Patents: A Means to Innovation or Strategic Ends?*

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Abstract

This paper utilizes a data set of over 208,000 U.S. patents applied for between 1975 and 2010 to study development of strategic patenting over time and across industries. With received citations as a measure of patent social value, we use data envelopment analysis to estimate firm-level relative importance of strategic versus protective patenting. Our novel identification strategy reveals there was an almost universal drop in patent social value in the second half of the 1990s, signaling a shift towards the strategic use of patents. But the development of patenting strategies continued even after 2000 with semiconductor companies increasing their focus on patent value relative to companies from other industries. On average, aerospace and software companies preferred the production of valuable patents, but patenting strategies can differ vastly even among companies operating within one industry. The results confirm our expectations regarding the focus of aerospace companies on socially valuable patents.

Keywords: Patents, patent value, strategic patenting, intellectual property rights

JEL Codes: D23, K11, O32, O34

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1 Introduction

Even before the English parliament enacted the Statute of Monopolies in 1623, the Crown had a history of giving monopoly privileges to selected individuals (Boldrin & Levine, 2010, p. 43). Although the primary reason was to raise money, the perception of patent rights shifted over the course of history. Today, patents are universally accepted as a method of providing incentives to innovators because, as the argument goes, the amount of innovation would be socially suboptimal without defining and enforcing intellectual property rights.

In some industries patents play a much more important role than in others. For example, it is hard to imagine what a world without the patent institution would look like in the case of pharmaceutics, where the reliance on patent protection has always been very strong due to the nature of products. But during the 1980s almost everyone started to patent all but the most elementary inventions (Macdonald, 2004) which led to socially wasteful patent inflation (Farrell & Shapiro, 2008). Nowadays, inventors do not even perceive patents as a useful tool to monetize innovations. Boldrin & Levine (2010, p. 62) quote results of Carnegie Survey of R&D directors in 2000: only about one third of respondents see patents as an effective method of appropriating gains from an innovation. As we would expect, the two industries with the highest importance of patents are the pharmaceutical and medical equipment industries. But even there, the proportion of respondents rating patents as an effective method was only slightly above 50%.

Interestingly, more than 370 years after the English parliament established the patent institution, over half of the respondents still saw secrecy as an effective means of appropriating gains from an innovation. One of the reasons would probably be the existence of strategic patenting confirmed by many authors (Cockburn & MacGarvie, 2011), which is connected with the issue of patent aggregation and the increased role of non-practicing entities (Nicholas, 2013), buildup of patent thickets (Bessen, 2003), and an increasing number of patent litigation cases (Graham & Vishnubhakat, 2013). Where innovation-protecting patents fulfill the role ascribed to the patent institution, strategic patents are used as a rent-seeking tool with a detrimental impact on the social welfare.

In order to fully understand the extent of this issue, it is important to be able to tackle the topic of strategic patenting empirically. However, distinguishing between strategic and

innovation-protecting patents is not an easy task. Some authors focus on strategic behavior as a manifestation of strategic patents (e.g., Munari & Toschi, 2014; Hegde *et al.*, 2009; Gallini, 2002). Others reveal that valuable patents focused more on innovation protection tend to receive more citations (Trajtenberg, 1990; Blind *et al.*, 2009; Moser *et al.*, 2015). Abrams *et al.* (2013) confirm that there is a difference between the economic and social value of a patent, as they find an inverted U-shaped relationship between economic value and the number of received citations.

Yet the existing studies do not empirically address the issue of strategic patenting over a longer time period, nor across technological fields. Even though the incidence of patent litigation, one of the manifestations of strategic patenting, seems to be increasing and unevenly distributed across industries (PricewaterhouseCoopers, 2013; Unified Patents, 2015). It is, therefore, unclear whether strategic patenting gained in importance only in the last years, or whether the strategic motive to obtain patents has always played an important role – either universally, or at least in some industries.

We fill this gap by building on the existing methods of patent valuation and using a data set of more than 208,000 U.S. patents applied for between 1975 and 2010 by 22 companies from four technological fields: aerospace, computer manufacturing, semiconductors and software industry. Based on the patent litigation statistics (PricewaterhouseCoopers, 2013, p. 14), we expect aerospace companies to participate the least in strategic patenting and produce more socially valuable patents than the rest of our sample. Following the literature, we use the number of received citations per year of patent lifetime after patent application as a proxy for patent value.

In order to address our hypothesis, we come up with a novel identification strategy using data envelopment analysis to estimate the relative importance of strategic versus protective patenting. By comparing the efficiency of producing valuable patents with that of producing strategically useful patent quantities, we reveal that there was an almost universal trend break with a drop in our patent value measure in the second half of the 1990s, signaling a shift towards the strategic use of patents. We further show that the development of patenting strategies continued after 2000 with semiconductor companies on average increasing their focus on patent value relative to companies from other industries. Even though aerospace and software companies on average preferred production of valuable patents, we show that patenting strategies can differ vastly even among companies operating within one industry. They do not follow a

common trend and seem to depend on decisions of respective managers and owners.

The remainder of the paper is structured as follows: in Section 2 we review related literature on this topic. Section 3 introduces the data set, explains the method of patent value estimation and describes the data on patent forward citations and renewals in detail. We describe our method in Section 4 and discuss our results in Section 5. Section 6 concludes the paper.

2 Related Literature

Reviewing existing research on the economics of patents, Hall & Harhoff (2012) reveal that patents serve as an incentive for innovation only in a few sectors, and relatively few firms find them an important tool of securing the returns from their innovation activities. But, at the same time, firms in all other industries also respond to the presence of the patent institution, either by using patent as a means to other ends, or by adapting their innovation strategies. For example, Peeters & Potterie (2006) notice that patents and their characteristics are imperfect indicators of innovation not only because of the effects of different firm size, age, ownership type, market power, or technological opportunities, but also because firms pursue different innovation strategies. To put it simply, industries and individual firms vary significantly in the average number of patents generated by each dollar of R&D investment (Levin *et al.*, 1987).

Hall & Ham (1999) interviewed patent managers and executives from several types of semiconductor firms. In general, they were told that patents are considered extremely important, but not because patents enable the firms to profit from the current-generation products or motivate to conduct R&D: "As one interviewee noted, 'semiconductor firms do not rely on patents [to profit from innovation or appropriate returns from R&D], but patent rights are still of critical importance to firms in this industry.'" (Hall & Ham, 1999, p. 10) One of the strategic uses of patents is their ability to directly influence competition. Gallini (2002) shows that the more areas some particular patent is involved in, the harder it is for other companies to enter the market with their own innovations without violating the original patent. Munari & Toschi (2014) analyze the nanotechnology industry and reveal that firms gather broad patents in the early stages of an emerging technology to be able to get a better position within the market in the later stages. The existence of broad patents then leads to the emergence of patent thickets around key technologies, which create further barriers to entry. Cockburn & MacGarvie (2011)

estimate that a 10% increase in the number of patents relevant to the market reduced the rate of entry by 3%–8% in the software industry from 1990–2004.

