# Mathematical Modelling of Innovation Dynamics: An Empirical Analysis of the Photovoltaic Market in Germany[1],[2]

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Abstract

The objective of this paper is the analysis of dynamics of innovation processes in science-driven markets. In order to gain deeper insight in the science-based market formation different empirical studies are taken. The empirical investigations are summarised in a stylized model which provides the basis for the econometric analysis. This paper is focused on the interaction of particular variables in the model and its reaction to exogenous parameters. The photovoltaic market (PV market) in Germany is chosen as an example for econometric modelling. Using an error-correction model (ECM) short and long term effects in interaction between patent applications and scientific publications are analysed. The results verify empirical evidence of long-run equilibrium between publications and patents and confirm the basic hypothesis that two quite different development phases due to basically different sets of determinants can be observed in the development of science-based markets. In the first period from 1973 to 1990, the oil price development influences the interdependency between science and technology. In the second period from 1991 to 2001 the Renewable Energy Sources Act and the Electricity Feed Act have significant effect on the development of science and technology.

Key words: science-based technologies, time-series analysis, non-stationarity, cointegration, error correction models.

JEL classification: C51, C32, O34, Q2

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## 1. Introduction

Technical progress and its dynamics are in the core of growth and employment problems of modern industrialised societies. Economic competition, high income, and prosperity are usually attributed to technical progress. Under the assumption that technological development shows an increasing trend towards the science base within a national innovation system, and if it is true that there is pressure from the international innovation competition of enterprises to get access to the science base of several nations, then the analysis of innovation processes in science-driven markets turns out to be of great importance for the common economic development and the competitiveness of industrialised nations. The importance of stimulation of the emerging new knowledge has been also recognized by the European Union (EU). The ambitious goals of Lisbon and Barcelona and the creation of the European Research Area (ERA) can be taken as a sure indication of this acceptance (see Commission's 2006 report; European Commission (2007)).

Certain institutional arrangements are required for creation and development of science-based technologies. However the nature of scientific knowledge has frequently a spontaneous order, i.e. it is the result of the activities from many individuals and groups, which neither individually nor collectively intend to bring about that particular state of the body of knowledge (e.g. Radnitzky (1989)). Therefore it appears to be difficult to precisely forecast the future trend of technological change. Nevertheless, it is helpful to enter into the black box of "science-based" models and try to understand the dynamics of innovation processes in science-driven markets. This paper aims to analyse the interaction of different factors like science and technological activities, state funding, legislation and the impact of external effects, such as oil price on the basis of econometrical analysis.

This paper is structured as follows: after introduction section 2 reviews some empirical investigations, which deal with the question of science-based market formation. A theoretical description of science-driven market is given. The stylized model offers descriptive summary of these empirical investigations. Section 3 considers particularly the Photovoltaic market and describes the model variables, which are selected to analyze the market development. Section 4 presents an econometric model for formation of the Photovoltaic markets. Section 5 concludes the paper by summarising the results.

## 2. Empirical Evidence and Stylized Model

The subject of this paper is the innovation process in case of science-based technologies. Unfortunately, there is not any clear, generally accepted categorisation of a specific technology as science-based. A pioneering typology for sectoral patterns of technical change was suggested by Pavitt (1984). In this empirical work Pavitt distinguishes between supplier-dominated sectors, scale-intensive sectors, special suppliers, and science-based ones. Based on an analysis of approximately 2000 innovations in British industry within the period of 1945-1979, Pavitt found typical innovation patterns in these broader sectors of industry. Innovations in science-based sectors display a close relationship to basic research and scientific progress. The innovations in these sectors require high investment in research (not only in product development), but offer properties of key technology with a strong diffusion potential in other industrial sectors (see also Martin, 1992). Marsilli (2001) suggests further splitting the science-based sectors into two main categories: the “life science-based” (drugs and bioengineering) and the “physical science-based” (computers, electrical telecommunications instruments). However, these studies offer sectoral classification. Segmentation according to technology fields was not intended.

Another quantitative possibility to identify scienced-based technologies was suggested by Narin and Noma (1985) and widely used for analytical proposes by Grupp and Schmoch (1992a); Schmoch (1993); Meyer-Krahmer and Schmoch (1998). This approach is based on the citations of scientific papers in official reports of patents. In checking the novelty of a patent application the inventors and the patent office examiners prepare a list of citations of published prior art documents. This list can include other patents or scientific publications. The patents are more preferable, because they describe technical features more clear then scientific articles. But occasionally relevant patents are not possible to find. In this case scientific papers are cited. According to this, science-based technologies are defined as fields with frequent references to scientific publications. A list of 28 technology fields, measured by the relative science reference, is documented in the work of Grupp et al. (1996). According to this study genetic engineering, pharmaceuticals and laser technology have the highest science linkage followed by telecommunications, information storage, data processing, image transmission as well as sensor technology.

The dynamics on the time scale of innovation processes in science-based markets has not been explored to a great extent. There are some empirical investigations which deal with the question of market formation in science-based sectors (Schmoch, 2007). The empirical exploration to study these special markets often uses one or several of the following indicators:

- Measurement of scientific activities based on bibliometric indicators (scientific publications) (van Raan, 1997),

- Measurement of technological development by patent applications or patent grants, respectively, and

- Measurement of installed or sold (shipped, respectively) products to grasp diffusion.

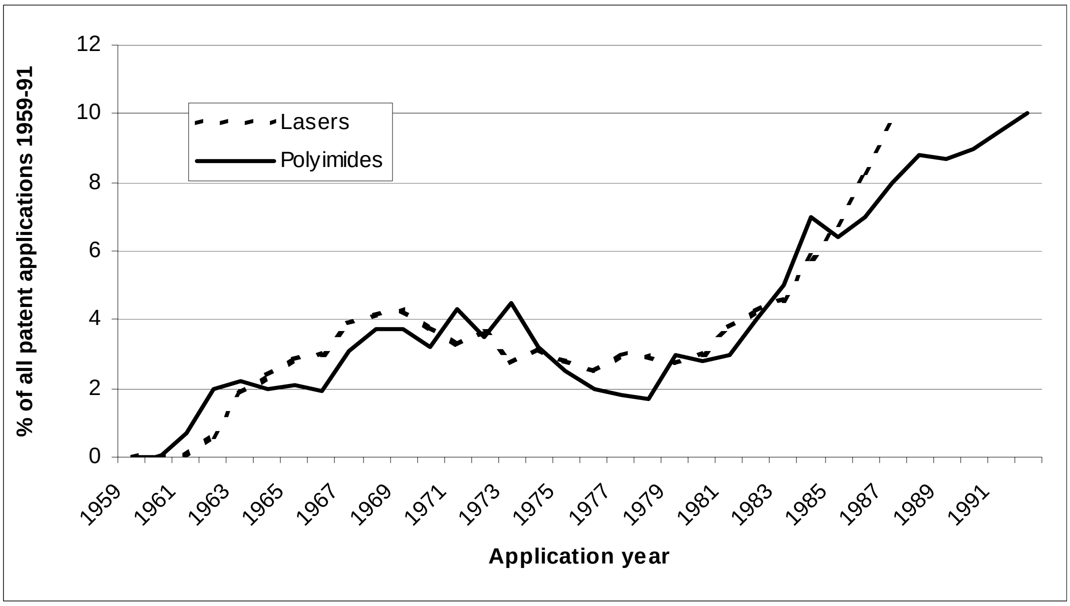



Figure 2-1: Long-term development of patent applications for lasers and polyimides from1959 to 1991.

Source: Grupp, Schmoch (1992b), p. 278.

Already at the beginning of the 1990s, patent applications for polyimides and lasers were studied and showed a characteristic non-linear pattern with two maxima (Grupp, Schmoch, 1992b). First, the number of patent applications increased continuously until a first maximum was reached. Later, the number decreased and a phase of stagnation started because the first inventions were considered not very tuned to user preferences and too much dependent on "laboratory thinking". Many years after these first activities in science and technology a second dynamic wave may start allowing patent applications to increase again and surpass the level of the first maximum (Figure 2-1).

In case of laser and polyimide basic scientific theories, the first wave of activities and the final market-driven growth lasted for a period of fifty years or more (Grupp, Schmoch, 1992b). In case of the laser market the number of scientific publications was very low during the first years of activity. Yet with an increasing number of patents also the number of scientific publications grew. From this observation it is concluded that scientific activities not always precede technological development but, due to intensive interaction in the scientific community, science and technology are intertwined.

Parallel to the observations by Grupp and Schmoch (1992b), Rickerby and Matthews (1991) described what they called the "technological commercial exploitation curve" for surface engineering (Figure 2-2). Their description is not supported by quantitative data, but is based on qualitative experience of engineers. Striking is the similarity of this qualitative experience with the indicator-based patent curves for lasers and polyimides.

