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Identification and monitoring of possible disruptive technologies by patent-development paths and topic modeling

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ABSTRACT

Understanding current technological changes is the basis for better forecasting of technological changes. Because technology is path dependent, monitoring past and current trends of technological development helps managers and decision makers to identify probable future technologies in order to prevent organizational failure. This study suggests a method based on patent-development paths, k-core analysis and topic modeling of past and current trends of technological development to identify technologies that have the potential to become disruptive technologies. We find that within the photovoltaic industry, thin-film technology is likely to replace the dominant technology, namely crystalline silicon. In addition, we identity the hidden technologies, namely multi-junction, dye-sensitized and concentration technologies, that have the potential to become disruptive technologies within the three main technologies of the photovoltaic industry.

1. Introduction

Technology plays an important role in keeping firms safe from their competitors in the market. In order to keep a competitive position in the market, firms have to rely on new technologies that have the potential to increase their revenues (Taşkin et al., 2004). One of the most important factors in establishing successful technological strategies is to understand and identify trends of technological development (Choi and Park, 2009; Porter and Roper, 1991). One of the most important tools to identify such future technological trends is technological monitoring (Porter and Roper, 1991). Monitoring refers to the scanning of a particular area of relevant information to understand the history of a technology. The gathered information can be used to identify future technological development because future changes in a technology are influenced by current and past changes in related technologies (Kostoff, 1994; Porter and Detampel, 1995; Porter and Roper, 1991).

Monitoring technological changes thus can provide key information for firms, especially if one considers disruptive technologies (Christensen, 1997). Disruptive technologies are a highly discontinuous or revolutionary type of innovation (Thomond and Lettice, 2002). Industry leaders often rely on obsolete technologies based on their sustainability while other companies take the opportunity to produce disruptive innovations, and consequently they become the new industry leaders (Mitchell, 1989). Unfortunately, this lack of focus on a new technology can create serious deficiencies in managers' decisions about firms' current and future technology and product portfolio. For example, the case of Kodak lends support to this point. Kodak was a pioneer in digital photography — a technology that was later considered as disruptive (Lucas and Henry, 2009). Kodak created, patented and developed many products and processes in several aspects of digital photography. However, Kodak followed its approved path by investing in traditional products and services, and by building on analogue photography instead of investing in the new digital technology. It also did not pay attention to the number of new entrants into the market that invested and patented new innovations in the digital technology. The neglect of the technological trend had a serious negative impact on Kodak's business. Evidently, Kodak could have had extraordinary benefit from the new digital photography if it had been able to monitor technological changes and to foresee that the digital technology would be the new standard in the market, making analogue photography obsolete.

The case of Kodak highlights the important role of monitoring the trends of technological change. Many prior applications and studies have suggested methods for technological forecasting, for instance, studies have used the history of product development (Iansiti, 1995),

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data mining[1] on websites to forecast future technologies (Albert et al., 2015), clustered analysis of documents to forecast how widely a paper will be cited (Kandylas et al., 2010), monitored technological changes within a particular area that may help to predict probable future technologies (Bhattacharya and Khan, 2001; Mogee, 1991), visualized information for technological forecasting (Zhu and Porter, 2002) and visualized patent-development paths of technologies to forecast promising technological niches (Choi and Park, 2009).

However, most of these suggested methods have limitations (Albert et al., 2015; Choi and Park, 2009; Porter and Roper, 1991; Small and Upham, 2009). First, sufficient information based on objective technological data is needed. Forecasting methodologies such as the consensus method, the Delphi method, structural models, scenarios and technological vigilance, rolling cluster algorithms, and blog analysis were not able to provide this information. They failed to underpin the process of technological development. Second, even though previous methodologies such as diffusion modeling, statistical analysis and trend extrapolation were applied to technological forecasting to increase the objectivity of the results, they were not able to explain the complex relationship between current dominant technologies and disruptive technological change. Third, previous forecasting methodologies were not able to forecast the direction of technological change at the micro level, so they were not accurate enough for firms to have detailed information about the direction of technological change. Finally, almost all previous studies are based on *ex-post* analysis. The limitation of experts' knowledge, for example due to the massive amount of information in patent documents, biases the final results. Building on these existing limitations, a new method is suggested.

In the following, we propose that firms, with the help of patent-development paths, k-core and topic modeling, can monitor technologies that are more likely to become disruptive technologies. Patent-development paths rely on patent citations to identify the complex relationships between patents and their relative importance, and can provide information about the current stage and the history of a technology. K-core is applied to identify and classify different subgroups of technology. Due to the huge information available for patent abstracts, topic modeling is suggested as a tool to provide an *ex-ante* perspective for patent–citation analysis and to help experts to identify the underlying technologies.

This suggested approach also offers insights on a firm's technological position based on the aggregate properties of its patent portfolio. This information can be applied in firm-level policy making and in the design or modification of strategies. In the following, we first introduce the proposed method. We will apply the method to the photovoltaic industry to illustrate the usefulness of our approach. This industry has been chosen because of the recent concerns over environmental pollution and energy demands, as well as the need for green energy solutions. Solar cells have the potential to become a major energy supply technology.

2. Identifying technological disruptiveness by patent paths and topic modeling

2.1. Revolutionary technological change

A disruptive technology is a product or a service designed for a new set of customers (Christensen, 1997) that brings a revolutionary change in the conduct of processes or operations more than other products offered by the incumbent firms (Christensen and Raynor, 2003). When a disruptive technology arrives, firms need to respond appropriately to maintain their competitive position in the market. Determining an appropriate response requires firms to identify potential disruptive technologies. While most firms are aware of the technologies before they achieve the status of disruptive technologies, for example the hard disk drive (Christensen, 1997), their inability to foresee the development of such technologies as *disruptive* technologies regularly takes top managers by surprise. Most managers do not expect the technology to evolve and spread so quickly (Govindarajan and Kopalle, 2006).

Christensen (1997) discusses that in a mature market, new products with a new competing design or approach, at the beginning, look relatively harmless, but after a while they displace the mature ones within the market. Disruptive technologies can be thought to have a combination of new and existing technologies that have the feasibility to shift existing technology products or create completely new ones (Walsh and Linton, 2000). Top managers often do not understand the disruptive potential of a technology because their knowledge of the world is deeply entrenched in their current experiences (Henderson, 2006) that affect their field of vision, selective perception, interpretation (Hambrick, 2007; Smith et al., 1994), the implemented technology strategy and the resulting products (Bantel and Jackson, 1989; Hambrick, 2007; Hambrick and Mason, 1984). Besides bounded-rationality, managers are often insufficiently trained in innovation and technology management (Christensen and Raynor, 2003).

2.2. Prior research on revolutionary technological change

Monitoring refers to watching, checking, observing and keeping up with developments for a particular purpose (Coates et al., 1986). Monitoring the technological changes in the particular environment a firm is interested in can help to identify emerging technological developments. This action, in turn, is expected to influence the firm's performance in the future (Kostoff, 1994; Porter and Detampel, 1995; Porter and Roper, 1991). Monitoring is considered as the most helpful technique for technological forecasting (Porter and Roper, 1991). Furthermore, it can be used as a complementary method together with other forecasting methods (Choi and Park, 2009; Lemons and Porter, 1992; Porter and Detampel, 1995; Porter and Roper, 1991).

There are different types of technological forecasting methodologies such as the consensus method, the Delphi method, structural models, scenarios and technological vigilance, rolling cluster algorithms, and blog analysis (Albert et al., 2015; Kandylas et al., 2010; Lemos, 1998; Small and Upham, 2009); however, each of those techniques has limitations. For instance, the consensus and Delphi method are based on subjective opinions and thus depend on human behavior such as experts' qualitative and intuitive knowledge that can be skewed or can influence the results (Betz, 1996; Godet, 1983; Tversky and Kahneman, 1974). In addition, the process of gathering data can be time-consuming and costly if questionnaires are posted by conventional mail (Lemos, 1998). Structural modeling is based on quantitative procedure but often neglects or removes subjective factors that are important for technological forecasting. Furthermore, the model is mathematically restricted in explaining some of the functional relationships within the factors. It can be only used to forecast trends of technological development at the macro level (Lemos, 1998). Scenarios and technological vigilance use subjective, cognitive and quantitative procedures. Although, this combination of techniques can be useful, the collection of informative data is difficult and costly (Lemos, 1998). Blog analysis and rolling-cluster analysis use quantitative procedures, and like other forecasting methodologies, they can only forecast trends of technological development at the macro level. In addition, the collection of informative data is highly dependent on experts' opinions and can be costly (Albert et al., 2015; Kandylas et al., 2010; Small and Upham, 2009). Even when such a systematic approach has been applied for analyzing and gathering data for forecasting technological changes at the micro level (Choi and Park, 2009), the final results suffer from the issue of *ex-post* analysis. Moreover, when the number of observations increases, interpretation of patents' abstracts for identifying the name of technological

[1] Blog analysis.

disruptiveness has difficulties. Therefore, an alternative methodology and an *ex-ante* analysis are needed to overcome this issue.

Bibliometrics is one of the most important tools for interpreting and measuring technological and scientific advantages (Narin et al., 1994). In bibliometric analysis, it is assumed that the number of patents or papers referring to a specific area is related to the validity and quality of R&D activities (Narin et al., 1994). A key characteristic of bibliometrics is that it allows us to determine the relationship between patents and scientific publications, or both. This key characteristic has led to the emergence of methods based on co-occurrences and co-citations. It is assumed that phenomena frequently occurring at the same time in a certain domain are related to each other. It is also assumed that the strength of the relationship depends on the frequency of the co-occurrence (Kostoff, 1994). Co-citation analysis, introduced by Small and Griffith (1974), identifies sets of patents or articles cited simultaneously in other patents or articles. Underlying this is the assumption that developing a cognitive structure provides useful information on future developments of R&D (Melkers, 1993).

Because bibliometric analysis can reveal linkages between patents and papers or both, mapping can be applied in order to show relationships. Maps can show firms' overlaps and interests or can identify the direction and the location of research fields relative to each other. In other words, a variety of bibliometrics maps increases the validity of analyses (Rip, 1988; Tijssen and Van Raan, 1994). Due to the important role of bibliometrics in gathering information on emerging technologies (Porter and Detampel, 1995), bibliometric analyses can be employed in order to increase the validity of technological monitoring and forecasting. For instance, the number of linkages between patents provides unique evidence that shows how different R&D activities are influenced by each other, which firm is involved in which technology, "*who cites what*", and can even be used to suggest new technological applications (Griliches, 1998; Narin et al., 1994; Porter and Detampel, 1995).