But producing patents with the main goal of blocking the competition is just one of many available patenting strategies. Hegde *et al.* (2009) analyze patent continuations between 1981–2000 to distinguish among the motives for continuing patents. The continuation procedure is used to restart the process of examining patent application while retaining the filing date, and is often connected with strategic use; such as in the case of the so-called submarine patents issued after long periods of examination and revision (Graham & Mowrey, 2004). Quillen & Webster (2001) find that 28.4% of the US utility, plant, and reissue applications filed between 1993–1998 were not new or original applications, but continuing applications using the benefit of filing dates of previously filed applications. And as the authors explain, continuations may be used to flood patent examiners with repeated filings of the same application with the goal of obtaining a patent of low quality. In 1995, a change in the U.S. patent law changed the term of patent protection from 17 years from the date of issue to 20 years from the date of application in order to limit the extent of continuations misuse. An applicant now has to face a trade-off between an extended term of pre-issue secrecy achievable through the use of continuations and a shorter period of post-issue protection. Graham & Mowrey (2004) show that these changes were effective.

The possibility, and even need, to use patents strategically has led to larger numbers of patent applications and grants, as well as an increasing focus on patent aggregation. Nicholas (2013) argues that patent aggregation is a self-reinforcing process because ever larger patent portfolios accumulated for offensive or defensive purposes increase the demand for intermediaries, often called non-practicing entities (NPE). Their activities then further increase the demand for their own services. Bessen *et al.* (2011) find that NPE lawsuits were associated with half a trillion USD of lost wealth to defendants between 1990–2010 and that a very small part of this sum goes to small inventors. However, Mazzeo *et al.* (2013) point out that neither NPE damage awards, nor patent assertion entities (PAE) awards, significantly differ from other damage awards, even though patent assertion represents a novel way of exploiting patent rights.

Fischer & Henkel (2012) compare a sample of U.S. patents acquired by known NPEs between 1997 and 2006 to control groups of patents acquired by practicing firms. And interestingly, they

find that the probability that a patent is acquired by an NPE rather than a practicing entity increases in the patent's technological quality proxied by the number of forward citations it has received. But as Pénin (2012) explains, the term NPE describes not only patent trolls, but many different types of organizations, such as technological firms, intellectual property brokers, or universities. Whereas patent trolling does, indeed, lower R&D investment, patent brokers, on the contrary, encourage specialized knowledge production.

Even though the largest NPEs have accumulated tens of thousands of patents worldwide each in the last couple of years (Ewing & Feldman, 2012), the surge in patenting activity is visible among the practicing entities, too. Around the time a specialized appellate court to hear patent cases, the Court of Appeals of the Federal Circuit, was established by Congress in 1982, the number of patent applications and grants started to grow steeply (Kortum & Lerner, 1999). Some industries, like pharmaceutics, have always relied on patents due to the nature of their products. But since 1982, companies in other industries, like semiconductors, started to increasingly patent their inventions in all but the most worthless cases as well, and would have been pushed out of the market by their competitors if they hadn't (Macdonald, 2004). As a consequence, the number of patent applications received by the USPTO more than tripled between 1983 and 2003, but the number of examiners did not keep that pace (Chan & Fawcett, 2005). Moreover, over forty percent of the 355,000 new applications filed in 2004 had more than twenty claims each. Limited resources of the examiners lead to very high approval rates of filed applications and a high percentage of examiner decisions overturned on appeal (Chuang, 2006).

Granting weak patents not justified by the applicant's novel invention induces significant social costs as it often leads to costly litigation, creates danger of patent hold-up, and motivates defensive patenting, thus creating a socially wasteful vicious circle of strategic patenting (Farrell & Shapiro, 2008) and a buildup of patent thickets with shared ownership of technologies (Bessen, 2003). von Graevenitz *et al.* (2013) confirm that growing technological complexity invokes an increase in firms' patenting activities. The software industry has been found to be especially prone to the inflation of patents of low technological value, a lot of litigation, and a high percentage of patent trolls (Rai, 2013; Graham & Vishnubhakat, 2013).

However, the identification of the above mentioned weak, or low quality, patents is not a trivial task. Generally, the term *patent value* can have two very different meanings. First, we

can be interested in *economic value* of a patent – meaning how valuable the patent is for its owner in terms of profit potential. Hall *et al.* (2005) find that the number of received *(forward)* citations works as a proxy for the economic value of a patent indicated by the firm's stock market valuation. Other authors confirm that the number of forward citations, and if a patent is repeatedly renewed by paying a maintenance fee, are correlated with the valuation of patents by their respective owners (Harhoff *et al.*, 2003; Bessen, 2008; Zeebroeck, 2011). Forward citations and the patent's family size also explain a part of the economic value obtained from real-world auction prices (Fischer & Leidinger, 2014).

Second, we can focus on whether a particular patent increases social welfare by protecting an innovation and, therefore, has some *technological* or *social value*. We expect most patents to be economically valuable because of their social value, but economic value doesn't implicate social value. It has been shown that the number of forward citations is positively correlated with the social value of patents (Trajtenberg, 1990; Moser *et al.*, 2015), analogically to how we perceive citations in science (Stephan, 1996; Gaulé & Maystre, 2011).

Blind *et al.* (2009) find that the more intensively companies use patents to protect their valuable innovation, the more citations their patent portfolio receives. If they obtain patents for strategic reasons, such as blocking their competitors and aiming at patent exchange, their portfolios receive less citations. Also, commercialized patents have a higher probability of being renewed (Svensson, 2012). de Rassenfosse (2013) confirms that firms face a trade-off between patent quantity and the quality of their research. If a firm focuses on the strategic use of its patents, we can expect that its patent portfolio would be of a lower technological value and, consequently, receive less forward citations.

Our distinction between the economic and social value of patents is also in line with the recent findings of Abrams *et al.* (2013), who analyze the relationship between forward citations and the economic value of NPE-owned patents. Rather than the generally assumed monotonic relationship, they reveal there is an important amount of extremely valuable patents with a low number of citations. The authors conclude that their findings suggest that some patents are obtained for purely strategic purposes.

To sum up, the topic of strategic use of the patent institution is very lively in the literature. Many authors agree that the production and acquisition of patents for strategic purposes induces

sizable social costs. However, the existing literature doesn't address the development of strategic patenting over time and across industries.

3 Data

Our analysis is based on 208,962 U.S. patents which were applied for between 1975 and 2010. The data were downloaded from the U.S. patent office database and cover whole patent portfolios of 22 companies from aerospace, computer manufacturing, semiconductors and software industries listed on NASDAQ Stock Exchange which exceeded market value of USD 2 billion and had operated for more than 10 years. The selection was made in order to be able to capture development in the firms' ability to pursue inventions over time using statistical analysis of their patent portfolios. Also, it appears that firm size has an impact on patent value (Bessen, 2008). Focusing on larger companies only should, therefore, ensure better comparability of their patents. The chosen industries are known to be more innovative than others (Griliches, 1980), promising a high degree of competition and a fast pace of patenting, yet they differ in aspects such as dependency on older patents, or product complexity, which leads to inter-group variance. The full list of the used companies, together with basic descriptive statistics, is in Table A1.

While all the companies in our data set are among practicing entities and perform substantial R&D, a part of the patents in their portfolios have been obtained through trade. For the purposes of our study, this does not constitute a major problem as we are interested in the patents that the firms *want* to hold, no matter what source they come from. There is an exception in patents obtained through trade of whole portfolios, e.g. during a merger, but these form a small subgroup and we consider them to be completely random, therefore not causing any systematic bias.