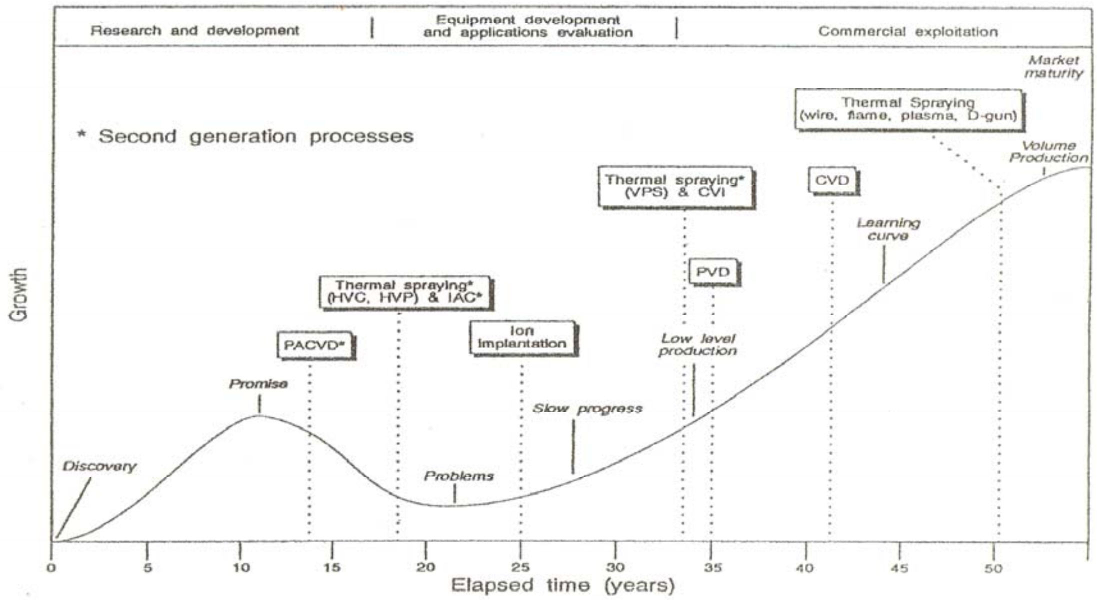



Figure 2-2: Technological commercial exploitation for surface technologies.

Source: Rickerby, Matthews (1991), p. 347.

Development of some emerging technologies are also illustrated by Gartner consultancy ([www.garthnergroup.com](http://www.garthnergroup.com)), giving a graphical modelling of the maturity, adoption and business application of specific technologies. This hype cycle approach highlights the progression of an emerging technology from market over enthusiasm through a period of disillusionment to an eventual understanding of the technology's relevance and role in a market or domain. Technologies are described in term of visibility and maturity. The dimension of visibility does not offer any clear differentiation between technology and market development but concludes both kinds of activities (Figure 2-3).

According to Gartner's Hype Cycle graph, handwriting recognition, software as service and location-aware applications have reached the bottom of the trough and are starting to climb into the "slope of enlightenment". In this phase, the majority of consumers, not just the early adopters and technology enthusiasts, start to see the benefits of the technology and become more educated.

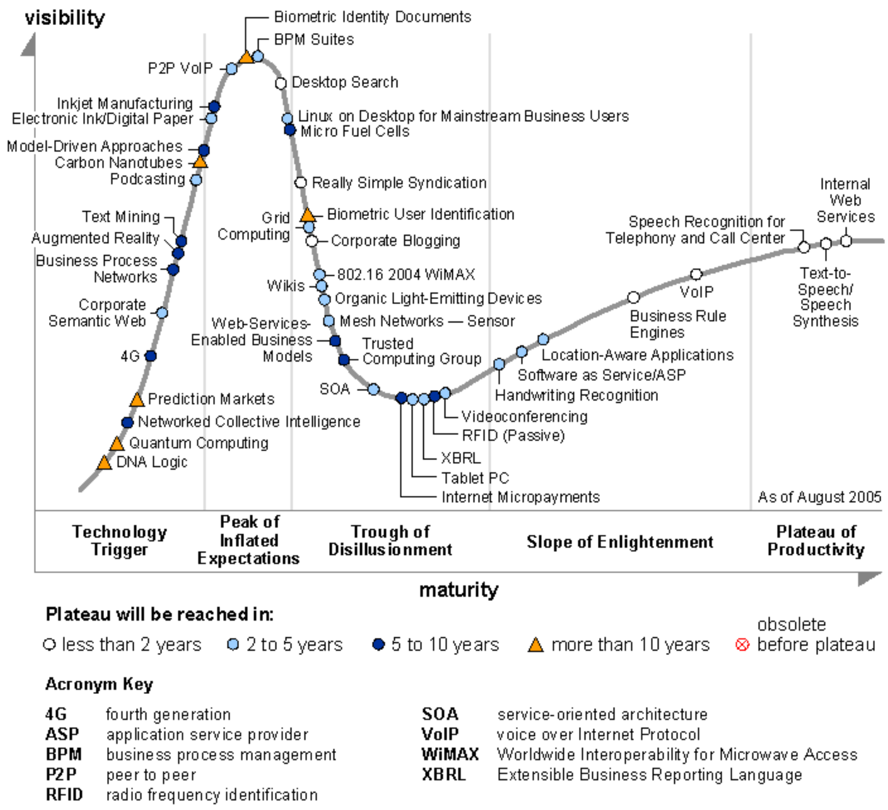



Figure 2-3: Hype Cycle for Emerging Technologies, 2005

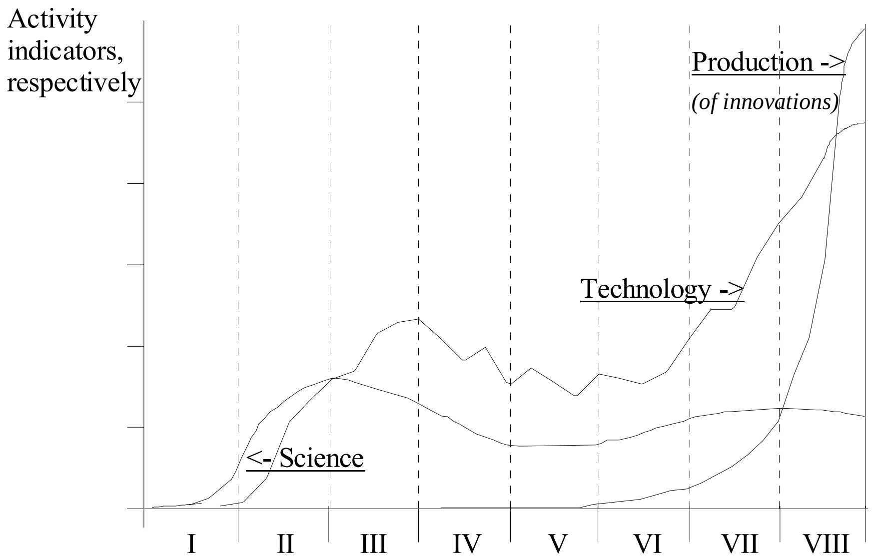
Source: Gartner(2005).

Laser, polyimides, technologies for surface engineering, genetic engineering, pharmaceuticals, emerging technologies of hype cycle represent quite different technologies in relation to scientific background, market size, industrial application, etc. The striking similarity in the development of these technologies seems to be unexpected. The reason for the “striking correspondence” is science-intensive nature of both technologies on the one hand and potential of numerous practical applications on the other hand (see also Grupp and Schmoch , 1992b, p. 282). Stokes (1997) pools such technologies together as "Pasteur's quadrant". Although research in this quadrant has potential real-world utility, its investigators never lose sight of the desire to advance scientific understanding.

Two main stages of market formation of “Pasteur’s” technologies can be distinguished. In the first phase "voice of the market" is largely absent and the development goals are oriented towards internal success in the scientific communities. (Hekkert et al. 2007). The misunderstanding or, better yet, non-interaction between the side of science and the demand side is largely due to intellectual, but also normative differences; questions of safety, standardisation, and compatibility are more often than not overlooked (Blind, 2004). Although some of these differences may be larger in perception and rhetoric than in reality, they tend to lead to stagnation and thus cause the end of the first maximum of activities as observed in the empirical studies. Consequently, the emergence of innovations is seen as "driven by individual genius" or as stochastic events (which are known as serendipity effects in basic research). If radical innovations had immediately a better price-performance ratio, then substitution on consumer markets would be a simple matter (Geels, 2006). But radical innovations are usually born as "hopeful monstrosities" (Mokyr, 1990), i. e. as interesting and promising ideas with crude performance. Much work is needed to make radical innovations technically and economically viable. Small market niches as "incubation rooms" are also essential to protect their early development. (Geels, 2005). Technical feasibility is not the same as product development and introduction to the market. Here, socio-technical alignment is required, where economics, politics, consumer circles, and aspects of quality of life play a role. But the topic of user preferences is underdeveloped in economics; what happens on the demand side remains largely a black box.