The accuracy of monitoring is highly dependent on the proper data. Therefore, gathering data on a specific purpose increases the accuracy of technological forecasting. Because patent data in different fields of technologies is available for many years (Griliches, 1998; Harhoff et al., 2003), it can provide longitudinal research opportunities. In addition, the number of linkages between patents can help to track history and current development of technology, and can suggest probable next steps. Thus, in this study, patent data is used to monitor the photovoltaic industry in order to identify technologies that have the potential to become disruptive.

Patents are a direct output category of industrial R&D and other inventive activity, and they mirror the cumulative process of technological change. It is suggested that patents and patent citations are an appropriate objective measure of innovation performance if the construct of interest is technological disruptiveness (Katila, 2004). Even though there are some drawbacks for patent-data analysis because not all of the inventions are patented, for example because they do not meet the patentability standard (Pottelsberghe et al., 2001), or inventors strategically decide not to patent their inventions (Trajtenberg, 1990b), patent–citation analysis helps us to understand technological changes (Choi and Park, 2009; Martinelli, 2008; Verspagen, 2007; von Wartburg et al., 2005).

When applying for a patent, the assignee has to prove the novelty, non-obviousness and usefulness of his invention. For this reason, his own invention is compared, both by the inventor and by the patent examiner, to prior art in the respective technological field. The relevant sources for judging novelty and inventive steps are referenced in the patent application. Therefore, patent citations measure whether a patent was the foundation for subsequent technological inventions and whether it can be used to monitor the evolution of technologies by investigating the citation paths between patents during a span of time (Harhoff et al., 2003; Trajtenberg, 1990b; von Wartburg et al., 2005). Patent citations make visible how the diffusion of relatively minor inventions that are linked to the further refinement and development of basic breakthroughs contribute to radical innovations (Verspagen, 2007). The underlying assumption is that a small number of basic innovations establish a technological paradigm or trajectory (Dosi, 1982). The paradigm limits the choice of incremental innovations that are able to adapt the paradigm to local circumstances (Verspagen, 2007). The final success of the paradigm depends on the number and persistence of incremental innovations that follow.

Due to these obvious advantages, former research heavily relied on patent citations to analyze technological change. However, the following limitations often appear in those studies. First, most studies use single-stage citation information, either "forward" citations (derived from the citations that a patent subsequently receives from other patents) to measure the technological value of a patent, or "backward" citations (derived from the citations made by a patent) to investigate the knowledge flows between technologies (Jaffe et al., 1993). However, there are only a few studies that investigate more generations of patents, which are crucial to identify path developments within a technological field over time, and thus potential disruptive technologies. For example, Trajtenberg et al. (2003) and von Wartburg et al. (2005) use three generations of patents to assess the importance (forward citations) or basicness (backward citations) of inventions.

Second, apart from a few exceptions, studies identify technologies by basing their algorithms on general network theory. However, patent–citation analysis should consider the special characteristics of patent citations to analyze technological trajectories (Choi and Park, 2009; Hummon and Dereian, 1989; Mina et al., 2007; Verspagen, 2007). In particular, the suggested algorithm for tracing the paths of patent development entails the weighting of patent citation links by the number of forward citations, the identification of origin patents as the starting points of the patent–development path, and the traceability of the main paths (Choi and Park, 2009).

Third, the identification and clustering of patent development paths remain less meaningful if there is no guide for interpretation and tests for external validity. There are only a few earlier studies that connect patent-development paths with the underlying topics of the patents to interpret the findings and with the scientific literature in order to validate the results (Mina et al., 2007). We suggest topic modeling of patents' abstracts to identify topic clusters. Topic clusters can be assigned to the identified technological trajectories to interpret the findings with respect to the underlying technologies. Moreover, topic modeling provides an opportunity for an *ex-ante* perspective on forecasting technological changes and can be a complementary method for patent–citation analysis that is based on *ex-post* analysis. The topic clusters are also used to identify the development of the relevant scientific literature within a topic field. Such knowledge is helpful to understand whether a trajectory is pushed from basic research (applications are often missing and may develop later) or from the respective industry market.

2.3. Suggested method to identify technological disruptiveness

Our method is a combination of path identification based on a forward-citation node pair algorithm, k-core analysis, topic modeling and academic literature research. Each step will be introduced in the following section.

2.3.1. Forward-citation node pair algorithm

Our forward-citation node pair algorithm relies on a method introduced by Choi and Park (2009). The algorithm uses a patent–citation matrix as input. A patent–citation matrix is a directed graph, meaning that a set of nodes (in our case patents) connected by arcs (in our case citations) have a direction, i.e., the graph shows if and how often patent i cites patent j and vice versa. The patent–citation matrix should entail all relevant patents of a technology. Using the patent–citation matrix, patents are classified into four groups based on the structural features of citation relationships (Wasserman and Faust, 1994):

1— Isolated patents: patents that are not cited and do not cite other patents.
2— Origin patents: patents that are cited, but do not cite other patents.
3— Terminus patents: patents that are not cited, but do cite other patents.
4— Intermediate patents: patents that are cited and do cite other patents.

In a next step, the algorithm proposes a methodology for identifying the main development path to understand a complex patent–citation network in its entirety and the history of a technology. The algorithm keeps the highly weighted arcs in the original patent–citation network and reduces the arcs linked from the origin patents. The main idea is that patents that are linked to the selected arcs can be evaluated as highly valued patents. Also, patents located at the position where various development paths gather are interpreted as points of converging technology where a technology is developed by converging two or more technologies that have different objectives or characteristics.

For this reason, a main path is selected based on the weight of all arcs, implying that the method for defining the weights is the most important part. The weights are calculated based on multiplying the number of forward citations of the two linked nodes and are called forward-citation node pairs (FCNPs). The calculation includes the number of forward citations of the linked patent itself to prevent the weight of terminus patents from being calculated as zero.

Following the former procedure, all origin patents among the collected patents are selected as the starting points of the patent-development path. Origin patents are developed in the early time of a technology and are therefore always the starting point of patent-development paths.

The next step extends the patent-development path from the origin patents. Every arc starting from an origin patent is selected, i.e., the arcs are linked to the patents that cite the origin patent. Arcs are evaluated based on the comparison of the FCNP of each arc, and arcs that have the highest FCNP among linked arcs from the origin patent, are selected. In this process, generally only one arc is selected. Two or more arcs can be selected if the FCNPs of these arcs are the same. The selected arcs are the first elements of the development path from an origin patent. A patent located at the end of the selected arc becomes the new starting point for another arc of the development path, i.e., patents located at the end of an arc are reclusively added to the development path by evaluating the arcs linked to the recently added patent based on the FCNP. Finally, the algorithm terminates when all of the patent development paths from every origin patent meet the terminus, i.e., the most recently registered patents. This method should be applied to the largest component, i.e., the largest connected sub-graph, of the entire patent–citation network, as it entails the most important independent technology (Choi and Park, 2009).

2.3.2. K-core analysis

To distinguish between technologies within the main path, we will implement k-core analysis. Basically, k-core analysis identifies subgroups of nodes within a network (Batagelj and Mrvar, 2000; Batagelj et al., 1999) and can be used to identify cohesive groups of technologies (Swan, 2001; Wang and Chiu, 2005). Mathematically, a k-core is a maximal connected subgraph C within a graph P in which all vertices have a degree of at least k. It is formed by repeatedly deleting all vertices of degrees less than k. The concept of a k-core was introduced to study the clustering structure of social networks and to describe the evolution of random graphs. This approach thus removes the lowest "corenesses" from the network and tries to split it into subgroups that help us to detect particular subsets of nodes in the network. Hence, we apply this approach for detecting technologies within the large scale of patents. The k-core analysis is implemented to analyze the largest component in the network and to divide this component into sub-fields.

2.3.3. Topic modeling

The topic modeling method has become a popular approach to identify future hidden topics from a corpus of text (Chang et al., 2009; Hall et al., 2008). It is used to study the cognitive content of language and to summarize the content of large and meaningless documents (Chang et al., 2009). Topic modeling is based on the Bayesian statistical technique of the Latent Dirichlet Allocation (LDA) to infer what each word might mean on the basis of its neighboring or co-occurring words (Blei et al., 2003). The assumption behind the method is the existence of latent sets of topics inside every document. Each word that appears in the document can be assigned to one of the topics with some probability, and the meaning of the word might change with the association of other words inside the document. This method provides an opportunity for researchers to explore sets of new topics that are hidden within documents. Topic modeling was developed for computer science applications to improve internet search algorithms. For instance, during the past decade, a few companies such as Google, Citeseer and Libra tried to use the topic-modeling method to improve their internet search engines and to provide ways for their users to explore particular topics that appeared in the large amount of literature (Tang et al., 2008). Recently, management studies have applied topic modeling to group words in order to outline the underlying topics beyond these words and to predict breakthrough innovations (Abrahamson and Hambrick, 1997; Chang et al., 2009; Duriau et al., 2007; Hall et al., 2008; Huff, 1990; Kaplan, 2012; Kaplan et al., 2003). In addition, topic modeling can provide an opportunity for an *ex-ante* perspective on forecasting technological change and could be a complement method for patent–citations analysis that is based on *ex-post* analysis. Furthermore, typically researchers or decision makers are confronted with hundreds of documents, making it impossible to identify important topics that are hidden in the documents.

We apply topic modeling to find out the name of prominent technologies that are hidden within each k-core. For this purpose we use the patents' abstracts of each cluster as an input in the Stanford topic-modeling toolbox software (Ramage et al., 2009). The output is a list of most repeated words and topics from the patents' abstracts. Tables 1 and 2 give an example of the method for thin-film technology, a technology that will be identified in our empirical example later in the paper. In Table 1, we have raw information available in each patent document. For instance, we have the application filing date of a patent and some more information such as the patent item and abstract. In Table 2, topic modeling has been used to structure the patents. One can see the most repetitive words with regard to their associations to other words in the patents' abstracts. The sequence of output is based on the most important topics by using the most repeated words within a number of patents. To interpret the results from topic modeling, it is advisable to rely on experts' opinions from the technological field. We asked two experts on photon management for solar energy conversion with special expertise in plasmonic nanoparticles. Table 4 shows the name of the identified hidden technologies within each cluster, namely multi-junction in crystalline silicon, concentration in thin-film and dye-sensitized in organic clusters.

2.3.4. Academic literature research

Finally, after having identified the names of prominent technologies via k-core analysis and topic modeling and experts' opinions, we search the names of those technologies in the Thomson Reuters Web of Knowledge to find out whether these technologies from patents' abstracts are also important from a scientific point of view. Previous research illustrates that there is often a significant relationship between science and technology (Mansfield, 1990; Schmoch et al., 1996). Of course, the process of disrupting an obsolete technology does not happen suddenly but instead takes some time and it contains a long process of "creative

Table 1
Input of the Stanford topic modeling toolbox.