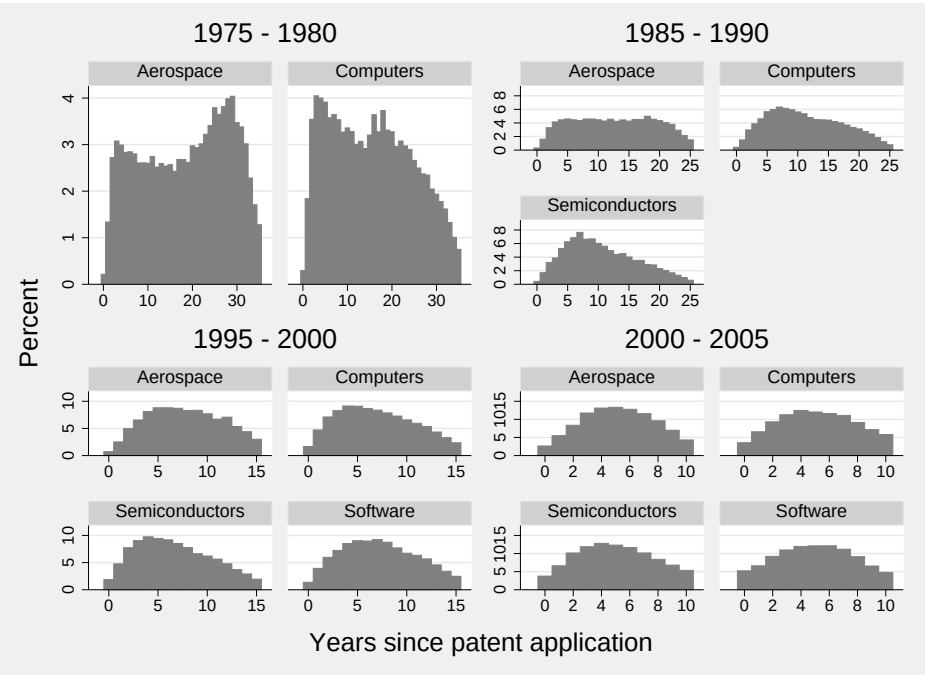
For every patent we gathered data on its number, assignee, application and grant date, number of backward citations, number and distribution of forward citations, and renewal. The information about the citations has been extracted from the U.S. patent office website, data on renewals have been obtained from the patent maintenance fee events database available on the USPTO Bulk Downloads Google page.[1] Our data on forward citations and renewals cover the

[1] `https://www.google.com/googlebooks/uspto-patents.html`.

information available in March 2015.

The number of received (*forward)* citations and the renewal of patents are generally accepted proxies for patent value and have been found to positively correlate with the valuation of patents by their owners (Harhoff *et al.*, 2003; Bessen, 2008; Van Zeebroeck & Van Pottelsberghe de la Potterie, 2011; Abrams *et al.*, 2013). But not every economically valuable patent also has to increase the social welfare – i.e., have a positive technological and, therefore, social value. A particular patent may be valuable for its holder not only because it protects an innovation which increased the social welfare, but also for strategic reasons. However, the literature shows that the number of forward citations is a good predictor of social value as well (Trajtenberg, 1990; Blind *et al.*, 2009; Moser *et al.*, 2015).

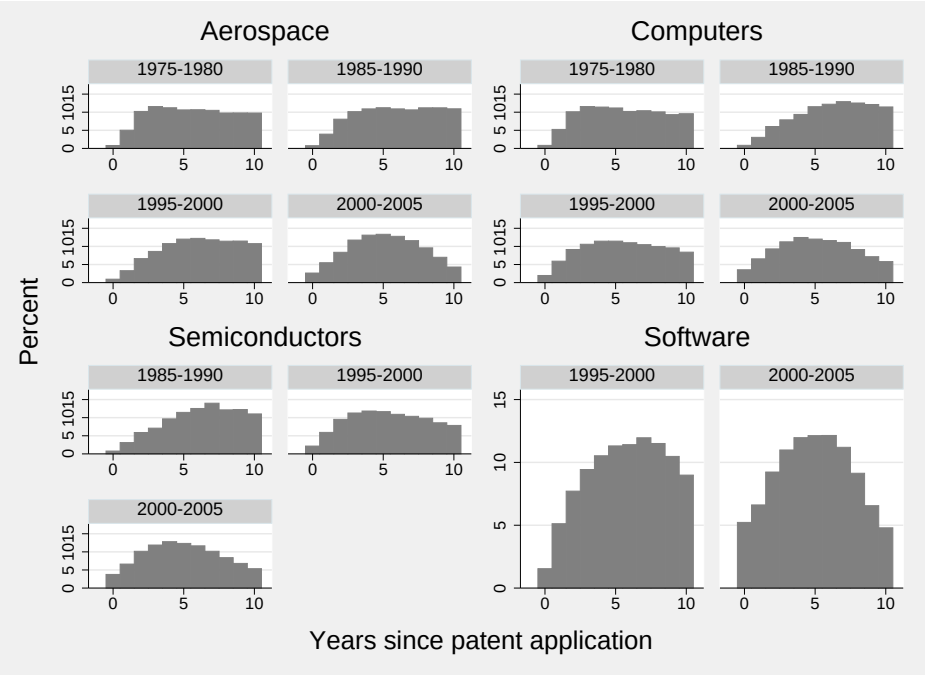
Figure 1: Time distribution of forward citations – industry comparison



A major complication when analyzing forward citations is the fact that they keep appearing long after a patent is granted. Some authors (Lanjouw & Schankerman, 2004; Sapsalis *et al.*, 2006; Gambardella *et al.*, 2008; Zeebroeck, 2011; Squicciarini *et al.*, 2013) propose a comparison of forward citations obtained only during the first few years. Figure 1 shows the distribution of citation lags for individual industries and reveals that patents receive citations even 30 years after their application. Moreover, the distributions seem to differ for individual industries and

change over time (see Figure 2).[2] As a consequence, cutting off the tails of citation distributions inevitably induces a bias. Hall *et al.* (2005) deal with this problem by estimating the shapes of the citation-lag distributions, and calculating the total number of citations a patent would probably receive over its lifetime if the distributions were stationary. But as we illustrate in Figure 1 and Figure 2, this stability assumption is highly questionable.