Obviously, some scientific discoveries can not break the deadlock after a first maximum of activities (Scherer, 1986). But it may also happen that further improvements and investigations open a bridge towards demand and consumer preferences after a while. The second stage of market formation begins. This regime shift may give rise to a wave of activities and, indeed, in the case studies mentioned above, this was always observed. Among the many factors that work against the introduction and diffusion of technologies, Kemp et al. (1998) mentions technological factors, government policy and regulatory frameworks, cultural and psychological factors, demand and production factors, infrastructure and maintenance, as well as undesirable social and environmental effects of new technologies. Other barriers include high investment costs, “split incentives”, lack of awareness of potential by customers as well as by policy makers and so on (Philibert, 2006). If the scientific and technological potentials of new technology fit with the demand side, market introduction and diffusion may take place.

Before turning to econometric modelling, a standardised reference scheme of the formation of science-based markets summarises empirical findings and provides basis for the further analysis (Figure 2-4). This model is to be found in Grupp (1998). Eight phases of market formation are comprised here. In the first two stages, principles and phenomena are clarified scientifically or theoretically, models are devised and the basic effects discovered. Academics, in this case extra-industrial research, are responsible for the lion’s share. In case of dominant designs (phase III and IV), industrial actors become involved in R&D, but extra-industrial research mostly with a fundamental bias, continues to be important. Even at launch of innovations (V and VI) extra-mural R&D activities of enterprises play an important part. Ultimately, it comes down to widespread utilisation and general application of new products and processes (VII and VIII), which according to imitation and diffusion arguments, likewise do not need to proceed without the extra-industrial research system (Grupp, 1998, pp. 34).




I: First explorations in the scientific domain.

II: Properly developed science; first technical achievements.

III: Science fully developed; technology still capable of extensions; prottypes.

IV: Difficulties discernible in economic transposition.

V: Temporary stagnation in science and technology; reorientations.

VI: Industrial R&D envisages new possibilities; but still capable of expansion.

VII: First commercial applications; industrial R&D fully developed.

VIII: Penetration of all markets; importance of R&D waning relative to turnover.

Figure 2-4: Standardised reference scheme of the formation of science-based markets measured by different types of indicators: publications (for science), patent applications (for technology) and installed or sold (shipped, respectively) products (for production).

Source: Grupp (1998), p. 34.

The present state in this research area provides us with a lot of studies on either the science push or the demand pull side. Most of these papers are of qualitative nature. It is the challenge of this study to reconcile both views into a formal mathematical model. The basic hypothesis is that in the development of science-based markets two quite different development phases due to basically different sets of determinants can be observed. The main aim is to transfer the stylized model (Figure 2-4) into a formal mathematical one. The interaction of particular variables in the model and reaction of models to exogenous parameter is the centre of attention.

## 3. Photovoltaic Market and Model Variables

Presently, it is still an open question whether this qualitative stylised model given in Section 2 can be transformed into a formal econometric model and verified for empirical case studies. The Photovoltaic market (PV market) in Germany is chosen as an example for econometric modelling. This decision is guided by the following factors:

(1) Strong dependency of the PV market on new scientific inventions and discoveries can be observed during common history of photovoltaic technology. Photovoltaic is the direct conversion of sunlight into electrical energy using a semiconducting material. The PV effect was discovered in 1839 by Edmond Becquerel. For a long time it was a scientific phenomenon with few device applications. The problem of the first practical solar cells was their lower degree of efficiency. After the introduction of silicon as the prime semiconductor material in the 1950s, silicon PV diodes became available (see Shah et al. 1999). The new way to make silicon solar cells helped reach an efficiency of nearly 6 percent. In the 1954 a solar-powered radio transmitter was presented at a meeting of the National Academy of Science. Technological improvement continued and solar cells with higher efficiency were developed. But commercial success evaded solar cells because of their prohibitive cost in the research and manufacturing processes. The industrial development in the 20th century and the use of fossil fuels slowed down research in the area of photovoltaic energy. Until 1960 this type of technology was used in situations where electrical power from the grid was unavailable, such as in space industry for satellites. Due to enormous oil and gas prices in the late 1970s and early 1980s many governments were forced to consider alternative technologies. This resulted in rapid development of photovoltaic programmes. The public expenditures were allocated to different components of the R&D chain: basic research, applied research, experimental (technology) development, and demonstration. Today we can encounter photovoltaic in a wide variety of applications for commercial, industrial and scientific purposes.

(2) Despite of the scientific character of the PV-technology solar cells have existed on the market for the last 40 years. However, it was not until the late 1980s before PV penetrated the market. From that time on, laboratory and commercial PV technology development has shown steady progress. There is a variety of PV technologies. Most of them try to achieve low cost or high efficiency, or a combination of the two. New technologies are at various stages of development. However, commercial PV modules have existed on the market for a long time and this allows the construction of econometric model which analysis the development pattern of this science-driven technology.

(3) Environmental and economic aspects of PV market: From an environmental point of view, the use of solar energy as a replacement for fossil fuel generated

electricity has a number of environmental benefits. Solar energy is clean, silent, and freely available. Although the Energy Pay Back Time (EPBT)[1] and the $CO_2$ emissions for present-day systems are still relatively high, the EPBT is lower than their expected lifetime, ranging from 4 to 9 years. It is important, however, that manufacturers claim to be able to optimise PV module energy requirements, making possible a future decrease in the EPBT for grid-connected PV systems to around 2 years. However, photovoltaic is now a proven technology which is inherently safe as opposed to some dangerous electricity generating technologies.

Photovoltaic industry has experienced a strong growth over the last 20 years. According the Photovoltaic Energy Barometer 2006[2] of the European Photovoltaic Industry Association (EPIA), this growth could be even greater under advantageous conditions. Demand for photovoltaic products is growing, but the temporary lack of silicon prevents the sector from growing as quickly as in the previous years. The German PV market dominates the European market now. The Photon International magazine announced 687 MWp[3] installed in 2004. PV systems with nearly 950 MWp were installed in 2005. Germany's overwhelming success has inspired other countries to set up conditions to develop their own solar sectors. Spain installed 20.2 MWp last year, followed by 6.4 MWp in France, 5 MWp in Italy, 2.5 MWp in the UK and 2.3 MWp in Austria (see Photovoltaic Energy Barometer 2006)

To analyze the market development of solar cells the following variables were selected: patents (notation: patents), scientific publications (notation: publ), public subsidies (notation: subs), compensation according to the Electricity Feed Act (StrEG) and the Renewable Energy Sources Act (EEG) (notation: compens), the price development of crude oil (variable: fueloil), and installed peak solar power capacity (MWp) (variable: sunenergy). It is only a very restrictive selection of indicators which reflect the development of the market and measure important exogenous factors. Therefore, the length of the time series poses several problems. It can also be expected that the future PV market development will be faced with another problems. For example the shortage of silicon that is used in semiconductors and photovoltaic cells offers a problem for the booming PV industry. But it is also possible to test the impact of other factors.

A short description of the model variables[4] is given below.

The number of scientific publications is commonly used as an indicator to quantify the relevant scientific activities. In order to collect data for the publication statistics for the PV market the online version of the Science Citation Index (SCI, host STN) was chosen. Thereby, the following keyword search strategy: (solar cell or solar cells or photovoltaic#) was used. Before 1991 searching for keywords was only possible for titles, after 1991 the search was extended to the Basic Index. From 1974 to 2004 23.390 scientific articles in the technology field 'solar cells' were identified. The curve of these scientific activities has a double peak structure. The first peak was year 1984; after year 1992 the number of scientific articles increased rapidly. The second extremum occured in 2004. Nonetheless, scientific activities in the PV field continued to rise.

Patents are frequently used as innovation indicators as patent records are publicly available and easily accessible. Moreover, patent data are classified by technical fields, and patent time series allow for the convenient study of historical trends. There are a lot of free and commercially available patent databases which are potentially helpful for the research. The decision to work with the World Patent Index (WPI) was guided by two factors:

- WPI provides the bibliographic details for patent records from 42 patent-issuing authorities including the applications from European Patent Office (EPO) and the Patent Cooperation Treaty (PCT) applications.

- Secondly, WPI allows search of the relevant patent records by using key-words.

Due to foundation of the EPO in the year 1978 there are two ways in which an applicant can file patent applications in Europe. The one possibility is to register an invention directly at the national office, such as the DPMA. As an alternative, the applicant may file an international application at the EPO in which he can designate different european countries in which patent protection is desired. Each option has its advantages. The best solution depend on invention and market where company operates in.