IDs	Year	Patent item	Patent Abstract
1	1980	The Schottky barrier photovoltaic detector	A platinum–cadmium sulfide Schottky barrier photovoltaic detector which is capable of sensing near ultraviolet and short wavelength visible radiation with extremely small response to wavelengths longer than about 5200 Å. The detector is fabricated.
2	1985	Photocell device for evolving hydrogen and oxygen from water	A photocell device for evolving hydrogen and oxygen from water using solar radiation is formed with a plurality of p–n junctions. A transparent ohmic window is disposed at the p–n junctions to avoid lattice mismatch and to provide maximized equal current

creation" (Christensen and Raynor, 2003; Hart and Christensen, 2002). However, in general, disruptive technologies are cited more than other innovations (Katila, 2004). Trajtenberg (1990a) illustrates that the technologies that underlie patents that receive a significant number of citations, will be used in many other future patents. From a market point of view, Murray (2002) states that when firms are able to balance between science and technology they are able to have better perspective for their future commercialization processes.

These findings imply that scientific publications that deal with technologies which later on become disruptive technologies, should receive more attention from other researchers; i.e., more scholars start to do research and to write papers on connected topics. We therefore expect that if a technology has the potential to become a disruptive technology we will observe that the number of scientific publications extraordinarily increases within this field over time. Based on this assumption, we aim to increase the validity of our analysis from patent data with regard to technological disruptiveness by additionally connecting the results to the output of science. Furthermore, many new technologies are invented in universities or research labs and not in the industry and vice versa.

3. Applying the method to the photovoltaic industry

3.1. History of the photovoltaic industry

The principle of photovoltaic technology is the transformation of sunlight (photon) to electricity. During the last thirty years, the photovoltaic industry has been developed and its efficiency has been significantly improved. The costs of electricity produced by photovoltaic technology have been rapidly reduced over time while fluctuations in crude oil prices have increased the costs of electricity produced by conventional technologies. Moreover, the increase of world population, the need for more energy, air pollution and disasters such as acid rains, typhoons, floods or nuclear accidents like Fukushima, make the photovoltaic technology an attractive, alternative source for clean, secure, sustainable and rather cheap energy within other renewable energies (Schleicher-Tappeser, 2012). There are, however, also other sources of renewable energy in the world. Nevertheless photovoltaic technology has some fundamental characteristics that may help it to become a frontier energy technology among other renewable energies (Schleicher-Tappeser, 2012).

Table 2
Output of the Stanford topic modeling toolbox.

Topic 11	Topic 23	Topic 21	Topic 18	Topic 1
Circuit	Optically	Photosensor	Solid-state	Photoelectric
Integrated	Traces	Imager	Current	Solid-state
Amorphous	Sensors	Improved	Efficiency	Charges
Doped	Transparent	Multi-trench	Diffusion	Film
Located	Conductive	Cmos	Improve	Converting
Pin	Packaging	Microlens	Example	Micro
Bottom	Embodimen	Use	Back-illuminated	Signal
Photodiodes	Directly	Capacity	Provide	Lens
Single	Interactive	Increased	Sensors	Insulation
Photon	Assembly	Oxide	Cmos	Pixels
Cell	Flip-chip	Accordance	Process	Regions
Fabricating	Systems	Fill	Increases	Filters
Process	Layers	Cell	Quantum	Electrodes
Electrode	Thickness	Polysilicon	Capable	Reflecting

First, when installed, photovoltaic devices do not need any necessary maintenance for their lifetime. Second, it takes just one week for installation, and users are able to install the technology anywhere. Third, the global photovoltaic market has grown very fast, for instance from 280 MW p in the year 2000 to closely 40,000 MW p in the year 2010, with an average annual growth rate of 50%. Fourth, the technology offers the possibility of mass production. For the last three decades this technology has doubled each year, but prices have decreased, on average, by more than 20%.

Fifth, photovoltaic technology provides an opportunity for its customers to have a price of electricity relatively close to the wholesale price. Sixth, customers of photovoltaic energy can be simultaneous producers of electricity for other users. Seventh, photovoltaic innovation cycles are significantly shorter than other types of power plants, facilitating the technological progress in the long run (Schleicher-Tappeser, 2012). In addition, Hart and Christensen (2002) predict that the photovoltaic technology, due to its characteristics, has the potential to become a frontier source of energy among other renewable energies. For instance, in developing countries in which no proper electricity infrastructure exists nor money for building or improving the existing ones, the photovoltaic technology could provide the necessary electricity needed for the rural areas. Also, due to the portable ability of this technology, they may be installed anywhere, for instance at the top of cars, roofs and even on backpacks. Finally, photovoltaic technology in comparison with other types of renewable energies is cheaper, more user friendly and lighter (portability) which makes this technology more attractive than other renewable energies.

Photovoltaic technology was discovered in the 18th century. Becquerel (1839) invented the photocurrent approach, which later on was called the *photo electrochemical process*, in which platinum electrodes covered with silver bromide were used to generate electricity. Some years later Smith (1873) and Adams (1876) were the first scientists who discovered that solid materials – known as selenium – can convert light into electricity. In 1883, Charles Fritts was the first inventor who produced and developed photovoltaic devices. Later on in 1954, researchers in Bell Labs accidentally discovered that p–n junction diodes generate electricity when they receive light. This led to the production of 6% efficient silicon p–n junction solar cells (Goetzberger et al., 2003).

The photovoltaic technology soon became popular among governments as well as scientists. In 1947, after the Second World War, scientists predicted that petroleum and other natural energy resources such as gas and coal had been extensively declining, and the world should look for new sources of energy. Furthermore, some years later in 1965, the United States and the Union of Soviet Socialist Republics heavily invested in their space programs, and many researchers tried to use new or different materials to revolutionize photovoltaic technology as an alternative energy source for space programs (Goetzberger et al., 2003). There was a significant advancement for photovoltaic technology in 1973, when the first violet cell was developed. It was much more efficient than other advanced silicon solar cells at that time. At this time, a conference about the next generation of photovoltaic technology convinced the US Department of Energy that photovoltaic technology had the potential to be a proper source of energy.

The first oil crisis finally convinced governments worldwide about the importance of renewable energy and, most notably, solar energy (Luque, 2002). However, photovoltaic technology received a severe blow in 1982, when national governments worldwide decided to cut public financial support. This decision was based on the reason that solar power without the support of substantial amounts of subsidies would not be successful. In addition, the international oil price during this time massively recovered and undermined the price advantages of solar energy. However, after the recent Fukushima nuclear accident, politicians from around the world decided again to come back to renewable energy and, most notably, to photovoltaic technology (Schleicher-Tappeser, 2012).

Today the photovoltaic industry consists of more than 18 different sub-technologies (NREL, 2013). These technologies can be roughly divided into three main technologies, namely crystalline silicon, organic solar cells and thin-film solar cells (WIPO, 2009).

In the year 2000, around 86% of the market belonged to the various forms of crystalline silicon. The technology strongly relies on silicon but silicon has several disadvantages. For instance, it is very brittle, which negatively affects the lifetime of solar cells (Goetzberger and Hebling, 2000). Therefore, researchers try to discover alternative sources of materials to overcome the problems of silicon and to increase the efficiency of the photovoltaic technology (McConnell, 2004). Recently two new types of technologies entered the market which are known as thin-film and organic solar cell (Goetzberger and Hebling, 2000; McConnell, 2004).

Thin-film solar cells also rely on silicon's photovoltaic material with its advantages and disadvantages. Solar cells made from amorphous silicon – which is used in thin-film solar cells – tend to have lower energy-conversion efficiency than crystalline silicon, but are less expensive to produce. Furthermore, amorphous silicon has a higher band gap than crystalline silicon, which means it absorbs the visible part of the solar spectrum more strongly than the infrared portion of the spectrum. Recently, solutions to overcome the limitations of thin-film silicon have been developed. For example, thermal processing techniques enhance the crystallinity of the silicon and pacify electronic defects, or light trapping schemes enhance the absorption of sunlight in the films (GBI Research, 2011). Consequently, thin-film solar cells have become popular for consumers. The market share grew gradually from 13% in 2000, to 20% in 2010 (Edoff, 2012; Goetzberger and Hebling, 2000).

Traditionally in photovoltaic technology, the transformation of sunlight to electricity is done by inorganic material. Recently, organic material has been used to absorb sunlight. The efficiency of this new technology is still quite low but organic materials have several advantages. They are cheaper than inorganic materials, more comfortable and more adaptable to other applications, such as the portable solar cell, to carry the heavy battery packs in military actions (McConnell, 2004). However, at the moment, the market share of organic solar cells is negligible.

Summing up, the photovoltaic industry is an interesting example for disruptive technological change. In comparison to traditional energy technologies, this industry still has a shadowy existence but may become a major alternative for energy production. Within the photovoltaic industry, new technologies such as organic solar cells or thin-films enter the market while the dominant technology, such as crystalline silicon solar cells, may gradually lose its market share (McConnell, 2004). Due to the role of photovoltaic technology as an important future energy source, from managers' and strategy planners' point of view, it is important to know which sub-technology has the potential to become a disruptive technology within this technology.

3.2. Data

Data were collected from the European Patent Office (EPO) Worldwide Patent Statistical Database, known as PATSTAT (October 2012 version). The database includes patents that have been published in DPMA (German Patent and Trade Mark Office), EPO (European Patent Office), INPI (National Industrial Property Institute — France), IPO (Intellectual Property Office), JPO (Japan Patent Office) and USPTO (United State Patent and Trademark Office). Data were collected from the year 1978 to the year 2012. We searched the keywords "Photovoltaic" and "Solar cell" on the EPO homepage, covering the different types of solar technologies. In order to include only patents of the photovoltaic industry we cleaned up the data by selecting patents from the IPC-class H01L 31/00. Extended patent family is used in order to collect all possible innovations. Then we collected all citations belonging to the extended patent families. Doing this ensures that all innovations and their relevant citations are considered. The final dataset covers 9328 patents from the year 1978 to the year 2012.

We note that a main problem associated with the use of patents from different patent offices (the nature of PATSTAT database) is the high number of patent citations made by examiners and just a small fraction made by inventors. However, prior research illustrates that citations made by examiners are a valid measure for knowledge flow and technological change (Breschi and Lissoni, 2005; von Wartburg et al., 2005). Based on these findings, we do not exclude patent citations that were made by examiners.