Figure 2: Time distribution of forward citations – time comparison



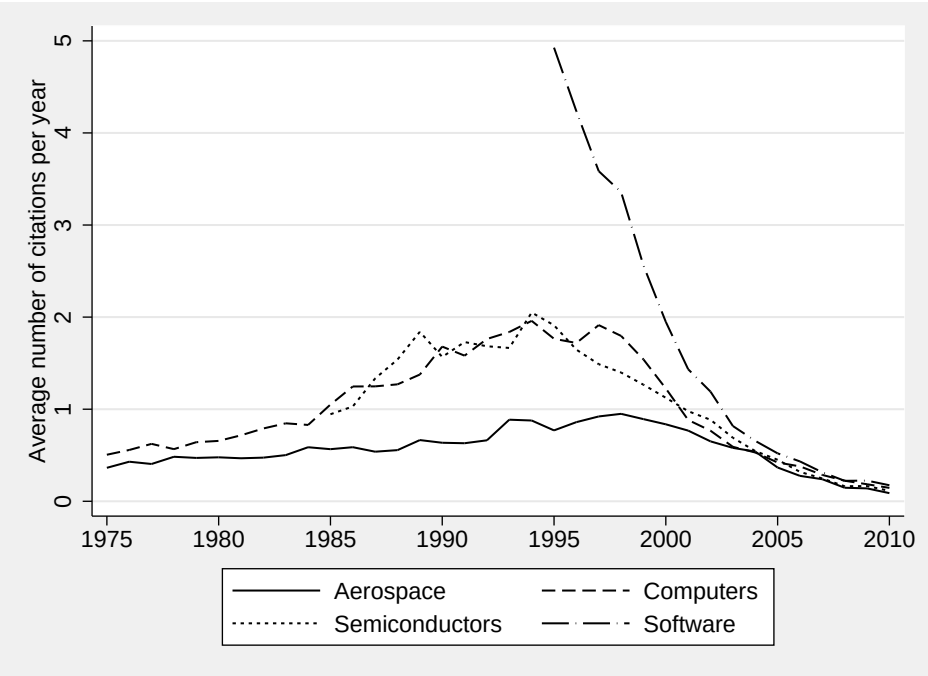
Therefore, in order to keep the methodology as simple as possible, we opted to use the number of forward citations per year of patent lifetime after patent application. Such an approach is common in literature dealing with comparison of the quality of academic publications (see, e.g., Havránek, 2015). Given the fact that the patents in our sample mostly received the highest number of citations around five years after their application, this method probably creates an upward bias for newer patents if observed for at least five years. But, as Figure 3 reveals, bias in this direction cannot influence our conclusions.

We use the patent application year as the base for our analysis mainly for two reasons. First, we are interested in the link between patents and their source in the form of R&D activities.

[2]Epps-Singleton two-sample test for the equality of distributions rejected the equality of distributions of citation lags during the first 10 years after application between 1995–2000 & 2000–2005 at the 1% level, and also between 1985–1990 & 1995-2000 at the 1% level with the exception of software patents, which started to appear in our sample during the second half of the 1990s.

If we focused on the date of patent grant, our results would be biased by the changing delay between the patent application and its subsequent grant. Based on the patents in our data set, the grant lag starts below 600 days in the late 1970s and reaches its peak with 1487 days in 2010. Moreover, starting in November 2000, USPTO publishes almost all applications for patents 18 months after their earliest filing date. To ensure comparability, we count forward citations from the patent application year for all patents in our data set. This could bias the number of forward citations per year of pre-2000 patents downward, but again, such bias cannot contradict our conclusions.

Figure 3: Average number of forward citations per year by industry



To have a reasonably high number of patents to average over individual industries, we drop all semiconductor patents applied for before 1985 (205 observations) and software patents applied for before 1995 (186 observations). Figure 3 depicts the average numbers of citations per year for our four industries and patents applied for between 1975 and 2010, and shows that there was an increasing trend for aerospace, computer, and semiconductor patents until the second half of the 1990s. The patent applications of software companies in our data sample started to appear only in the 1990s, and their forward citations statistics indicate that the first software patents were probably of high social value and formed the base of subsequent research

in this field. But in the second half of the 1990s we observe a break in the trends and the number of forward citations per year started to deteriorate quickly.[3]

Even more is happening in the distribution of forward citations per year (Figure 4). The majority of patents get cited only a very few times – in the 1975–1980 cohort, more than 25% of patents in aerospace and computer industries received less than 0.25 forward citations per year of their lifetime, meaning they probably did not carry much social value.[4] Generally, the distribution of patent value is extremely skewed to the right with a small number of very valuable patents (see, also, Scherer & Harhoff, 2000). The distribution of patents' value in the 1995–2000 cohort confirms that the proportion of almost-not-cited software patents applied for in this period was much lower compared to other industries. This means that the high average we observe in Figure 3 was not caused solely by a small number of extremely well cited and, therefore, valuable patents.

In the last cohort of 2000–2005, we observe a sharp increase in the proportion of patents with up to 0.25 citations per year. It coincides with the drop in industry averages around the year 2000, as described above. Figure 5 and Figure 6 show that this increase was mostly caused by patents ceasing to receive any citations at all. Given the fact we recorded the forward citations in 2015, and the proportion of patents getting their first citation more than five years after their application was well below 20% in 2000, the absolute lack of citations should not be caused by censoring.[5]

US utility patents generally expire 20 years after the application filing date. But to keep a patent in force, repeated maintenance fee payment is required for all patents based on applications filed after December 12, 1980. We call this act of maintenance fee payment *patent renewal*. If a maintenance fee is not paid, the patent is not renewed and the rights protected by a patent are no longer enforceable.[6] During the lifetime of a patent, it is possible to renew it three times by paying a maintenance fee: 3–4 years, 7–8 years, and 11–12 years after the date of patent issue. Therefore, we cannot observe any renewals for patents younger than 3

[3] Mean-comparison test rejects the hypothesis of equality of means between 1990–1995 and 2000–2005 for all industries.

[4] Aerospace patents from this cohort received on average 0.44 citations per year and computer patents 0.6 citations per year of their lifetime.

[5] Figure A1 shows the proportion of patents getting their first citation more than five years after application only on patents that did get cited at least once. It indicates that if censoring played a role, it was probably not before 2005 and, therefore, cannot explain the change in the trend in the second half of the 1990s.

[6] See `http://www.uspto.gov/patents-maintaining-patent/maintain-your-patent` for more information regarding maintenance fees.

Figure 4: Distribution of average number of forward citations per year

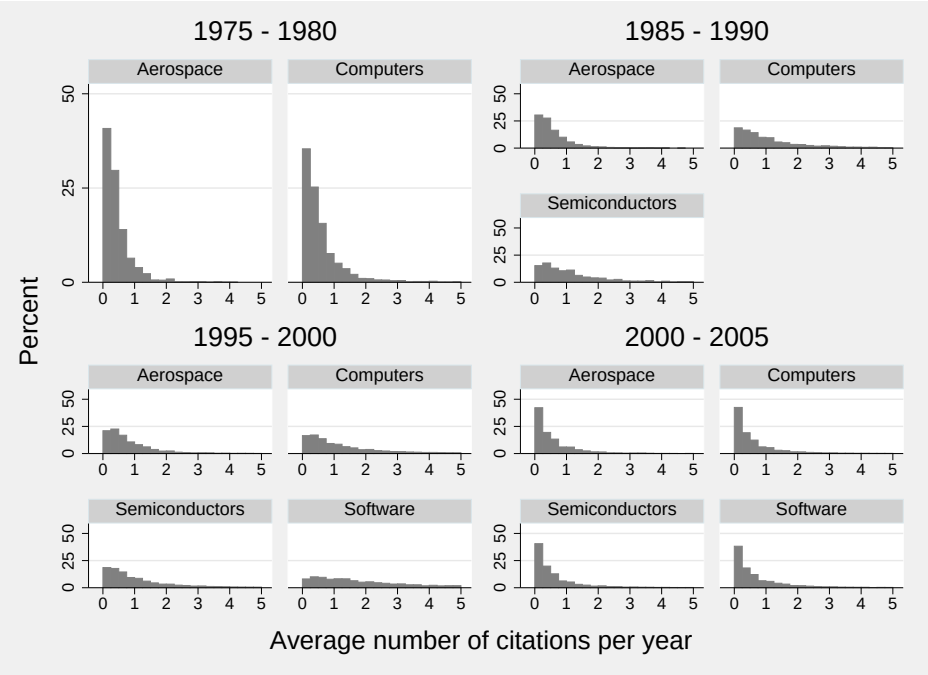


Figure 5: Proportion of patents getting their first citation more than five years from application or not cited at all

