationship exists between the production and the patent data. A coefficient of correlation can be statistically generated to calculate the percentage of variation in the patent data that can be attributed to variations in the production data [80,81]. Best-fit analysis is then applied to the production data sets to generate the life cycles of each material, and then to the patent data sets to discover if any origin shifts in the equation result, which could indicate a driving force being present for the innovative activity that could be ascribed to the patent activity [1–3].

2. Section 1: patent activity and production activity data correlations

This section describes the method of comparison between the data gathered representing the production activity (in tons per year) of a material and the number of patents published per year for the same material. To determine if the production data and patent data sets are linear, autocorrelation analysis was conducted on both data sets for each material (Table 2). It was revealed that both the production and patent data sets for each material were non-random and linear through the presence of strong autocorrelation approaching 1 in all cases [82]. What this means is that the data is not random but it also implies that materials, which are in Stage III and Stage IV, may not be easily predictable even when a pattern equation captures all the features. In correlation theory, two data sets, x and y, are tested to determine the existence of correlation between them. In this case, x is the production activity of a specific material in metric tons per year and y represents the number of patents published involving the same material for the same year. Through correlation theory, a number called the correlation coefficient is generated that expresses the amount of correlation that exists between two groups of data [80–82]. When the coefficient is squared and then multiplied by 100 a percentage is given, which expresses the total variation of the values of group y that can be accounted for by a linear relationship with the values of group x [80,81]. In this manner, a percentage of the changes in the patent numbers of a material can be attributed to changes in the production of the material [83]. Examples of strong and weak correlations, with graphical representation of both production activity and patent activity, are discussed below in Figs. 1 and 2.

As is shown below in Table 2, most materials investigated showed some degree of correlation between their production activity and their patent activity. Although most of the materials studied showed some degree of correlation, mercury and potash showed a negative correlation, possibly expressing a lack of a linear relationship between production and patent data and indicating a percentage of non-linear correlation.

3. Section 2: best-fit

The two data sets for each material can also be used in conjunction with the common pattern equation [2,3] for the long-life cycle production of metals (production activity) initially proposed by Yerramilli and Sekhar [3] and modified by Connelly and Sekhar [1], in order to obtain the life cycle constants (for production or patent activity) for any material. A similar hypothesis for shorter life-span products, which postulates that most successful products pass through recognizable stages during their life cycles was first proposed by Levitt and has been applied by others in evaluations of industry, kinetics and business activities for various products and product groups [84–96,109,110]. The pattern equation predicts and illustrates a four-stage life cycle for metals. These four stages are the Initial Stage (I), the Lift-Off and Decay Stage (II), the Revival and Rapid Growth Stage (III) and the Survival Stage