3.3. Method

Based on collected patents, we construct a patent–citation network to analyze our data. In a first step we identify the largest connected subgraph, i.e., the largest weak component, in the patent–citation network. As shown in Table 3 we find five weak components. The largest component entails 5029 patents and is assumed to represent the most important independent technology within the photovoltaic industry.

We select the largest component and apply the proposed algorithm of Choi and Park (2009) to draw patent-development paths. From 5029 patents, 735 patents remain on the path representing all highly cited patents that contributed to technological advancement within the industry (Katila, 2004; Smith, 1993). The patent-development path consisting of the 735 highly cited patents is illustrated in Fig. 1. The color and form of each node denotes the types of patents. Red circle nodes are origin patents, yellow squares nodes are intermediate patents and blue squares nodes are terminus patents. The direction of the arrow represents the development direction of forward citations, or the history of the technology. Within the figure, highly cited patents can be evaluated as more valuable if they are located on two or more development paths or if they are located in gathering positions.

We carry out a k-core analysis to understand the detailed inner structure of the patent citation network. The method was applied to the patent-development paths. Three k-cores, i.e., three areas containing cohesive subsets with clique-like structures, are identified (Nooy et al., 2005). As shown in Table 4, the experts on photon management distinguished three main photovoltaic technologies, namely crystalline silicon, organic solar cells and thin-film, underlying each k-core. This corresponds to the recent developments in the photovoltaic industry.

From the 735 highly cited patents of our patent-development path, 204 highly cited patents belong to crystalline silicon, 358 highly cited patents belong to thin-film and 173 highly cited patents belong to organic technologies. Due to the number of highly cited patents in each cluster, identifying the name of the prominent technology is difficult,

Table 3
Large components in the network of patent development paths for the photovoltaic industry.

Components	Number of patents
C1	5029
C2	64
C3	46
C4	45
C5	40

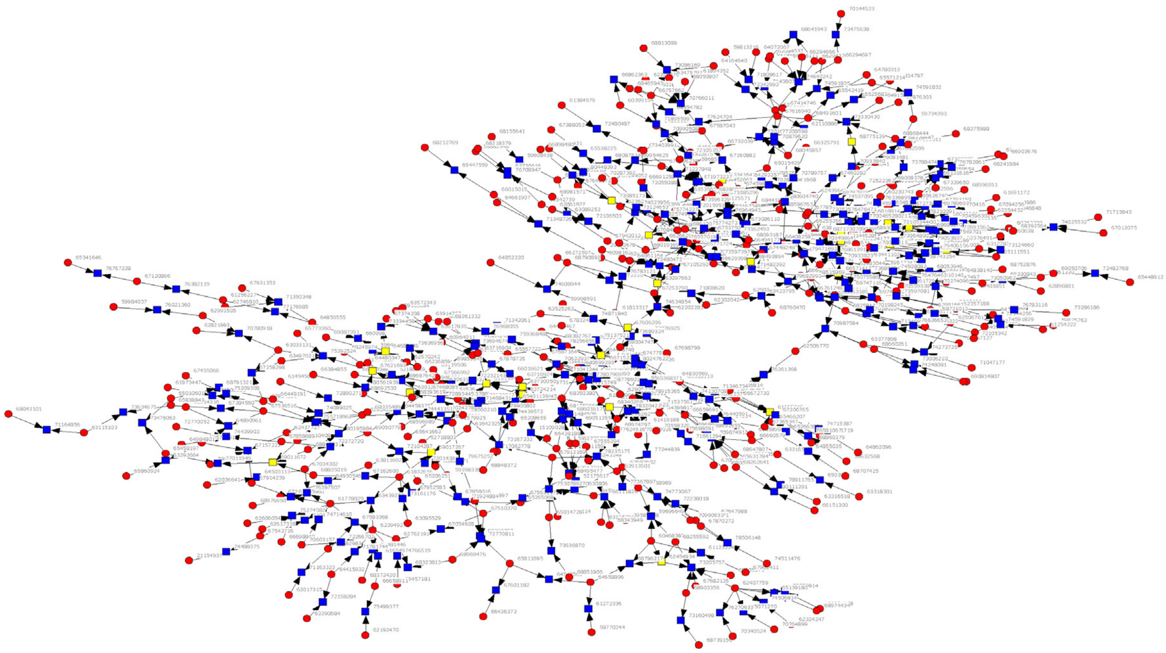

Fig. 1. Patent-development paths for the largest component of photovoltaic industry. (For interpretation of the references to colors in this figure, the reader is referred to the web version of this article.)

and therefore we implement topic-modeling analysis on all three clusters separately.

As shown in Table 4, based on the results of topic modeling, experts identify the names of the most prominent technologies; in the crystalline silicon cluster the name of this prominent technology is multi-junction. This technology achieves the highest efficiency of solar conversion compared with other types of photovoltaic devices. However, the production costs of this technology are high (Yamaguchi, 2003). In the thin-film cluster, the name of the most prominent technology is concentration technology. This technology consists of a new design of solar cell with optical elements and – with similar costs of production – improves the performance of the photovoltaic technology (Barnett et al., 2006; Zahedi, 2011). In the organic cluster, dye-sensitized technology is identified as the most prominent technology. While dye-sensitized technology may provide technological and economic opportunities for the photovoltaic industry, this technology still has disadvantages. For instance, the efficiency is low and the technology is less stable than conventional photovoltaic devices (Grätzel, 2004). In the following, the three clusters will be used to interpret the development stages of the photovoltaic technology.

Table 4
Names of prominent technologies within the photovoltaic industry.

Cluster	Name of underlying technology
Crystalline silicon	Multi-junction
Organic	Dye-sensitized
Thin-film	Concentration

Table 5
Development stages of the photovoltaic technology.

Stage	Description	Development path map
Introduction stage (1978–1984)	Emergence of new patents	Fig. 2
Growth Stage (1984–2001)	Developing exist technology	Fig. 3
Maturity stage (2001–2007)	Developing and exploring	Fig. 4
Converging stage (2007–2012)	Linking between two components	Fig. 5

4. Development stages of the photovoltaic technology

We use four different time periods, i.e., introduction, growth, maturity and converging stage of the technology (Choi and Park, 2009), to interpret the development stages of the photovoltaic technology. We divide the patent-development paths into the time periods 1978–1984, 1985–2001, 2002–2007 and 2008–2012. The extent of each time period varies and is based on formal reflections about the development of the technology and obvious upheavals in the patent-development paths. Table 5 summarizes the four time periods. We discuss each time period in detail below.

4.1. Introduction stage of the photovoltaic industry (1978–1984)

Fig. 2 shows all highly cited patents of the patent-development paths developed in the introduction stage of the photovoltaic industry. Because we only analyze highly cited patents in the photovoltaic industry, it is very likely that there are other ordinary photovoltaic patents or even patents from other possibly related IPC before this time period, which are, however, not highly cited. In Fig. 2, the highly cited patents are assigned to our three clusters identified by the k-core analysis.[2]

In the introduction stage, we find only four highly cited patents with the patent publication IDs 61514316 (1980), 64658896 (1982), 65811695 (1983), and 66436373 (1984). The four highly cited patents represent the early origin patents in the introduction stage of the industry. The earliest origin patent, patent 61514316 (1980), is located in the crystalline-silicon cluster, indicating that the photovoltaic industry originated from this technology. This finding is in line with a previous study that illustrates that the first generation of solar cell technology benefited from crystalline-silicon technology (Goetzberger and Hebling, 2000). The patent represents a technology about the Schottky barrier photovoltaic detector. Patents 64658896 (1982), 65811695 (1983), and 66436373 (1984), are located within the organic solar-cell technology cluster. These highly cited patents refer to a technology about a layer of organic electronic materials that is sandwiched between two metal

[2] We should note that the patent–development path is conducted based on patent publication IDs of patents generated by PATSTAT for linking different tables. However, the interpretation of the results is based on the information of unique patents.

Fig. 2. Introduction stage of the photovoltaic industry (1978–1984).

electrodes. According to Katila (2004), highly cited patents reflect that an innovation is radical. Therefore, according to the number of highly cited patents, one could conclude that in this period of time, organic technology is more dynamic than crystalline-silicon and thin-film technologies.

4.2. Growth stage of the photovoltaic industry (1985–2001)

Fig. 3 shows all highly cited patents of the patent-development paths that were developed in the growth stage of the photovoltaic industry. We find more origin patents, namely 25, and the first links between highly cited patents, namely 4 terminus patents, i.e., the patents built on the former technologies but that were not (yet) picked up by subsequent technologies. The most terminus patents, namely a cluster of 4 origin patents linked by 3 terminus patents, occur in the organic photovoltaic-cell cluster. In the organic solar-cell cluster, the latest technology – patent 61272336 (1998), built on two origin patents, patent 64658896 (1982) and patent 58770244 (1993) – implies that it took 16 years before the technology was developed further. Moreover, in the organic cluster, 11 origin patents and 3 terminus patents occur, while within the crystalline-silicon cluster, there are only 9 origin patents and 1 terminus patent, and for the thin-film cluster, there are only 5 origin patents. According to previous studies that highlight the significant role of highly cited patents as representatives of important technologies (Choi and Park, 2009; Harhoff et al., 2003; Katila, 2004; Trajtenberg, 1990c; von Wartburg et al., 2005), one could conclude that at this time, the organic solar-cell cluster was more developed than the other two clusters. This suggests that, although crystalline silicon was generated earlier than organic and thin-film technologies, the organic technology seems to be an important feature of technological progress within the photovoltaic industry. Moreover, the findings are in line with Bernede (2008). He finds that in the 1990s, organic solar technologies were significantly developed and that they opened a new perspective of using organic material in the photovoltaic industry.

4.3. Maturity stage of the photovoltaic industry (2002–2007)

Fig. 4 shows all highly cited patents of the patent-development paths developed in the maturity stage of the photovoltaic industry. In this period, the numbers of highly cited patents increase significantly. In this stage we find 356 origin patents, 96 terminus patents and 23 intermediate patents. Concerning the number of highly cited patents, all three technologies (crystalline silicon, thin-film, organic solar) developed quickly in comparison to the previous time frame. There are 119 highly cited patents in the crystalline-silicon area, 101 highly cited patents in organic area and 192 highly cited patents in thin-film area. As it becomes clear in Fig. 4, most links between highly cited patents are obtained in the thin-film solar-cell technology. In addition, the patent development paths show that thin-film has been growing independently from the two others, namely crystalline silicon and organic. This indicates that this technology made the largest progress within this time. This observation corresponds with the fact that currently, the market share of thin-film solar-cell technology is growing faster than the market share of the dominant crystalline-silicon technology (Edoff, 2012). In addition, based on a previous study about the important role of highly cited patents for technological disruptiveness (Katila, 2004), one could conclude that because the number of highly cited patents for thin-film technologies are more than the two other technologies, thin-film technology is more likely to be involved in the disruptive technology. Also according to the characteristics of disruptive technology (Christensen, 1997), the new technology itself develops very quickly, namely in the photovoltaic industry, and thin-film developed within the short period of 2001 to 2007.