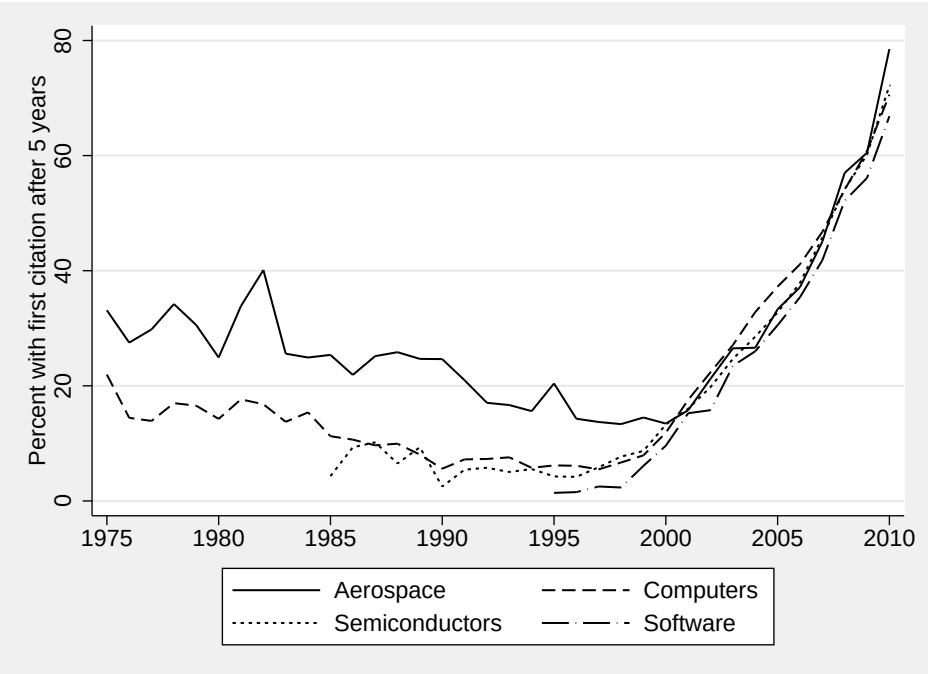
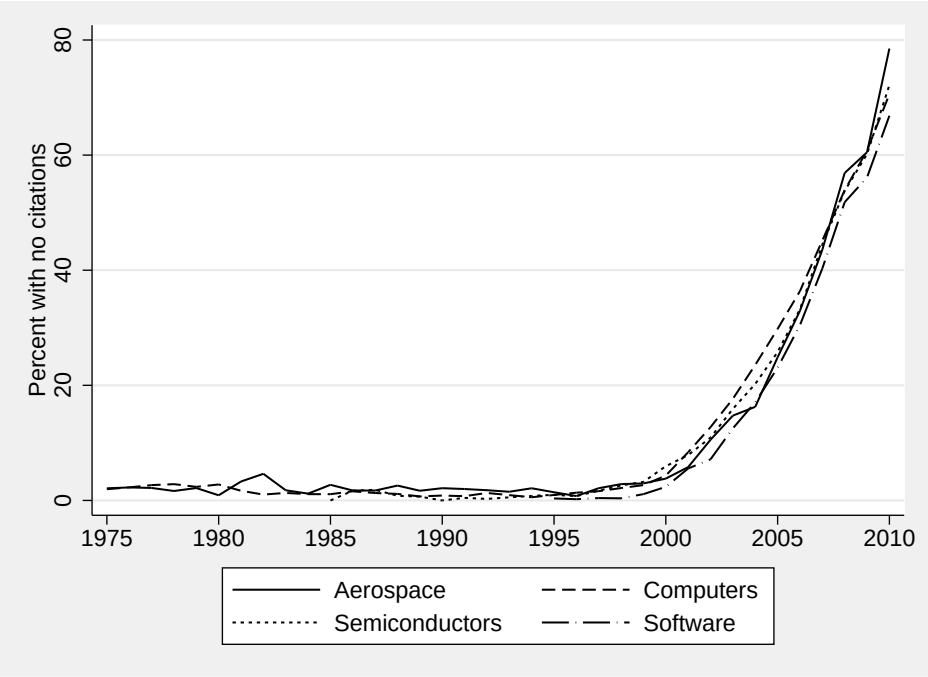


Figure 6: Proportion of patents with no forward citations

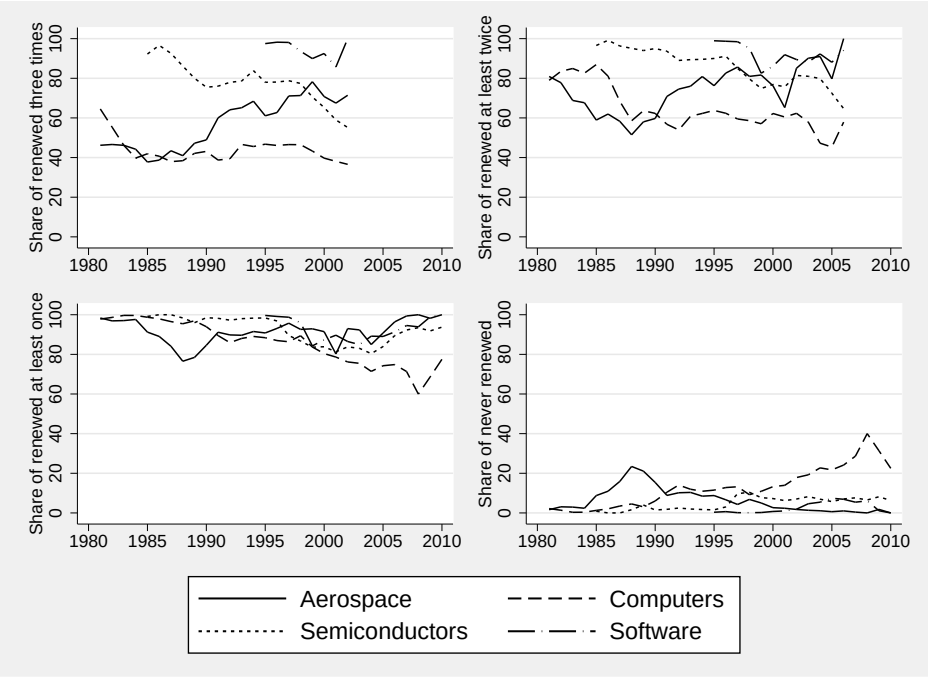


years, more than one renewal for patents younger than 7 years, and more than two renewals for patents younger than 11 years. We limit the data by the upper deadline for each category to allow for all potential renewals.