In order to create long time series for patent activities in photovoltaic patent applications at the DPMA and the EPO have to be considered. The patent sample includes documents which were researched with the following retrieval strategy:

1. Patent records with the IPC = H01L 031/04 or IPC= H01L 31/06 in the main group or subclasses.

2. Patent records with the IPC = H01L 31 and the keyword solar+[5] in the title.

3. Union of the sets 1, 2.

4. From 1970 to 1990 the patent applications at the DPMA and from 1990 to 2001 the patent applications at the EPO were considered. The absolute levels from both time intervals were matched in 1990.

There are 2.874 retrieved documents from 1970 to 2001. The graph of patent activities referring to the technology field ‘solar cells’ clearly qualifies as a ‘double-boom’ cycle. The first maximum (95 documents) was reached in 1982, then a decrease of patent activities is apparent. The second peak (271 documents) occurred 17 years later, in 1999.

In general, there is an equilibrium between scientific and patent activities. It is interesting to see, that scientific activities have a lag in development in comparison withtechnological activities. In this particular case the PV Market is similar to empirical investigations for laser market. Further analysis of interaction between scientific community and industrial R&D is worthwhile.

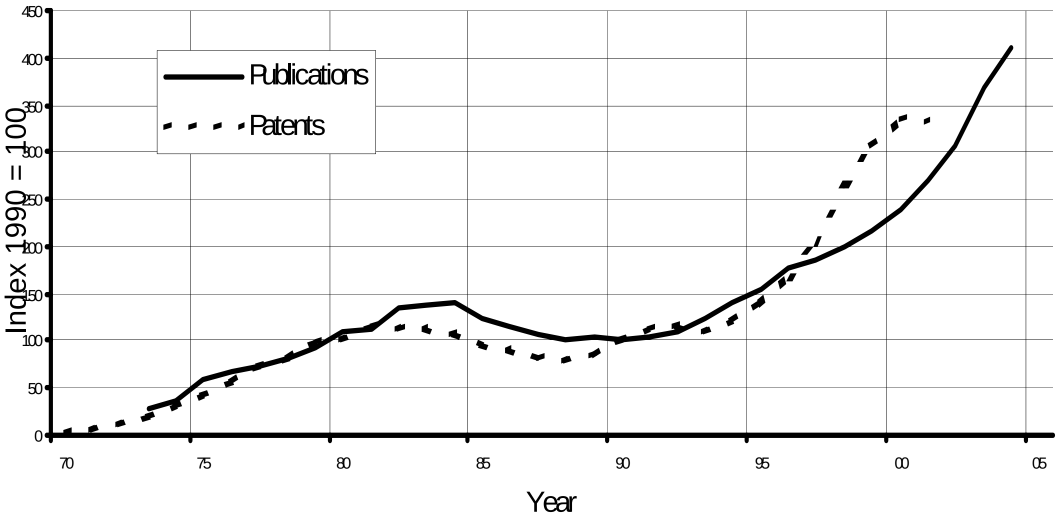



Figure 3-1: Long-term development of patent applications and scientific articles for solar cells since 1970.

Source: WPI and SCI.

Subsidies given by the government are very important for the PV market. A time series of public subsidies is the third relevant variable in the econometric model. According to the Public Promotion Catalogue[6] of the Federal Ministry of Education and Research nearly 850 million EUR were spent by the government from 1975 to 2006 for photovoltaic promotion. About 60% of all public expenditure for photovoltaic energy was spent in the years between the 1987 and 1997. Since year 1993 subsidies are stagnant at the constant value (Figure 3-2).

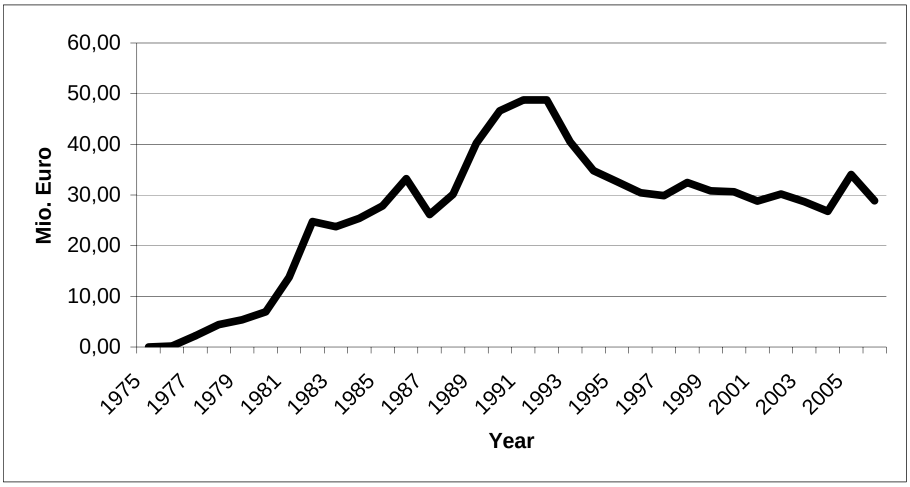



Figure 3-2: Photovoltaic subsidies given by the German government from 1975 to 2006.

Source: FöKat

There are different programmes that support the PV industry in Germany. For example there was the 100.000 Roofs Programme, which aimed to install 300 MW of solar cells by the end of 2003. A total of 350 MWp PV capacities were installed on more than 60,000 roofs under the programme. The empirical data of this programme is going to be included in the model as dummy variable.

Replacing the Electricity Feed Act, the Renewable Energy Sources Act (Erneuerbare-Energien-Gesetz; EEG) regulates the prioritisation of grid-supplied electricity from renewable sources. These two of Germany's principal renewable energy support instruments are also going to be treated in the model. (Figure 3-3).

The price of crude oil has a wide influence on the development of the PV market. Especially the first oil crisis in 1973 and the second oil crisis in 1979 revealed the fragility of energy supply systems of industrialized countries. (Figure 3-4).

Installed capacities of photovoltaic system are the last indicator in the model. Unfortunately, there are a lot of contradictory statements in empirical data for this indicator. According to AGEE-Stat[7] (statistics organisation of the Ministry of the Environment) the German Photovoltaic Market reached 600 MWp installed solar power in 2005, bringing the cumulated total of installed German capacity to 1 508 MWp. Germany now represents 85.8% of the total capacity installed in the European Union. (EurObserv'ER 2006, p.13). Based on data collection of Photon[8] (the Solar Electricity Magazine), in 2005 there was 857,78 MWp of new solar capacity installed which corresponds with total cumulated solar power of 1694,22 MWp. Photon's statistics are grounded on information from grid operators and energy supply companies which are committed to purchase the electricity generated from renewable energies. The problem is that this data are collected only for the short period from 2000 to 2005. For this reason statistics from AGEE-Stat are used.

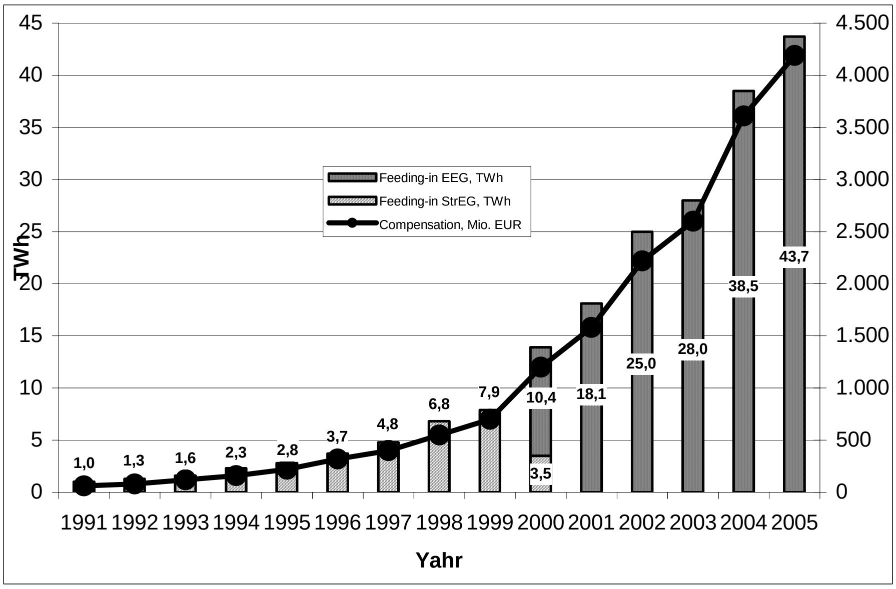



Figure 3-3: Feeding-in and Compensation according to the Renewable Energy Sources Act (StrEG) and the Electricity Feed Act (EEG)

Source: BMU (2006), p. 23.