Furthermore, in this period of time, three important connections appear between crystalline-silicon and organic solar-cell technologies, namely highly cited patents 68350380 (2001), 67555394 (2001), and 68495477 (2001). These highly cited patents show that technologies originate from organic solar-cell technology and are transferred to crystalline-silicon technology. This finding is in line with Bernede (2008) who finds that organic material provides new facilities for the other photovoltaic technologies. The most impactful of the three highly cited patents is patent 68350380 (2001) that contains a technology to increase the efficiency of the photovoltaic device and has been applied in 2 intermediate patents and 1 terminus patent. One intermediate patent 63730050 (2003) suggests a material in the form of a fiber that is more flexible than other types of material. The other intermediate patent 63724214 (2003) contains information about a photosensitized interconnected nanoparticle layer. The terminus patent 65401139 (2006) includes a technology for the display with integrated photovoltaic cells.

4.4. Converging stage of the photovoltaic industry (2008–2012)

Fig. 5 shows all highly cited patents of the patent-development paths developed in the converging stage of the photovoltaic industry.

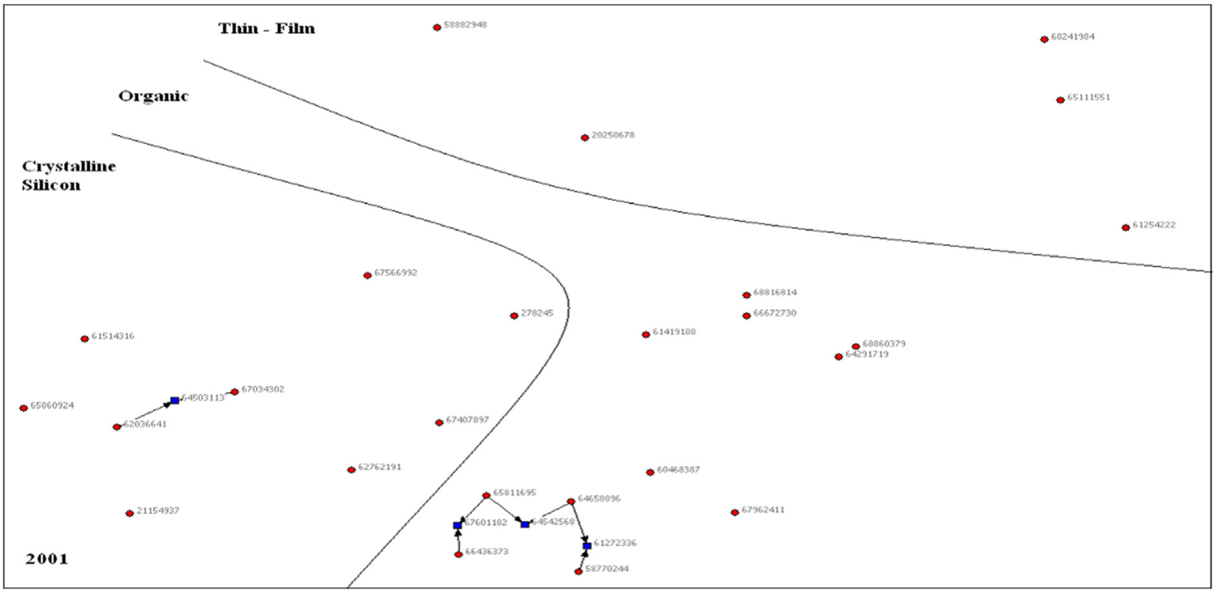

Fig. 3. Growth stage of the photovoltaic industry (1985–2001).

Again, the number of highly cited patents in the industry has grown considerably. First, the two unconnected clusters of thin-film solar-cell technology and the remaining technologies, crystalline silicon and organic solar cells, are now connected by three links. In two cases, the technology transfer goes from origin patents developed in thin-film to patents in organic solar cells, suggesting that the organic solar-cell technology started to absorb and apply knowledge from thin-film. Second, there are 16 links that show knowledge is transferred from organic solar cell to crystalline silicon. Most of these references go from organic solar cells to crystalline silicon, suggesting that knowledge invented for organic solar cells becomes applied in the dominant paradigm of crystalline silicon. The high number of links may be interpreted as an indication for the convergence of both technologies with respect to certain methods and applications. The direction of the technology transfer from organic solar cells to crystalline silicon suggests that knowledge invented for organic solar cells has reached a development stage in which it is applicable to conventional methods and procedures. Third, the patent-development paths show that crystalline-silicon and thin-film technologies have developed independently from each other. They can only reach each other via organic solar cells. This result is in line with the findings of Hart and Christensen (2002). The authors predict that the thin-film technology – based on its characteristics such as, lower cost of production, portable ability and the potential for electricity for rural areas – is more likely to replace the dominant technology, namely crystalline silicon.

According to these previous studies, we assume that the highest highly cited patents are more likely to be involved in disruptive technologies (Trajtenberg, 1990a; Katila, 2004). K-core analysis helps us to identify important independent technology, i.e., subgroups of highly cited patents within the patent development path (Batagelj and Mrvar, 2000; Batagelj et al., 1999).

As shown in Fig. 5, the three red circles represent the most important independent technologies within the patent-development path. For instance, in the crystalline-silicon cluster there are 82 highly cited patents out of 204; in the thin-film cluster there are 191 highly cited patents out of 358; and in the organic cluster there are 76 highly cited patents out of

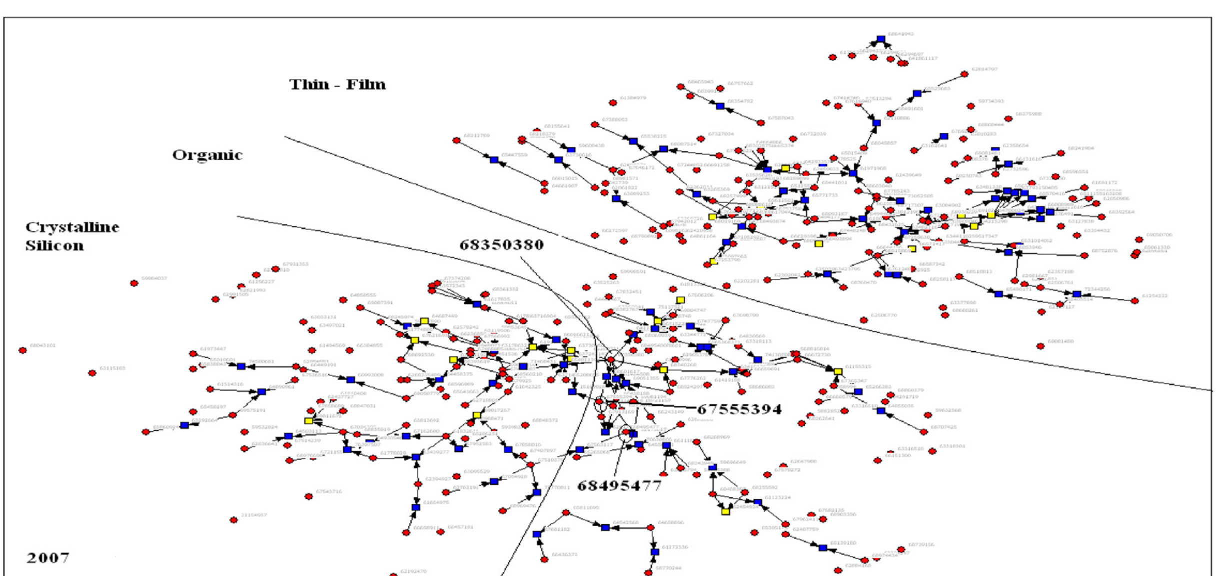

Fig. 4. Maturity stage of the photovoltaic industry (2002–2007).

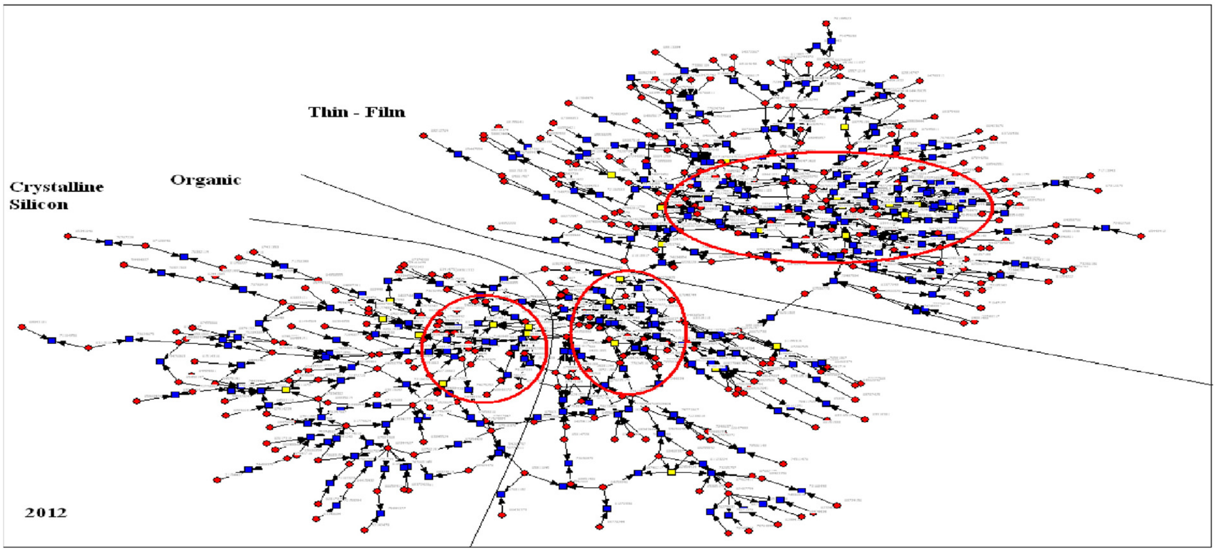

Fig. 5. Converging stage of the photovoltaic industry (2008–2012). (For interpretation of the references to colors in this figure, the reader is referred to the web version of this article.)

173. As mentioned in Section 2, based on the results of topic modeling analysis, experts identify the names of these independent technologies within each cluster (see Table 4).