Figure 7 shows renewal patterns averaged over whole industries for patents applied for between December 12, 1980 and 2010. Even though the maintenance fees, especially for the large companies that form our data set, probably do not constitute prohibitively high costs, we see differences among individual industries. Only 40% of computer patents were renewed three times over the observed period. Moreover, the proportion of computer patents not renewed even once increased from 1% to its peak of 40% in 2008. On the other hand, whereas just 40% of aerospace patents applied for in the 1980s were kept in force for the whole 20 years period, their proportion increased to 70% by 2002.

The only industry in which we observe a drop corresponding to the one in forward citations is semiconductors. After a decrease in the proportion of patents renewed for three times in the 1980s, we observe stability until the end of the 1990s and a subsequent decrease to under 60%. The share of never renewed semiconductor patents increased from zero in 1980s to 10% in 1998 and fluctuates around 7% thereafter.

Figure 7: Proportion of patents renewed three times, at least twice or once, and never



However, in contrast to forward citations, the link between patent renewal and its social value is much weaker. If there is a purely strategic patent and its owner expects it to keep being economically valuable in the future as well, there is no reason to expect it won't be renewed. Even though its technological and social value may approach zero. Therefore, we further use forward citations as the only proxy for patents' social value. Nevertheless, the renewal statistics reveal an interesting variation in patenting strategies among industries which is not reflected in forward citation data and calls for further analysis, which we introduce and carry out in the following sections.

Apart from patent-related data, we obtained firm-level information about the number of employees and R&D expenditure from the Compustat database and industry-level prices of intermediate inputs from the World KLEMS database for the US (Jorgenson *et al.*, 2012).

4 Methodology

Even though statistical properties of the data provide interesting facts about the general trends in patent quality, they are able to tell only a part of the story. For example, what if the overall lower number of forward citations of patents in the aerospace industry, and, therefore,

their presumed lower value, is just a consequence of a lower amount of resources going to R&D activities in this industry? Or, what if the patents in the aerospace industry get systematically cited less with no implication for the patents' value? And, similarly, the general break in the citation trends in the second half of the 1990s could have been caused by a universal decline in R&D expenditure. Moreover, judging from the data, some external shock could have hit the whole institution of patent at that time and reduced everyone's citation probabilities. In such a case, it would be incorrect to attribute this development to the strategic decision-making of company managers.

There is literature estimating the efficiency of technological innovation (see, for example, Cruz-Cázares *et al.*, 2013) using the quantity of patents as one of the observed outputs of the innovation process. But due to data limitations, the existing efficiency studies do not take into account the value of patent outcomes. We follow this literature and estimate firm-level efficiency of transforming inputs into outputs using input-oriented data envelopment analysis (DEA), a method introduced by Farrell (1957) and further developed by Charnes *et al.* (1978), which has been extensively applied to evaluate performance in manufacturing and service operations. Comparing estimates of relative efficiency among companies or industries over time would enable us to address all the aforementioned issues in a formalized way.

DEA is a non-parametric method which makes it suitable to estimate the best-practice production frontier without assuming a specific form of the production function. This may be useful especially in sectors and areas of the economy where prices, or other common nominators, are not available or reliable. DEA proceeds by assuming decision-making units (DMU) capable of processing inputs into outputs and estimating the relative efficiency score of each DMU p by solving a fractional program defined as a ratio of weighted sum of outputs to weighted sum of inputs:

$$\begin{aligned} \max \quad & \frac{\sum_{k=1}^{s} v_k y_{kp}}{\sum_{j=1}^{m} u_j x_{jp}} \\ s.t. \quad & \frac{\sum_{k=1}^{s} v_k y_{ki}}{\sum_{j=1}^{m} u_j x_{ji}} \leq 1 \quad \forall i, v_k, \quad u_j \geq 0 \quad \forall k, j, \end{aligned} \tag{1}$$

where y_{ki} denotes amount of output k produced by DMU i, x_{ji} denotes amount of input j used by DMU i, v_k and u_j are weights given to output k and input j. The fractional program (1) may be solved by transforming into the linear program

$$\begin{aligned} \max \quad & \sum_{k=1}^{s} v_k y_{kp} \\ s.t. \quad & \sum_{j=1}^{m} u_j x_{jp} = 1, \quad \sum_{k=1}^{s} v_k y_{ki} - \sum_{j=1}^{m} u_j x_{ji} \leq 0 \quad \forall i, v_k, \quad u_j \geq 0 \quad \forall k, j. \end{aligned} \tag{2}$$

In practice, most of the DEA-solving programs use the dual form of the linear program (2) which lowers the number of constraints and computational demands:

$$\begin{aligned} \min \quad & \theta_p \\ s.t. \quad & \sum_{i=1}^{n} \lambda_i x_{ji} - \theta_p x_{jp} \leq 0 \quad \forall j, \quad \sum_{i=1}^{n} \lambda_i y_{ki} - y_{kp} \geq 0 \quad \forall k, \quad \lambda_i \geq 0 \quad \forall i, \end{aligned} \tag{3}$$

where θ is the efficiency score, and λ are the dual variables derived from the primal form of the linear program (2). Program (3) assumes constant returns to scale (CRS). Even though the assumption of CRS is widely used in literature, it correctly reflects the reality only in the case of no scale inefficiency. In our specific case it would mean that in order to remain fully efficient, an inventor employing 10 units of R&D input and producing 10 patents would have to produce 100 patents when increasing the R&D expenditure to 100 units. But there is no reason to expect this assumption to be true. We can even argue in favor of both decreasing and increasing returns to scale: larger amount of R&D activities can create positive synergy effects and, as a consequence, increase efficiency with scale. On the other hand, there is no reason why diseconomies of scale should not be present also in R&D. For example, an additional unit of innovation may be harder and more costly to produce if the innovator optimizes his activities and starts with projects with the best cost/benefit ratio (e.g., Bound *et al.* (1982) find evidence compatible with decreasing returns to scale in patenting).

Because we are not interested in scale inefficiency, we use the model developed by Banker *et al.* (1984), allowing for variable returns to scale (VRS) by imposing a restriction $\lambda_p = 1$ for $p = 1, ..., n$ to (3). VRS model excludes scale inefficiency from the final efficiency scores which makes them, by definition, larger than or equal to efficiency scores obtained using the CRS

model.[7]

As we have already mentioned, DEA estimates relative efficiency of each DMU defined by a vector of inputs and a vector of outputs. By not including any control variables capturing, for example, the changing environment where the DMUs operate and the technological progress, DEA in its basic form expects solely cross-sectional data. In order to follow and compare the DMUs over time, a special model is needed. Generally speaking, there are two main approaches to panel DEA. First, Färe *et al.* (1994) shows that it is possible to use DEA to calculate the Malmquist Productivity Index for individual DMUs and decompose the obtained productivity growth into efficiency changes and technology shifts. Second, Charnes *et al.* (1985) introduced a moving average approach to estimating the efficiency of data with time dimension, called DEA window analysis.