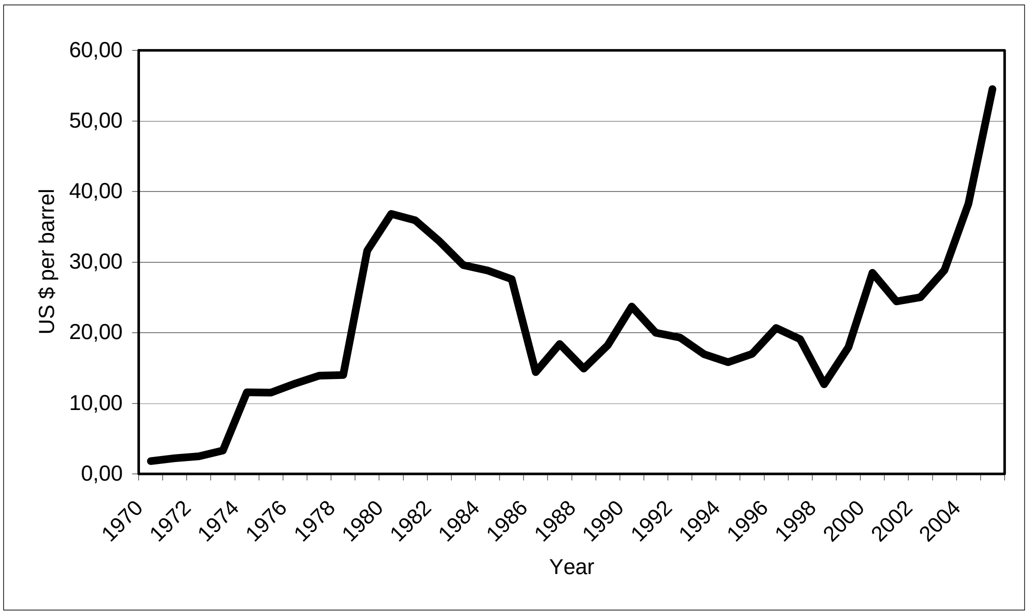



Figure 3-4: Crude Oil Prices 1970 – 2005.

Source: BP Statistical Review of World Energy.

# 4. The Model

Every analysis of an economical system is based on some underlying logical structure (known as model) that describes the behaviour of agents in the system and is the basic framework of analysis. This model is set up in the form of equations, which describe the behaviour of economic and related variables[9]. The economic agents try to reach their aims with given factor endowment. The required decisions are based on individual or collective need and run through complex evolutionary selection mechanism, which is not observable in total. The representation of the PV market processes in this study is given by selected variables which will be compiled as time series in equal intervals and in a common measurement system of market formation. Yet time series data only give us a very crude numerical picture of the complex econometric decision making on various levels. In addition there may be data problems from measurement and compilation errors.

A short description of main steps in modelling is given here: The construction of the model starts with an univariate data analysis. Here the properties of single variables, like trend and order of integration are checked. All time series seem to be non-stationary[10] and follow non-linear trend. A common assumption in many time series techniques is that the data are stationary. Standard techniques are often invalid where data are non-stationary. The knowledge about non-stationarity of the time series helps to identify some features of the underlying data-generating process. In the next step the causal relationships between variables are tested by Granger Causality Test. The results of Granger Causality Test help to identify bidirectional causal relationships between the variables. Estimates of cointegrating relations are obtained using Johansen's multivariate procedure. Statisticaly significant cointegration vectors will be included in the estimation of the error correction model (ECM). ECM's are widely used in econometrics studies due the following advantages: Firstly, the ECM allows to analyse both short term and long run effects of explanatory time series variables. Second, the estimated equation includes only stationary variables: cointegrating relationship between the level variables (long run) and the short run relationship between the first differences of the variables. Hence there is no problem with spurious correlation. The ECM is the final result of this empirical study. An interpretation of achieved empirical results concludes the model construction.

## 4.1 Unit Root Tests

There are different ways of testing the stationarity of time series. The most popular test in literature is the augmented Dickey-Fuller (ADF) test. The ADF-Test is also used in this approach. The starting point of the ADF-test is the ordinary least squares (OLS) estimation of regression model:

$$(1)\ \Delta y_t = (u-1)y_{t-1} + \sum_{j=1}^{p} \alpha_j \Delta y_{t-j} + \varepsilon_t \ ,$$

where $\Delta$ is the first difference operator, $\varepsilon_t$~i.i.d.(0, $\sigma^2$ ) are the error terms, p is the autoregressive lag length large enough to eliminate possible serial correlation in $\varepsilon_t$, and u is the coefficient of interest. If u=1, then the data series contain a unit root implying non-stationarity, whereas if u<0, there is no unit root implying stationarity. In the ADF-Test, the null hypothesis of unit root, i.e. $H_0$: u=1 is tested against the alternative hypothesis of no unit root, i.e. $H_1$: u<0 using a t test[11]. Two major issues in performing ADF tests are the inclusion (or non-inclusion) of an intercept term, a trend term, or both, and a selection of a truncation lag. ADF test results are very responsive to the presence of intercept and trend terms, and to the number of lags which are included. In general, including too many deterministic regressors results in lost power, whereas not including enough of them increases the probability of not rejecting the unit-root null[12].

Table 1 presents the ADF-test results for the levels and first differences of the variables. The results of the ADF test show that time series are not stationary in levels. After observing the first difference of the variables the null hypothesis can be rejected with a significance level of 5%. This means that all variables are integrated of order one, I(1), in level forms. Since the variables are considered to be I(1), cointegration analysis, using an error correction model (ECM), is appropriate to equilibrium model.

| Variable | Level | First difference |
|---|---|---|
| log_patents | -3.296699 | -3.253264* |
| log_publ | -3.201560 | -3.96844* |
| log_compens | -2.592318 | -4.642917* |
| log_subs | -2.670163 | -6.767453* |
| log_sunenergy | -2.973974 | -6.632623* |
| log_fueloil | -3.286873 | -5.110945* |

Notes: Significance level of 5% level is indicated with *. A time trend was not included in the first differences of the variables.

Table 4-1: ADF Tests for unit roots: levels and first differences of variables.

## 4.2 The Granger Test for Causality

The next step in model construction is the identification of bidirectional causality relationships between the variables using the Granger Test for Causality. The idea of this test is quite straightforward. The test states that $x_t$ is Granger causal for $y_t$ if the past values of $x_t$ help predict future values of $y_t$. It should be noted that Granger causality is not causality in the more common sense of the term. It is often in the economy that the variables of the models react to some unmodeled factor (for example the oil crisis) and if the response of $x_t$ and $y_t$ is staggered in time Granger causality can be observed though the real causality is different. Regrettably, it is not possible to solve this problem. Granger causality measures whether one thing happens before another thing does and helps predict it - and nothing else. But it can be accepted that it partly catches some real causality in the process (see Sørensen (2005)).

Granger causality can be described by the following model:

$$y_t = \sum_{i=1}^{p} \alpha_i y_{t-i} + \sum_{j=1}^{q} \beta_j x_{t-j} + u_t$$

where $u_t$ is white noise, $p$ is the order of the lag for $y$, and $q$ is the order of the lag for $x$. The null hypothesis that $x_t$ does not Granger-cause $y_t$ is that $\beta_j = 0$ for $j=1,2,\dots,q$. The test statistic is the standard Wald F statistic. If the F statistic is significant (p-value $< 0.05$) then the null hypothesis is rejected and the alternative hypothesis is accepted. The Granger causality test is carried out for all possible pairs of the time series. In order to test whether the linkage between the variables is stable or not, different lag length was selected. As a result of the Granger Causality Test the following hypotheses were tested:

*Hypothesis 1:* The scientific publication Granger-causes the patent applications and visa versa.

Only a few decades ago it was a fact that patents were a matter of industrial firms and private inventors. However, academic researchers preferred to publish their achievements in scientific papers. Today, there is not any traditional boundary between the industrial and academic research. On the one hand it becomes apparent that there is a clear trend toward commercialisation of academic science, on the other hand the industrial research is increasingly dependent on new acquisitions of the science[13]. In either case these considerations hold for the science-driven markets in general, and also for the PV market. Therefore it can be accepted that there is a strong causal relationship between the patent applications and scientific publications.

*Hypothesis 2:* Compensation from the Electricity Feed Act and the Renewable Energy Sources Act is Granger-causes the installed solar power.

Replacing the Electricity Feed Act (Stromeinspeisungsgesetz; StrEG), and the Renewable Energy Sources Act (Erneuerbare-Energien-Gesetz; EEG) regulates the prioritisation of grid-supplied electricity from renewable source[14]. Compensation according to the StrEG, and later the EEG, has to be paid for electricity generated from different kind of renewable energy and not only from solar radiation energy. But according to the EEG the amounts for solar generated electricity are the highest in comparison to other renewable energy sources. Because of this, the EEG has a crucial role in the development of the PV market in Germany.