Finally, we cross-validate the former results by extracting the highly cited patents located at a position where various development paths converge. It is very likely that highly cited patents located at converging positions are economically or technologically valuable ones because the patent-development paths are generated by starting from origin patents and then by selecting arcs of the highest weight. These highly cited patents are expected to serve as seeds for another advanced technology. Table 6 shows the ten most important converging patents of all the whole patent-development paths measured by the number of inflows and FCNP and additional attributes of filed years, and the clusters.

The findings in Table 6 show that all converging patents were filed after 2002. This indicates that the more impactful technologies for the field tend to use newer technologies rather than older ones. As noted earlier, intermediate patents contain the possibility of shifting existing technologies. The position of each converging patent on the patent-development paths shows the way converging patents develop, and a particular technology starts to absorb and apply that knowledge. In this regard, the highly cited patents 67606206 (2004, organic) and 63724214 (2003, crystalline silicon) have occupied a strategically important position for technological development because they connect organic solar-cell technology to crystalline-silicon and thin-film technologies. A technology from the organic solar-cell cluster, namely a method about the manufacturing of photovoltaic devices based on nanostructure template, goes through highly cited patent 6760206 (2004) to the thin-film cluster, namely highly cited patent 74634854 (2009) that contains a new technology for manufacturing more efficient CMOS-image sensors, indicating that knowledge invented for organic solar cell becomes applied to thin-film. Furthermore, another technology from the organic solar-cell cluster, namely a new structure for interconnecting photovoltaic cells to photovoltaic modules, goes through highly cited patent 63724214 (2003) to the crystalline-silicon cluster, namely to highly cited patent 61911648 (2002) that contains a new method of manufacturing photovoltaic modules with contacting a cross-linking agent with semiconductor particles, to highly cited patent 74439572 (2008) about safety polymeric laminates and to patent 79900802 (2011) that suggests a photovoltaic module that includes a plurality of photovoltaic cells. These findings highlight the importance of organic solar cell technology for the further development of the crystalline-silicon technology.

Table 6
Ten most important converging patents in the patent development paths.

Patent publication ID	Year	Cluster	Inflow number	FCNP
65612501	2006	Thin-film	5	2
61911648	2002	Crystalline silicon	5	1
61155315	2005	Organic	4	3
69017267	2004	Crystalline silicon	4	2
67621693	2004	Crystalline silicon	3	1
64478748	2003	Organic	2	8
67606206	2004	Organic	2	4
63724214	2003	Crystalline silicon	2	3
73085173	2009	Thin-film	2	2
62454934	2002	Organic	2	2

4.5. Academic progress within the photovoltaic technology

In this step, we crosscheck the former results from patent analysis with the results of an academic literature research from Thomson Reuters Web of Knowledge. In our literature research we use the keywords identified via topic modeling and experts interviewed, in order to identify the number and relevance of scientific research about the three technologies that have the potential to become disruptive within the three main photovoltaic technologies, namely in crystalline-silicon solar-cell multi-junction technology, in organic solar-cell dye-sensitized technology, and in thin-film solar-cell concentration technology (see Table 4). The results are presented in Fig. 6. In order to avoid counting unrelated scientific publications from Thomson Reuters Web of Knowledge, the keywords have been searched with two terms "solar cell" and "photovoltaic". Because the number of citations and items of multi-junction technology are not equal to the other two technologies, namely concentration and dye-sensitized technologies, Fig. 6 indicates the information on multi-junction technology separately on another axis.

The results show that the number of scientific publications and citations is increasing over time, indicating that the photovoltaic industry is also of academic interest. The earliest scientific publication was published in 1991 on dye-sensitized technology. However, the earliest patent on dye-sensitized technology in the patent-development paths was not filed until 1998. This implies a time lag of 7 years before the trajectory was pushed from basic research in the industry to the market. With the other technology clusters, the results show that the earliest scientific publication on multi-junction technology was published in 1974. The time lag to the earliest patent in 1996 is 22 years. The earliest

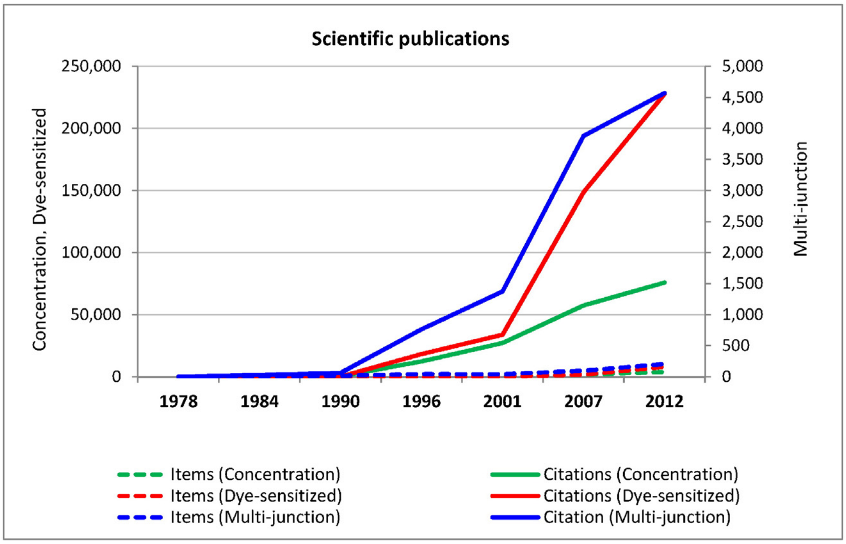

Fig. 6. Number of Items and their citations for three technological disruptiveness.

scientific publication on concentration technology was published in 1977. The time lag to the earliest patent in 1995 is 18 years. This suggests that the developments of concentration and multi-junction technologies run parallel to each other, were of later interest for science, and faster to have led to realizable applications.

With respect to the number of scientific publications, we find the highest number and growth rate on the topic of dye-sensitized technology. In 2012, this number was more than 1.5 times higher as compared to the number of scientific publications on concentration technology, and more than 25 times higher as compared to the number of scientific publications on multi-junction technology. The huge scientific interest in dye-sensitized technology, followed by concentration technology, corresponds to our findings on the patent-development paths. These findings are also in line with the results of Hart and Christensen (2002). They find that the process of disrupting dominant technology does not happen suddenly in the market. It is a long process of "creative creation". These findings can be interpreted as important signs that show that dye-sensitized and concentration technologies are more likely to change the direction of the technology and perhaps may become disruptive technologies in the photovoltaic industry.

4.6. Robustness test

For a robustness test we compare the patent-development path that has emerged from patents published and cited up to 2008, with the patent-development path that emerged from patents published and cited up to 2012. The intuition of such a proceeding is easy: If we had no information on the patents published and cited from 2008 to 2012, would the method come to the same conclusions? If this is the case, the suggested method of technological monitoring can be indeed used as a basis for technological forecasting because the assumption that technology is path dependent holds (Choi and Park, 2009; Porter and Roper, 1991). Fig. 7 graphically illustrates the patents' development path up to 2008. Table 7 statistically compares both alternative paths by analyzing how many patents of the patent-development path up to 2012 had been already identified as patents of the patent-development path up to 2008. Apart from terminus patents which are only identified in 64% of all cases, all other categories of patens are identified in 70% up to 80% of all cases. This shows that there is a strong correlation between past and future developments within patent-development paths. This also suggests that a clear trend of technological development can be detected. Therefore, the results of patent-development paths are helpful to identify probable future developments, for example in the photovoltaic industry. In addition, the identified trends of the 2012-path can be also already seen in Fig. 7.

5. Discussion and conclusions

Considering the increasing speed and complexity of technological change, from managers' point of view it is crucial to understand and identify past and current technological changes which influence future changes in a particular field (Choi and Park, 2009; Lemos, 1998; Porter and Roper, 1991). In this research we proposed a new systematic tool based on patent-development paths, k-core analysis and topic-modeling analysis for analyzing the complex relationship between important highly cited patents and technological disruptiveness. The proposed method helps managers to have a better understanding of the history of a technology as well as future dynamics of technological development.

Previous methods for technological forecasting have limitations. First, these methods often use subjective procedures that highly depend on experts' opinions.[3] Second, they are often only accurate to forecast technological developments at the macro but not at the micro level. Third, obtaining and maintaining information for a previous method is very costly and difficult.[4] We proposed a relatively cheap method that relies on objective information about a technology that is able to forecast technological developments at the micro level, and we showed a complex relationship between technologies and that this method does not forecast only numerical changes in data.[5]

In our research, patent-development paths, rather than individual patents, have been explored to identify technological disruptiveness. In many industries, the output of R&Ds is patented (Griliches, 1998), and the literature demonstrates that patent citations can be used to learn more about technological advancement and the disruptiveness of innovations (Katila, 2004; Smith, 1993). We discussed a new approach to identify disruptive technological change in the photovoltaic industry. To identify disruptive technological change, we suggested a combination of three methods, namely patent-development paths, k-core analysis and topic-modeling analysis. By identifying current

[3] Examples would be, for instance, the Delphi, consensus, and scenario methods. Therefore reliable databases like PATSTAT and Thomson Reuters Web of Knowledge are needed for identifying current trends of technological development.

[4] Such methods would be, for instance, technological vigilance and blog analysis.

[5] Because almost all previous studies are based on *ex-post* analysis, a combination of *ex-post* and *ex-ante* analyses using an external database like Thomson Reuters Web of Knowledge can increase accuracy of forecasting trends of technological development.