The rationale behind DEA window analysis is that technology development is usually gradual and doesn't cause abrupt year-on-year changes in the production process. It is therefore possible to pool a couple of years of observations together and treat a DMU, for example, in year t and in year $t+1$ as two separate DMUs. Suppose the DMUs are observed for T years and the window length is set to K years. In every period $t = 1, ..., T-K+1$ we pool observations of DMUs from periods $t, ..., t+K-1$ and estimate their efficiency scores using the linear program (3). With the exception of the first and last $K-1$ time periods, we thus obtain K estimates for each DMU and time period; but always at least one efficiency score estimate for every time period. To get a time series of mutually comparable estimates, we follow the literature by calculating a simple mean over the $1, .., K$ estimates in each period for each DMU.

For our analysis of patent production efficiency, we chose window length $K = 3$.[8] The maximum span of our data is 1980–2010, but our panel is unbalanced due to the limited availability of data on the number of employees and R&D expenditure (see Table A1). This means that the first window is composed of DMUs with observations from 1980, 1981, and 1982, the second window from 1981, 1982, and 1983, and so on.

The usual inputs used in the above mentioned innovation efficiency literature are R&D expenditure or R&D capital stock, and the number of employees or specifically R&D personnel

[7]See Figure A2 and Figure A3 for scores obtained using the CRS model. The relative scores, of course, differ, but the main conclusions of our analysis hold. We believe that the VRS model is more appropriate.

[8]As a robustness check, we also performed the analysis with $K = 2$ and $K = 4$ (see Figures A4 – A7). The efficiency scores differ slightly, mainly at the ends of the time series. But the main conclusions of our analysis hold.

(Cruz-Cázares *et al.*, 2013). Because we don't have data on R&D personnel, we utilize the total number of employees as a proxy for the size of the company. The second input variable we use is R&D expenditure deflated using the industry-level prices of intermediate inputs from the World KLEMS data set for the US (Jorgenson *et al.*, 2012). Following the recent literature, we use one-year lags of the input variables to take into account the time it takes before R&D projects are completed and patentable outputs are achieved.

We use two specifications with one output variable each – the average quality of patents applied for in the given year measured by the number of forward citations, and the number of patent applications in the given year. We do not include both output variables because we are not interested in estimating the efficiency of innovative activities *per se*. Our goal is to identify differences in patenting strategies among individual companies by comparing the efficiency in the production of patent quantity to the efficiency in the production of socially valuable patents.

5 Results

Analyzing the relative efficiency in patent value production enables us to overcome the shortcomings of a mere statistical comparison of trends in the data mentioned at the beginning of Section 4. If, for example, the source of the differences in the cross-section dimension or in the time dimension is a variation of R&D activity, DEA with R&D expenditure among the inputs should take this source of variance into account and still produce comparable efficiency scores. Also, if an external shock reduces the citation probabilities of all the patents, the ranking of companies according to their efficiency scores should stay unchanged. But if it was a strategic decision of a couple, or even a majority, of companies in our sample, then we should observe changing rankings.

Above we explain the methodology of obtaining two sets of efficiency scores estimated using DEA window analysis: one with the average quality of patents applied for in the given year measured by the number of forward citations, the second with the number of patent applications in the given year as the output variable. This means we get two estimates for each company and year, totaling 908 estimates of efficiency scores.

In Figure 8 we present the relative efficiency of producing valuable patents on the level of whole industries. In order to identify the strategic decisions regarding patent-value pro-

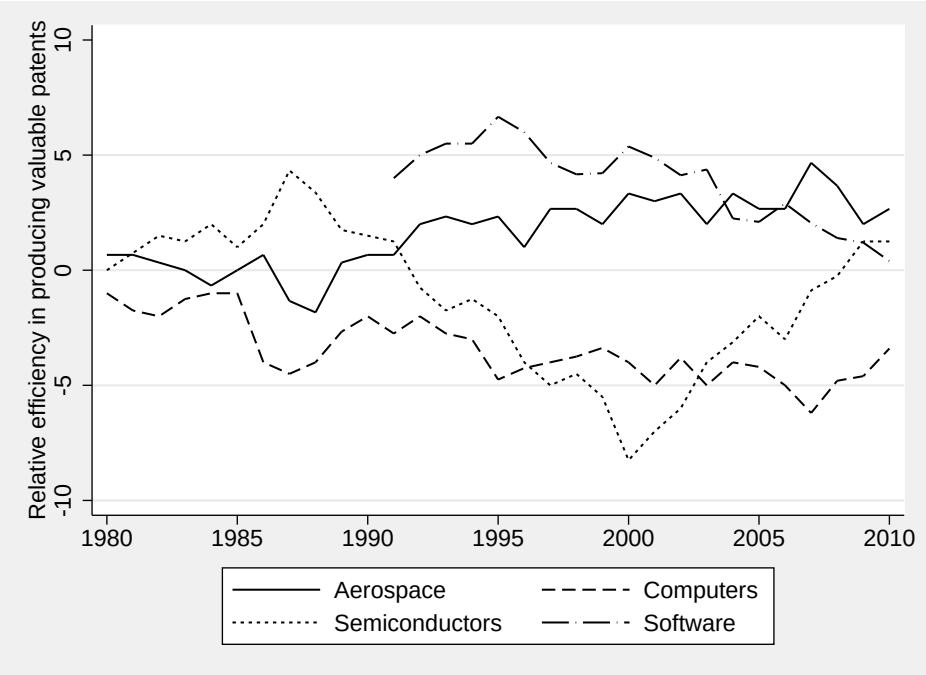
duction, we produce a *doubly relative* measure of efficiency: First, using DEA we estimate efficiency scores of patent value production and patent quantity production. Recall that DEA calculates efficiency scores relatively to the rest of the included DMUs. Therefore, unlike the above presented statistical facts about forward citations which provide information about the development of patent value in absolute terms, efficiency scores are useful solely for comparing patenting strategies among observed companies and their development over time.

Then we sort the DMUs according to their efficiency score in each period to obtain two panels of efficiency rankings: for patent value production, and patent quantity production. Because we do not want to analyze propensities of individual companies to patent (Peeters & Potterie, 2006), we take differences between these two ranks. de Rassenfosse (2013) shows that firms face a trade-off between the quantity and the quality of their research output. Therefore, we implement a second level of relativity: We understand a DMU relatively more efficient in producing valuable patents if it ranks higher in patent value production than in patent quantity production. In this way, we are able to deal with company-level fixed effects to some degree. If a company, in comparison to its competitors, puts a smaller emphasis on patents and protects its intellectual property using trade secrets or other methods, it will channel only a small part of its R&D expenditure to patenting. As a consequence, the model may see it as less efficient in producing both patent value and patent quantity. For the sake of simplicity, let's assume it will be ranked 10th in both categories. The resulting relative score $0 = 10 - 10$ then indicates no preference for either patent value, or patent quantity.

On the other hand, if a company ranks 10th in patent quality production but 5th in patent quantity production, then the resulting relative score $-5 = 5 - 10$ signals the extent of the company's preference for the production of patent quantity at the expense of patent value – again, relative to all the other companies in the sample. To sum up, the positive value of the final relative efficiency score indicates a higher relative efficiency in producing valuable patents than mere patent quantity. We interpret this finding as a probable preference of the company to produce valuable patents.