*Hypothesis 3:* The subsidies of the government are Granger-cause the patent applications.

R&D expenditures for PV may be used as a yardstick for a willingness to establish a market for PV. Under the terms of the priority that Germany gives to R&D related to PV it has in third position after the USA and Japan. Funding of R&D projects by the German government supports improvements of PV technologies. These improvements can be measured by the number of patent applications.

*Hypothesis 4:* There is a link between installed solar power and patent applications / scientific publications.

Sold and installed solar plants connote the refinancing of the investment costs for PV industry and progress of PV technologies. This development is reflected in increase of patents and publications.

Table 4-2 reports the Granger causality test results. All hypothesis could be confirmed at a significance level of $p<0.05$. Results show a strong evidence for bidirectional causality between the patent applications and the science publications, and installed solar power and compensation from the StrEG and the EEG. For first pair of variables the existence of a long run-equilibrium relationship was investigated using Johansen cointegration methodology. Since the variables have similar development, two kinds of cointegration relationships were tested including trend (linear and nonlinear). The last pair of causality seems to be obviously because the EEG provides compensation for solar power fed into the grid and in Europe photovoltaic is primerly used with grid-connected systems. For this reason this relationship is not considered in this study.

| Pairs of time series | Lag's number | | | | |
|---|---|---|---|---|---|
| | 2 | 3 | 4 | 5 | 6 |
| fueloil compens | ← | - | - | | |
| patents compens | → | - | | | |

| | | | | | |
|---|---|---|---|---|---|
| publ compens | ← | - | ← | | |
| sunenergy compens | ←→ | ←→ | - | | |
| subsid fueloil | → | → | → | - | - |
| publ patents | ← | ←→ | ← | ←→ | ←→ |
| subsid patents | - | → | → | → | → |
| sunenergy patents | → | → | → | - | ←→ |
| subsid publ | - | ← | ← | ← | - |
| sunenergy publ | → | ←→ | - | - | → |
| sunenergy subsid | - | - | - | - | ← |

Table 4-2: Results of Granger-Causality Tests.

## 4.2 Cointegration Analysis

The Johansen approach (Johansen (1995)) for testing the existence of cointegrating relationships has become standard in the econometric literature because its advantages. An important aspect of the Johansen approach is that it allows us to test for various restrictions on the cointegrating vectors. We can also test the impact of exogenous shocks. The Johansen approach can be applied to the models with several endogenous variables. The appropriate estimation procedure contains three steps:

1. Determining the number of cointegrating vectors (cointegration rank).

   Two tests are used to determine the number of cointegrating vectors: the trace test[15] and the maximum eigenvalue test[16]. Both tests are carried out sequentially. The trace test has a null hypothesis of r cointegrating vectors against the alternative that the cointegration rank is equal to r+1. According to the trace test, the null hypothesis of no cointegrating vectors is rejected (p=0.0124) and the null hypothesis that there is no less than 1 cointegrating vector is accepted (p=0.3172). The maximum eigenvalue test provides an alternative check for the number of cointegrated variables and achieves the same result. The null hypothesis of 0 cointegrating vectors is rejected (p=0.01106) and the null hypothesis that there is at the most one cointegrating vectors is accepted (p=0.3172) (see Table 4-3). Therefore, there is a long term equilibrium relationship between patents and publications.

| Hypothesized No. of CE(s) | Eigenvalue | Trace Statistic | 0.05 Critical Value | Prob.** |
|---|---|---|---|---|
| None* | 0.493404 | 19.36152 | 15.49471 | 0.0124 |
| At most 1 | 0.036373 | 1.000383 | 3.851466 | 0.3172 |

Table 4-3: Johansen's Cointegration Test Results: unrestricted cointegration rank test (Trace)

2. The estimation of cointegrating vectors.

   Since the variables have similar developing, two kinds of cointegration relationships including trend linear and nonlinear are tested. As a result of the causality test some different factors can be identified which have an influence on the relationship between publications and patents. These factors are included in the model as exogenous variables. The purchase of following exogenous variables is evaluated: log_compens, log_subsid, and log_sun_energy. Dummy variable 100000_roof was also included to represent the implementation of the 100.000 roof program. Because the time series have a short length, all exogenous variables were not included at once, i.e. the impact of every factor is tested one by one. The best results is achieved with compensation from the StrEG and the EEG as exogenous variable and with non linear trend. The analysis provides a significant adjustment coefficient of 0.522 (s.e. 0.07621), indicating that 52 per cent of disequilibrium in publications is eliminated every year and the disequilibrium is corrected quite fast. (Table 4-4).

| 1 Cointegration Equation: | | Log likelihood 36.42467 |
|---|---|---|
| Normalized cointegration coefficients (standard error in parentheses) | | |
| log_patents | log_pub | |
| 1.000000 | 3.353231<br>(0.43059) | |
| Adjustment coefficient (standard error in parentheses) | | |
| d(log_patents) | -0.029768<br>(0.14172) | |
| d(log_publ) | -0.522288<br>(0.07621) | |

Table 4-4: Cointegration Equation

3. In the next stage of the model building an error correction model (ECM) is estimated.

According to the Granger representation theorem, two or more integrated time series that are cointegrated have an error correction representation. If there is an error correction representation for two or more time series, then these variables are cointegrated. This means that for any set of I(1) variables error correction and cointegration are two equivalent concepts. The idea of ECM is based on the behavioural assumption that there is one equilibrium relationship between two or more time series which causes both short- and long-run dynamics. In this study there is a bivariate ECM:

$$(2)\ \Delta y_t = \alpha_0 + \alpha_1(y_{t-1} - \beta_1 x_{t-1}) + \alpha_3 \Delta x_t + \alpha_4 z_t + \varepsilon_t$$

The current changes in *y* are the function of current changes in *x* and the gap of two time series from their equilibrium in the previous time period. Specifically, $\alpha_3$ captures any immediate effect that *x* has on *y*. Therefore, this term of the equation describes the short dynamics of the relationship between *x* and *y*. The coefficient, $\beta_1$, reflects the equilibrium effect of *x* on *y* and is estimated in the cointegration vector. The absolute value of the coefficient $\alpha_1$ can be interpreted as the speed of adjustment parameter. The coefficient $\alpha_4$ displays the impact of exogenous variables.

The interpretation of the coefficients will be demonstrated with a simple example. Let's assume we regress the first difference of publication numbers on one lag of publication numbers, one lag of patent applications, one lag of the first difference of patent applications and the impact of exogenous factor for example effect of the EEG. The estimated coefficients are $\alpha_1$ = -0.52, $\beta_1$ = 3.35, $\alpha_3$ = 0.64.

If the number of patent applications increases by 3%, the number of scientific publications will increase by 1.92% immediately (3*0.64, the coefficient $\alpha_3$). The ECM reveals an equilibrium relationship between patent applications and publications, i.e. the changes in patents applications disturb the equilibrium, causing the number of scientific papers to be too low. Consequently, the number of publications will increase by roughly 10% (3*3.35, the coefficient $\beta_1$), but this will not happen at once. This return back to the equilibrium extends over several years. The speed of adjustment is determined by the coefficient $\alpha_1$, i.e. 52% of the derivation from equilibrium is eliminated during the next time period. It means that the number of scientific papers rises 5.2% one year later, 2.7% two years later and 1.4% three years later and so on, until the number of scientific publications has increased 10% in total. And this will happen in about four years. In this way patent activity has two effects on scientific activities: one that occurs immediately, and another that is dispersed across future time periods.

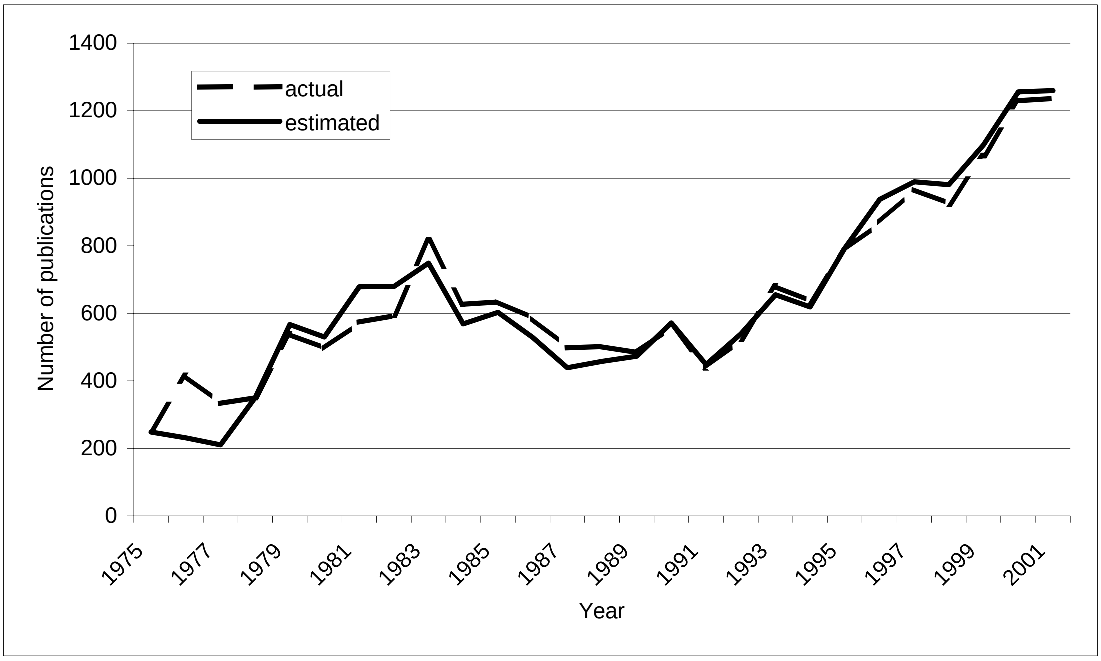



Figure 4-1: Publications statistics for the PV market 1975 until 2001. Real data (SCI) and model results.