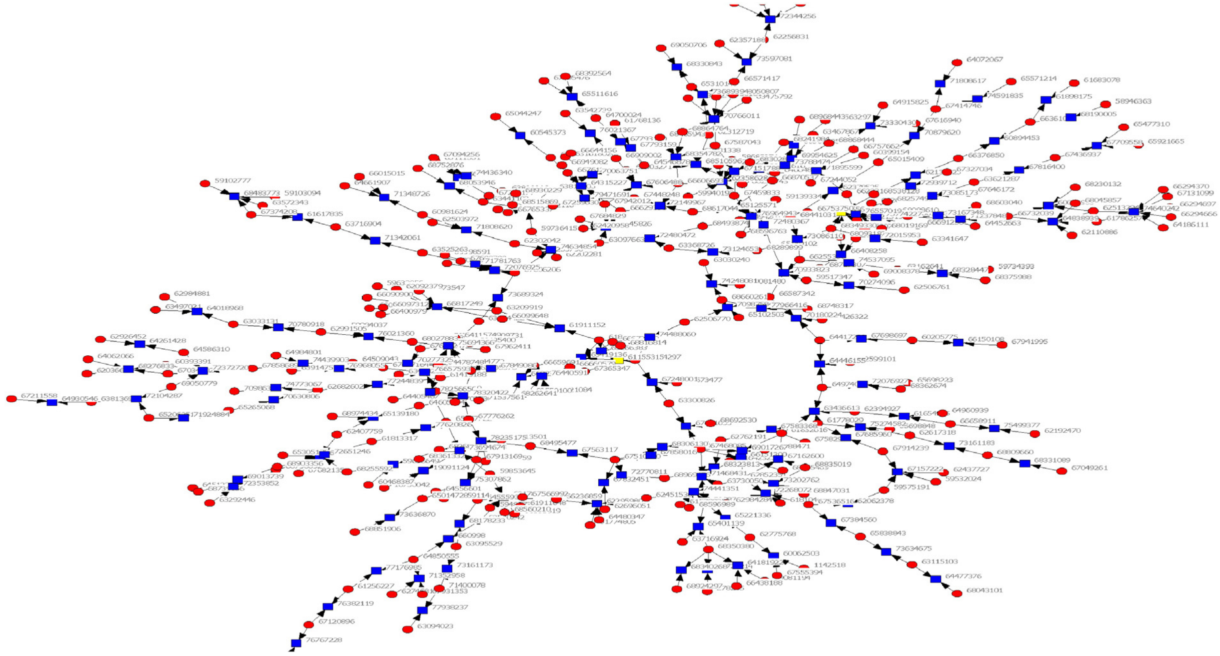

Fig. 7. Patent-development paths until 2008.

technological changes with the important latent technologies on the patent-development paths and providing an *ex-ante* perspective on technological changes, the suggested method provides insights into technological forecasting especially if one considers disruptive technologies.

In this regard, for our illustrative example, we found that the photovoltaic industry is currently facing a transition from silicon-based material to organic material. The major implication for the dominant technology, namely crystalline silicon, is that new technologies, such as organic solar cells and thin-film solar cells, are growing quickly and, in the near future, may replace the current technology. The patent-development paths demonstrated that crystalline silicon solar cells absorb and apply knowledge and technologies from organic solar cells. This indicates that organic solar cell technology may be an alternative technology that provides low costs and more stable material for conventional photovoltaic technologies, namely crystalline silicon and thin-film technologies. Organic solar cells thus have the potential to become mature by acquiring sufficient credentials to be widely used. According to our results, not only organic solar cells but also thin-film solar cells made technological progress. The thin-film technology has grown quickly and independently over time compared with crystalline silicon solar cells and organic technology. The technology has the most highly cited patents in the patent-development paths, namely 358 patents. Furthermore, we identified within each of the three main photovoltaic technologies one hidden technology that is most likely to become the "disruptive technology" within each cluster, namely multi-junction technology within the crystalline silicon cluster, concentration technology within the thin-film cluster and finally dye-sensitized technology within the organic cluster.

The methodology and results of this study may enable managers who are working in the photovoltaic industry to predict their own position in the industry and make better decisions based on the technological trend. For instance, based on our findings, thin-film technology has grown more quickly after 2001 as compared to the dominant technology. In addition, technological trend shows that the direction of technology is changing from crystalline-silicon technology to thin-film technology and here, in particular, to concentration technology. Moreover, managers may invest in dye-sensitized technology of organic solar cells because in the future it may replace silicon-material technology. Our methodology not only provides a unique opportunity for exploring the complexity of the photovoltaic technologies but also provides a new perspective for using patent documents and an external database, namely Thomson Reuters Web of Knowledge, as a complementary method for identifying disruptive technological changes.

This study has limitations. First, in this research we were not able to overcome the fundamental problem of patent analysis. For example,

Table 7
Path dependency between patent–development path until 2008 and 2012.

Items	Patent-development path until 2008	Patent-development path until 2012	Overlap between the patents included in the path until 2008 with the patents included in the path until 2012 (in %)
Filed patent	6610	9328	100.00
Size of the largest component	3124	5029	100.00
Number of highly cited patents in the path	480	735	72.92
Number of origin patent	317	394	77.29
Number of terminus patent	161	313	63.98
Number of intermediate patent	2	28	100.00
Thin-film	227	358	73.13
Organic	95	173	70.52
Crystalline silicon	158	204	74.05
Concentration technology	76	191	80.26
Dye-sensitized technology	21	76	76.19
Multi-junction technology	50	82	78.00

strategically not all the inventions are patented nor do they meet the patentability criterion (Pottelsberghe et al., 2001; Trajtenberg, 1990b), therefore analyzing all inventions has been not possible in this study. Second, information loss occurred during the analysis. The algorithm only took into account major patent-development paths by neglecting minor paths. Thus, the suggested method neglected to analyze other patents that are not part of the major patent-development path. Third, the suggested method was restricted to a limited number of patents. For example, if the number of patents would exceed more than 12,000 patents, none of the available conventional computers and software would be able to calculate the algorithm. Fourth, the dataset was limited to the selected IPC class, namely H01L 31/00. Earlier-issued patents from other IPC classes that might be related to the photovoltaic technologies were not included with the suggested methods. Fifth, to test the validity of the method, the analysis would need more testing of a wider range of technologies. Sixth, because there is no clear classification of a technology or a market, any misclassification distorted the conclusions. We tried to reduce this problem by relying on technological classification done by the European Patent Office and by relying on the help of experts in photovoltaic technology. Seventh, the differences between the number of citations in different patent offices, like USPTO and other patent offices can be considered as a limitation of this study. However, we tried to overcome this problem by only using granted patents from the US patent office. This ensures us that we only analyze important citations that have been reported world widely.

Some possibilities for future research are as follows. First, the method of this study can be applied to other industries to acquire more perspectives and knowledge about technological disruptiveness in those industries. Second, it would be useful if future studies implement other internet search methods to exploit the full extent of patent-document information. Third, other factors such as country, companies and universities could be incorporated to understand the nature of technological changes. Fourth, it would be useful to use multi-stage analysis to link our path to other possible technologies in order to identify the direction of technologies between the photovoltaic industry and other industries. Fifth, due to the importance of patents located at converging positions, a new algorithm that draws paths based on the most important intermediate patents, i.e., on patents that have the possibility to shift existing technologies, may be useful. Such an approach would allow us to identify technological disruptiveness more accurately.

Sixth, because prior studies find a strong relationship between science and technology (Mansfield, 1990; Schmoch et al., 1996) a combination of patent data, e.g., PATSTAT, with scientific data, e.g., Thomson Reuters Web of Knowledge, in one bibliographic dataset on which our methodology can be applied, may enrich further research on the evolution of technological disruptiveness. Seventh, it may be useful to identify and monitor those firms that have very similar knowledge to our patent-development paths in order to find out how they develop over time. Studying firms' knowledge level could help managers to have a better understanding of technological changes especially if one considers technological disruptiveness. Eighth, future research could systematically compare patent-developments paths of different time horizons and different technologies in this industry in order to substantiate the assumption that technology is path dependent, and monitor the trend of technologies to help to identify future changes (Kostoff, 1994; Porter and Detampel, 1995; Porter and Roper, 1991). Finally, because the patent-development path is based on the number of citations between *each* patent, normalization as used in the patent citation literature is not possible. Former approaches that used normalization worked with patent–citations counts, but not with relationships between patents. However, the issue may be of interest for further work on patent-development paths. This requires that the method include probability weights for patent citations between patents that are driven by the number of issued patents within the citation year.

References

Abrahamson, E., Hambrick, D.C., 1997. Attentional homogeneity in industries: the effect of discretion. J. Organ. Behav. 18, 513–532.

Adams, W.G., 1876. Proc. R. Soc. Lond. 25.

Albert, T., Moehrle, M.G., Meyer, S., 2015. Technology maturity assessment based on blog analysis. Technol. Forecast. Soc. Chang. 92, 196–209.

Bantel, K.A., Jackson, S.E., 1989. Top management and innovations in banking: does the composition of the top team make a difference? Strateg. Manag. J. 10, 107–124.

Barnett, A., Honsberg, C., Kirkpatrick, D., Kurtz, S., Moore, D., Salzman, D., Schwartz, R., Gray, J., Bowden, S., Goossen, K., Haney, M., Aiken, D., Wanlass, M., Emery, K., 2006. 50% Efficient Solar Cell Architectures and Designs. Photovoltaic Energy Conversion, Conference Record of the 2006 IEEE 4th World Conference on, pp. 2560–2564.

Batagelj, V., Mrvar, A., 2000. Some analyses of Erdos Collaboration Graph. Soc. Networks 22, 173–186.

Batagelj, V., Mrvar, A., Zaversnik, M., 1999. Partitioning approach to visualization of large graphs. Proceedings of 7th International Symposium on Graph Drawing.

Becquerel, A.E., 1839. C. R. Acad. Sci. 9, 145–561.

Bernede, J., 2008. Organic photovoltaic cells: history, principle and techniques. J. Chil. Chem. Soc. 53, 1549–1564.

Betz, F., 1996. Forecasting and planning technology. Handbook of Technology Management 1996. McGraw-Hill, NY.

Bhattacharya, S., Khan, M.d.T.R., 2001. Monitoring technology trends through patent analysis: a case study of thin film. Res. Eval. 10, 33–45.

Blei, D.M., NG, A.Y., Jordan, M., 2003. Latent Dirichlet allocation. J. Mach. Learn. Res. 3, 993–1022.

Breschi, S., Lissoni, F., 2005. Knowledge networks from patent data: methodological issues and research targets. Handbook of Quantitative Science and Technology Research. Springer, Netherlands, pp. 613–643.

Chang, J., Boyd-Graber, J., Gerrish, S., Wang, C., Blei, D.M., 2009. Reading Tea Leaves: How Humans Interpret Topic Models. Proceedings of Neutral Information Processing System 2009.

Choi, C., Park, Y., 2009. Monitoring the organic structure of technology based on the patent development paths. Technol. Forecast. Soc. Chang. 76, 754–768.

Christensen, C.M., 1997. The Innovator's Dilemma: When New Technologies Cause Great Firms to Fail. Harvard Business School Press, Boston, MA.

Christensen, C.M., Raynor, M.E., 2003. The Innovator's Solution: Creating and Sustaining Successful Growth. Harvard Business School Press, Boston MA.

Coates, J.F., Coates, V.T., Heinz, L., 1986. Issues Management. Lomond, Mt. Airy, MD.

Dosi, G., 1982. Technological paradigms and technological trajectories: a suggested interpretation of the determinants and directions of technical change. Res. Policy 11, 147–162.