According to the basic hypothesis that there are two different phases in development of science-driven market with different sets of determinants. The ANOVA F-statistic (21.4666) suggests significant difference (p-value < 1%) in means for two time periods: from 1973 to 1990 and from 1991 to 2001. Correspondingly, the time between 1973 until 2001 is splitted up in two time periods: 1973 until 1990 and 1991 until 2001. (Figure 4-1)

The estimated results for publication statistics are illustrated in. Table 4-5 and Table 4-6 show the results of Error Correction estimates for the time period between 1973-1990, and 1991-2001 respectively. The fit of the model was improved in due consideration to exogenous variables. Different exogenous variables were included in the account. The best results were achieved including the impact of the fuel oil prices for the first time period and including the impact of the StrEG and the EEG for the second time period. The models were compared using adjusted $R^2$ and "information criteria" such as the Akaike Information Criterion (AIC) and Schwartz Criterion. If scientific publications are taken as dependant variables then the fit of the model improves. Basically, all coefficients are significant. The comparison of the ECM’s for two time periods follows below.

| Cointegration Equation: | CointEq 1 | |
|---|---|---|
| log_patents (1) | 1.000000 | |
| log_publ(-1) | 10.06718 | |
| | (1.05040) | |
| | [9.58411] | |
| C | -66.26657 | |
| Error Correction : | d(log_patents) | d(log_publ) |
| CointEq1 | -0.041104 | -0.124823 |
| | (0.01291) | (0.01784) |
| | [-3.18309] | [-6.99729] |
| d(log_patents(-1)) | -0.174286 | -1.264204 |
| | (0.27419) | (0.37877) |
| | [-0.63564] | [-3.33763] |
| d(log_publ(-1)) | 0.195682 | 0.129222 |
| | (0.10016) | (0.13836) |
| | [1.95368] | [0.93393] |
| C | -0.331441 | -1.840807 |
| | (0.25380) | (0.35060) |
| | [-1.30593] | [-5.25043] |
| log_fuelog_oil | 0.241306 | 1.205227 |
| | (0.15616) | (0.21572) |
| | [1.54525] | [5.58694] |
| R-squared | 0.818192 | 0.858479 |
| Adj. R-squared | 0.752079 | 0.807016 |
| F-statistic | 12.37581 | 16.68170 |
| Log likelihood | 22.77421 | 17.60440 |

Table 4-5: Vector Error Correction Estimates for the period 1973-1990. (Standard errors in () & t-statistics in [ ])

| Cointegration Equation: | CointEq 1 | |
|---|---|---|
| log_patents (1) | 1.000000 | |
| log_publ(-1) | 3.353231 | |
| | (0.43059) | |
| | [7.78744] | |
| C | -27.31604 | |
| Error Correction : | d(log_patents) | d(log_publ) |
| CointEq1 | -0.029768 | -0.522288 |
| | (0.14172) | (0.07621) |
| | [-0.21005] | [-6.85293] |
| d(log_patents(-1)) | 0.821573 | 6.642510 |
| | (0.52916) | (0.28458) |
| | [1.55260] | [2.257775] |
| d(log_publ(-1)) | 0.272983 | 0.253222 |
| | (0.33226) | (0.17869) |
| | [0.82161] | [1.41713] |
| C | 0.015894 | 0.817880 |
| | (0.17275) | (0.09290) |
| | [0.09201] | [8.80370] |
| log_compens | 0.028834 | 0.708735 |
| | (0.18139) | (0.09755) |
| | [0.15897] | [7.26542] |
| R-squared | 0.395023 | 0.926195 |
| Adj. R-squared | -0.0088295 | 0.876992 |
| F-statistic | 0.979433 | 18.82386 |
| Log likelihood | 13.48513 | 20.308816 |

Table 4-6: Vector Error Correction Estimates. (Standard errors in () & t-statistics in [ ])

The estimated coefficients are $\alpha_3$ = -1.26 and 0.64, $\beta_1$ = 10.067 and 3.35 and $\alpha_1$ = -0.12 and - 0.52, respectively. It is remarkable that the sign of coefficient $\alpha_3$ is not the same for both time periods. It can be interpreted as follow: although the coefficient $\beta_1$ shows the statistical significance of the equilibrium effect between patents and publications during both intervals, the short-term fluctuations of patents and publications can have different trends in the first and in the second interval.

For example the decrease of the number of patents can be used as evidence for rising technical problems in the first phase and it can be taken as a challenge for science. Consequently, the number of publications increases. But in the second phase the main problems seem to be solved, and a decrease of the number of patents can be taken as a temporary lack of interest implicating a decrease in publication statistics.

The speed of adjustment is the time it takes to reach a new equilibrium after an initial shock is determined by the coefficient $\alpha_1$. The data indicate magnitudes varies across years, from very low speed of adjustment in 1973-1990 (-0.12), or 12% of the derivation from equilibrium is eliminated in the next time period to relatively fast adjustment in 1991-2001 (–0.52) or 52%. Adjustment to equilibrium takes only about four year.

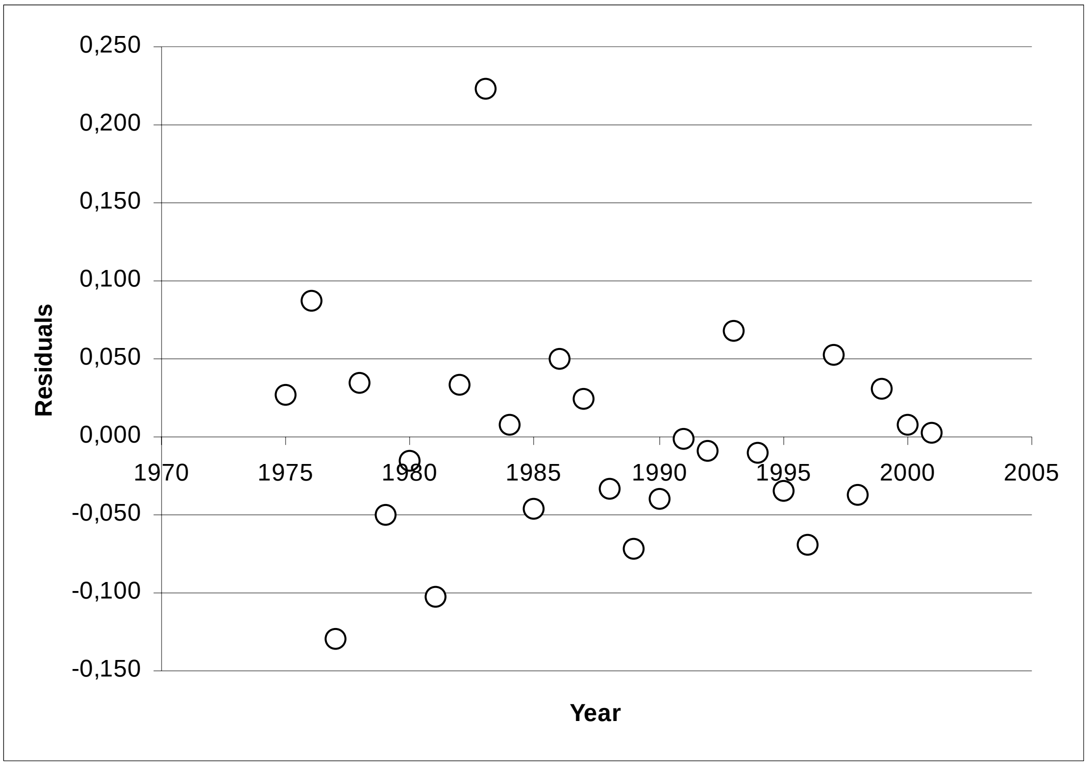
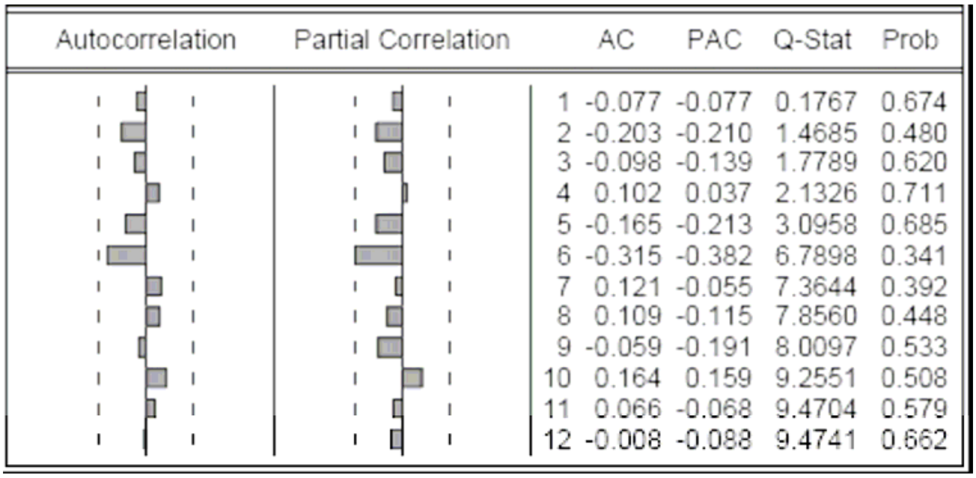