Duriau, V.J., Reger, R.K., Pfarrer, M.D., 2007. A content analysis of the content analysis literature in organization studies: research themes, data sources, and methodological refinements. Organ. Res. Methods 10, 5–34.

Edoff, M., 2012. Thin film solar cells: research in an industrial perspective. Ambio 41, 112–118.

GBI Research, 2011. Thin film photovoltaic PV cells market analysis to 2020 CIGS (Copper Indium Gallium Diselenide) to emerge as the major technology by 2020. www.gbiresearch.com (Retrieved 29 January 2011.)

Godet, M., 1983. Reducing the blunders in forecasting. Futures 15, 181–192.

Goetzberger, A., Hebling, C., 2000. Photovoltaic materials, past, present, future. Sol. Energy Mater. Sol. Cells 62, 1–19.

Goetzberger, A., Hebling, C., Schock, H.-W., 2003. Photovoltaic materials, history, status and outlook. Mater. Sci. Eng. R. Rep. 40, 1–46.

Govindarajan, V., Kopalle, P.K., 2006. Disruptiveness of innovations: measurement and assessment of reliability and validity. Strateg. Manag. J. 27, 189–199.

Grätzel, M., 2004. Conversion of sunlight to electric power by nanocrystalline dye-sensitized solar cells. J. Photochem. Photobiol. A Chem. 164, 3–14.

Griliches, Z., 1998. Patent Statistics as Economic Indicators: A Survey. University of Chicago Press, pp. 287–343.

Hall, D., Jurafsky, D., Manning, C.D., 2008. Studying the histories of ideas using topic models. Proceedings of The Conference on Empirical Methods in Natural Language Processing. 2008, pp. 363–371.

Hambrick, D.C., 2007. Upper echelons theory: an update. Acad. Manag. Rev. 32, 334–343.

Hambrick, D.C., Mason, P.A., 1984. Upper echelons: the organization as a reflection of its top managers. Acad. Manag. J. 9, 193–206.

Harhoff, D., Scherer, F.M., Vopel, K., 2003. Citations, family size, opposition and the value of patent rights. Res. Policy 32, 1343–1363.

Hart, S.L., Christensen, C.M., 2002. The great leap. Sloan Manag. Rev. 44, 51–56.

Henderson, R.M., 2006. The innovator's dilemma as a problem of organizational competence. J. Prod. Innov. Manag. 23, 5–11.

Huff, A.S., 1990. Mapping Strategic Thought. John Wiley and Sons, Chichester, New York.Schumpeter, J., 1939. Business Cycles. McGraw-Hill, New York.

Hummon, N.P., Dereian, P., 1989. Connectivity in a citation network: the development of DNA theory. Soc. Networks 11, 39–63.

Iansiti, M., 1995. Technology integration: managing technological evolution in a complex environment. Res. Policy 24, 521–542.

Jaffe, A.B., Trajtenberg, M., Henderson, R.M., 1993. Geographic localization of knowledge spillovers as evidenced by patent citations. Q. J. Econ. 108, 577–598.

Kandylas, V., Upham, S.P., Ungar, L.H., 2010. Analyzing knowledge communities using foreground and background clusters. ACM Trans. Knowl. Discov. Datas 4, 1–35.

Kaplan, S., 2012. Identifying Breakthroughs: Using Topic Modeling to Distinguish the Cognitive From the Economic. Acad. Manag. Proc.

Kaplan, S., Murrary, F., Henderson, R., 2003. Discontinuities and senior management: assessing the role of recognition in pharmaceutical firm response to biotechnology. Ind. Corp. Chang. 12, 203–233.
Katila, R., 2004. Measuring Innovation Performance. Cambridge University Press, pp. 304–318.
Kostoff, R.N., 1994. Research impact quantification. R&D Manag. 24, 207–218.
Lemons, K.E., Porter, A.L., 1992. A comparative study of impact assessment methods in developed and developing countries. Impact Assess. 10, 57–65.
Lemos, A.D., 1998. Technological forecasting techniques and competitive intelligence: tools for improving the innovation process. Int. Manag. Data Syst. 98, 330–337.
Lucas, J., Henry, C., 2009. Disruptive technology: how Kodak missed the digital photography revolution. J. Strateg. Inf. Syst. 18, 46–55.
Luque, A.H., 2002. Handbook of Photovoltaic Science and Engineering. Jonh Wiley & Sons, New Jersey.
Mansfield, E., 1990. Academic research and industrial innovation. Res. Policy 20, 1–12.
Martinelli, A., 2008. Technological Trajectories and Industry Evolution: The Case of the Telecom Switching Industry. Working paper.
McConnell, R., 2004. Next-generation technologies in the USA. Semiconductors 38, 931–935.
Melkers, J., 1993. Bibliometrics As a Tool for Analysis of R&D Impacts, Evaluating R&D Impacts: Methods and Practice. Springer, pp. 43–61.
Mina, A., Ramlogan, R., Tampubolon, G., Metcalfe, J.S., 2007. Mapping evolutionary trajectories: applications to the growth and transformation of medical knowledge. Res. Policy 36, 789–806.
Mitchell, W., 1989. Whether and when? Probability and timing of incumbents' entry into emerging industrial subfields. Adm. Sci. Q. 34, 208–230.
Mogee, M.E., 1991. Using patent data for technology analysis and planning. Res. Technol. Manag. 34, 43–51.
Murray, F., 2002. Innovation as co-evolution of scientific and technological networks: exploring tissue engineering. Res. Policy 31, 1389–1403.
Narin, F., Olivastro, D., Stevens, K.A., 1994. Bibliometrics/theory, practice and problems. Eval. Rev. 18, 65–76.
Nooy, W.d., Mrvar, A., Batagelj, V., 2005. Exploratory Social Network Analysis With Pajek. Cambridge University Press, Cambridge.
NREL, 2013. Best Research Cell Efficiencies. National Renewable Energy Laboratory.
Porter, A.L., Detampel, M.J., 1995. Technology opportunities analysis. Technol. Forecast. Soc. Chang. 49, 237–255.
Porter, A.L., Roper, A.T., 1991. Forecasting and Management of Technology. John Wiley & Sons.
Pottelsberghe, B.V., Denis, H., Guellec, D., 2001. Using Patent Counts for Cross-country Comparisons of Technology Output. 27. Univ. Libre de Brux., pp. 129–146.
Ramage, D., Rosen, E., Chuang, J., Manning, C., McFarland, D.A., 2009. Topic Modeling for the Social Sciences. Stanford University.
Rip, A., 1988. Mapping of Science: Possibilities and Limitations.
Schleicher-Tappeser, R., 2012. How renewables will change electricity markets in the next five years. Energ Policy 48, 64–75.
Schmoch, U., Hinze, S., Jackel, G., Kirsch, N., Mayer-Krahmer, F., Munt, G., 1996. The role of the science community in the generation of technology, in: G. Reger, U. Schmoch (Eds),. Organization of Science and Technology at the Watershed. The Academic and Industrial Perspective, Physica, Heidelberg, 1–138.
Small, H., Griffith, B.C., 1974. The structure of scientific literatures I: identifying and graphing specialties. Sci. Stud. 17-40.
Small, H., Upham, P., 2009. Citation structure of an emerging research area on the verge of application. Scientometrics 79, 365–375.
Smith, A.W., 1873. Nature 7.
Smith, K.G., Smith, K.A., Olian, J.D., Sims, H.P.J., O'Bannon, D.P., Scully, J.A., 1994. Top management team demography and process: the role of social integration and communication. Adm. Sci. Q. 39, 412–438.
Smith, V.M., 1993. Who's who in additives — a technological approach. Chemical weekly Bombay 38, pp. 137–142.
Swan, W., 2001. Social Network Analysis in Construction Project Teams. University of Salford, Manchester.
Tang, J., Jin, R., Zhang, J., 2008. A Topic Modeling Approach and Its Integration Into the Random Walk Framework for Academic Search. 8th IEEE international Conference on Data Mining, pp. 1055–1060.
Taşkin, H., Adali, M.R., Ersin, E., 2004. Technological intelligence and competitive strategies: an application study with fuzzy logic. J. Intell. Manuf. 15, 417–429.
Thomond, P., Lettice, F., 2002. Disruptive innovation explored. 9th IPSE International Conference on Concurrent Engineering. Research and Applications.
Tijssen, R.J., Van Raan, A.F., 1994. Mapping changes in science and technology bibliometric co-occurrence analysis of the R&D literature. Eval. Rev. 18, 98–115.
Trajtenberg, M., 1990a. Economic Analysis of Product Innovation: The Case of CT Scanners. Harvard University Press.
Trajtenberg, M., 1990b. A penny for your quotes: patent citations and the value of innovations. RAND J. Econ. 21, 172–187.
Trajtenberg, M., 1990c. A penny for your quotes: patent citations and the value of innovations. RAND J. Econ. 172–187.
Trajtenberg, M., Jaffe, A.B., Henderson, R.M., 2003. University Versus Corporate Patents: A Window on the Basicness of Invention. In: J. A., Trajtenberg, M. (Eds.), Patents, Citations and Innovations — A Window on the Knowledge Economy. MIT Press, Cambridge, MA, pp. 19–50.
Tversky, A., Kahneman, D., 1974. Judgment under uncertainty: heuristics and biases. Science 185, 1124–1131.
Verspagen, B., 2007. Mapping technological trajectories as patent citation networks: a study on the history of fuel cell research. Adv. Complex Syst. 10, 93–115.
von Wartburg, I., Teichert, T., Rost, K., 2005. Inventive progress measured by multi-stage patent citation analysis. Res. Policy 34, 1591–1607.
Walsh, S., Linton, J., 2000. Infrastructure for emerging markets based on discontinuous innovations. Eng. Manag. 12, 23–31.
Wang, C., Chiu, C., 2005. Detecting Online Auction Inflated Reputation Behaviors Using Social Network Analysis. Paper Presented at the North American Association for Computational Social and Organizational Science. Notre Dame, Indiana.
Wasserman, S., Faust, K., 1994. Social Network Analysis Methods and Applications. Cambridge University Press.
WIPO, 2009. Photovoltaic Thin Film Cells. France Innovation Scientific and Transfer.
Yamaguchi, M., 2003. III–V compound multi-junction solar cells: present and future. Sol. Energy Mater. Sol. Cells 75, 261–269.
Zahedi, A., 2011. Review of modelling details in relation to low-concentration solar concentrating photovoltaic. Renew. Sust. Energ. Rev. 15, 1609–1614.
Zhu, D., Porter, A.L., 2002. Automated extraction and visualization of information for technological intelligence and forecasting. Technol. Forecast. Soc. Chang. 69, 495–506.

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