Figure 4-2: Residual plot for EC model.

Using different goodness of fit tests the validity of the model was checked. The adjusted R-squared statistic is 0.807 and 0.877 respectively, which is relatively good explanatory power. The F-test for the significance of the goodness of fit is 16.68 and 18.82, respectively. The critical values are 5.67 and 15.98 respectively. As F-test statistics are greater, the goodness of fit of regression is significant for both time periods.

In order to have a first impression for identifying the presence of autocorrelation in the residuals the residual plot (Figure 4-2) is considered. Although there are no obvious systematic patterns of any type in this plot, application of formal tests for autocorrelations is necessary. Figure 4-3 displays the autocorrelation and partial autocorrelation functions up to the 12 order of lags. The dotted lines are the approximate two standard error bounds. The autocorrelation and the partial correlation are within these bounds; therefore these statistics are not significantly different from zero at the 5% significance level. The last two columns reported in the correlogram are the Ljung-Box Q-statistics and their p-values. The high p-values indicate also the absence of autocorrelation in the residuals. The same conclusion provides the Durbin Watson (DW) statistic=2.147, well above the upper bound for this test when k=4 and n=27. The null hypothesis of no autocorrelation cannot be rejected.



| Autocorrelation | Partial Correlation | | AC | PAC | Q-Stat | Prob |
|---|---|---|---|---|---|---|
| | | 1 | -0.077 | -0.077 | 0.1767 | 0.674 |
| | | 2 | -0.203 | -0.210 | 1.4685 | 0.480 |
| | | 3 | -0.098 | -0.139 | 1.7789 | 0.620 |
| | | 4 | 0.102 | 0.037 | 2.1326 | 0.711 |
| | | 5 | -0.165 | -0.213 | 3.0958 | 0.685 |
| | | 6 | -0.315 | -0.382 | 6.7898 | 0.341 |
| | | 7 | 0.121 | -0.055 | 7.3644 | 0.392 |
| | | 8 | 0.109 | -0.115 | 7.8560 | 0.448 |
| | | 9 | -0.059 | -0.191 | 8.0097 | 0.533 |
| | | 10 | 0.164 | 0.159 | 9.2551 | 0.508 |
| | | 11 | 0.066 | -0.068 | 9.4704 | 0.579 |
| | | 12 | -0.008 | -0.088 | 9.4741 | 0.662 |

Figure 4-3: Correlogram of Residuals for the ECM.

Finally, using White Heteroscedasticity Test the null hypothesis that there is no heteroscedasticity cannot be rejected, since the p-value of the F-statistic is quite high (0.7272 resp. 0.3578). Summarizing, the diagnostic tests support the validity of the estimated model.

## 5. Conclusions

The subject of this paper is an empirical analysis and dynamic mathematical modelling of innovation processes in science-driven markets. Numerous empirical studies provide evidence that science-driven markets underlie different development patterns then consumer markets, in which the science base of the underlying technological development is rather unimportant. The purpose of this work is the construction of an econometric model which has the power to explain the nonlinear dynamics of science-based innovation processes using a few relevant variables. The model is tested and validated with empirical data in terms of regression and time series analyses.

In the first step and for a better understanding of the relevant influence factors, the evolution of selected technologies is discussed and supported with quantitative data (innovation indicators). The envisioned examples include photovoltaic market. It is a relatively new market with a strong dependence on science and, so far, on an intensive amount of public subsidies for research and development (R&D). Other examples are lasers, polyimides and polyamides, surface technologies, and the like.

In the second step, a stylised model of the formation of science-driven markets is presented. In so doing, the main hypothesis is constructed, namely: in the development of science-based markets two quite different development phases can be observed due to basically different sets of determinants ("double-boom hypothesis"). This corresponds to the mathematical modelling of more than one steady state in the overall development of a new innovative market rather than the usual diffusion modelling ("S-type curves").

The third step consists of model building based on the previously described careful empirical analyses. First, a univariate examination of statistical properties of the selected time series is done. The next step of model construction is the identification of bidirectional causality relationships between the variables using the Granger Test for Causality. Based on these findings, the cointegration vectors are estimated. According to "double-boom hypothesis" the whole data set is splitted into two time periods: from 1973 to 1990 and from 1991 to 2001. For both time intervals the existence of a long-run equilibrium between publications and patents is verified. Although the speed of adjustment to the equilibrium for both time intervals varies strongly, from relatively slow speed of adjustment of -0.12 (≙-12%) in first time period to very fast speed of adjustment of -0.52 (≙-52%) in second time interval. Using an error correction model the impact of different exogenous factor is tested. For the first phase of the PV market development the fuel oil prices play an important part. The influence of the StrEG and the EEG is important in the second phase of market formation.

The current condition in the research of science-driven markets provides a lot of studies on either the science push or the demand pull side. Most of these papers are of qualitative nature. We do not know of major work trying to reconcile both views into a formal mathematical model. This is the challenge of the proposed work: to come up with first solutions to this problem.

## 6. Notes:

1. The EPBT by EPBT = $E_{input}/E_{saved}$, where $E_{input}$ is the energy input during the module life cycle (which includes the energy requirement for manufacturing, installation, energy use during operation, and energy needed for decommissioning) and $E_{saved}$ the annual energy savings due to electricity generated by the PV module.

2. http://www.epia.org/03DataFigures/barometer/Barometer_2006_full_version.pdf

3. MWp = Megawatts peak installed (electrical power unit).

4 Before calculation all variables are preliminary log-transformed to achieved a more homogenous variance.

5 + = open truncation

6 FöKat (Funding catalogue of the Federal Ministry for Education and Research): Hhttp://oas2.ip.kp.dlr.de/foekat/foekat/foekatH.

7 AGEE-Stat uses data from the Energy Accounting Association (AGEB); Baden-Württemberg Centre for Solar Energy and Hydrogen Research (ZSW); Federal Statistical Office, Leipzig Institute for Energy Systems and the Environment (IE); Federal Solar Industry Association (BSi); Electricity Industry Association (VdEW); Association of German Network Operators (VdN).

8 www.photon.de/download

9 Ramanathan (2002): p.4.

10 The stationary time series have the property that the mean, variance and autocorrelation structure do not change over time.

11 Note that under the null hypothesis this t statistic is not asymptotically normally distributed, and therefore special critical values are required. Actually, critical values depend on the regression specification and on the sample size. Dickey and Fuller (1979), among others, provide tables with appropriate critical values for some cases.

12 A complete description of unit root tests is beyond the scope of this article. For a more detailed explanation, see Enders (1995), chapter 4.

13 These close relationships between academia and industrial research have many positive aspects, but at the same time there are some doubts about consequences of these changes. The quality of fundamental research can suffer from this trend as research substance might become increasingly applied and field of research without marketing orientation could be disregarded. (see Czarnitzki et al. 2007).

14 http://www.bmu.de/files/pdfs/allgemein/application/pdf/res-act.pdf

15 The name comes from the fact that the test statistic involved is the trace (= the sum of the diago-nal elements) of a diagonal matrix of generalized eigenvalues.

16 The name comes from the fact that the test statistic involved is a maximum generalized eigenvalue.

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