Coming back to Figure 8, we take these final relative scores and average them over whole industries in each year. We see that contrary to what Figure 3 shows, the aerospace industry didn't produce the least valuable patents over the whole period. Since the beginning of the

Figure 8: Relative efficiency of industries in producing patent value vs. patent quantity



Notes: The relative efficiency of a company in a given year is calculated as the difference between the rank of the company with patent quantity as the output variable and the rank of the same company with patent quality as the output variable. A positive value means higher relative efficiency in producing valuable patents than mere patent quantity. For industry-level results, this relative efficiency score is averaged over the whole industry in each year.

1990s, companies from the aerospace industry, on average, systematically preferred patent value over patent quantity compared to companies from computer and semiconductor industries. Computer industry companies, with the exception of the years 1996–2003, focused relatively the least on the quality of produced patents.

Judging from the development of relative efficiency measures, we can identify two pieces of characteristics regarding the observed break in the forward citations trends around the year 2000. First, the relative efficiency measures of all industries, with the exception of semiconductor companies, stayed on their trends over the whole period. Therefore, the change in patenting strategy toward less patent value production during the second half of the 1990s must have been almost universal. Otherwise we would observe more changes in our relative efficiencies.

But, interestingly, semiconductor companies do stick out as a notable exception as their relative efficiency started to increase sharply in 2000 and even overtook the software industry in 2010. This divergence shows that the observed deterioration of patent value after the year 2000 was not a result of an economy-wide economic or legal shock, or some universal reaction to

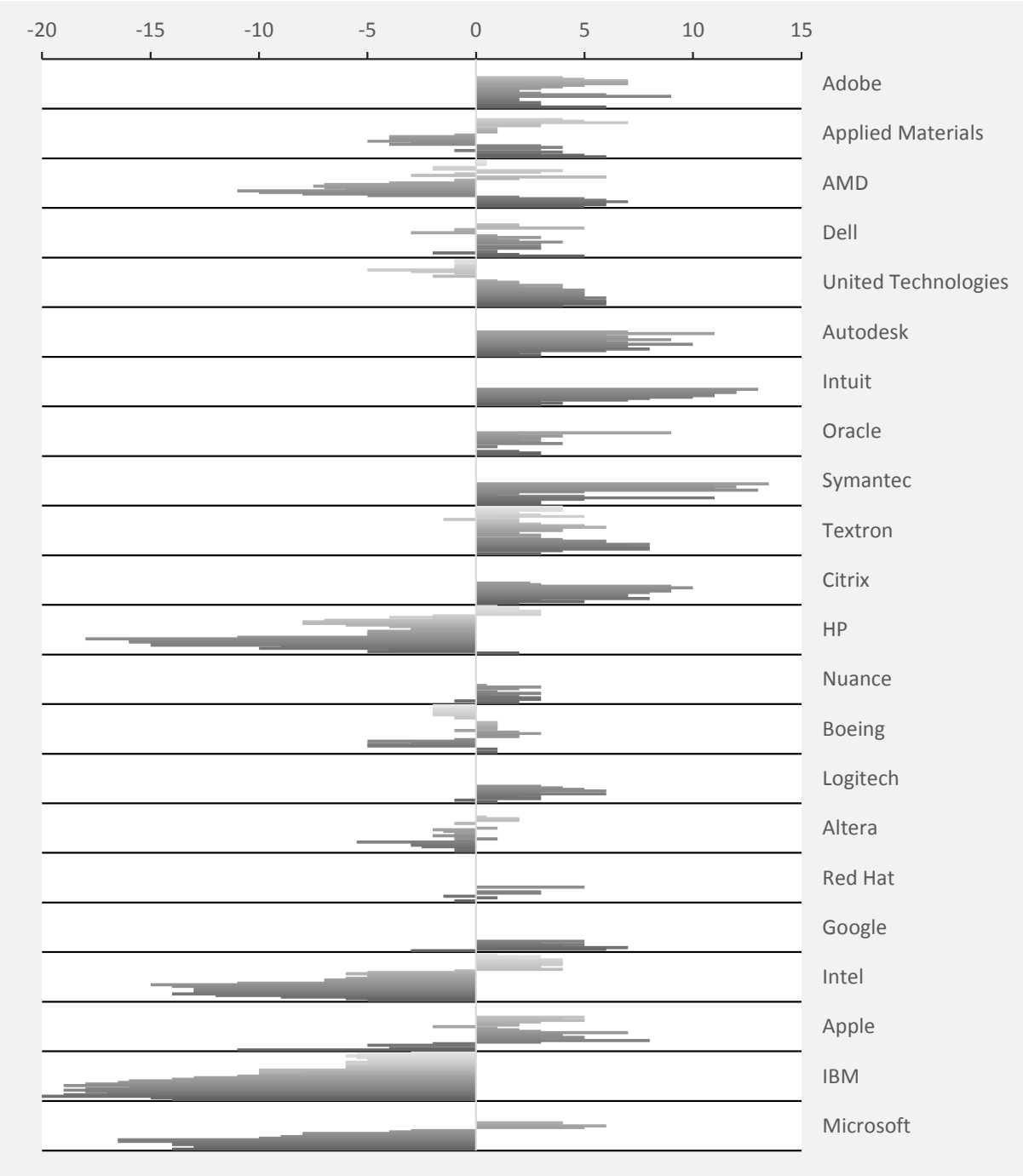
changes in the institution of patent itself, but rather a deliberate change in patenting strategy towards producing high number of low-valued patents. And this managerial decision was not taken to such an extent by companies in the semiconductor industry which enabled them to improve their relative stance vis-à-vis the other industries.

Figure 9 depicts the development of relative efficiency for individual companies and sorts them by their relative efficiency in 2010. The first message the figure conveys is that there is no industry-related strategy: Both Adobe, the number one, and Microsoft, the very last company in the ranking, operate mainly in the software industry but clearly follow different patenting strategies. The same is true for semiconductor companies (Applied Materials vs. Intel), computer companies (Dell vs. IBM), and, to a lesser degree, aerospace companies (United Technologies vs. Boeing).

Moreover, it is true that the strategy is stable for some companies. Adobe, Autodesk, Textron, or IBM systematically focus either on patent value production, or on patent quantity production. But there are a number of companies in our sample which seem to adjust the patenting strategy to their changing needs. For example, all the semiconductor companies first preferred valuable patents but then gradually altered their strategy towards the production of a high number of low-valued patents. But whereas Applied Materials and AMD went back to their original strategy after 2003, we do not observe comparable development by Altera and Intel. HP and Microsoft also started to patent with a preference towards patent value, but after a couple of years completely changed their strategies. Even though it seems that HP has again started to turn its attention to the production of valuable patents in the last years. On the other hand, Apple kept focusing on patent value until 2005 but switched its focus towards patent quantity production afterwards.

To sum up, the relative efficiency view reveals the following. First, the patenting strategies clearly differed among companies from different industries during the last decade of our sample, too. Moreover, the development of strategies continued even after the universal drop in forward citations around 2000 with semiconductor companies on average increasing their focus on patent value relative to companies from other industries. Second, aerospace patents in our sample are not the least valuable, as the simple count of their forward citations suggests. With the exception of the years 1983–1988, aerospace companies on average preferred the production of valuable

Figure 9: Relative efficiency of companies in producing patent value vs. patent quantity



Notes: The relative efficiency of a company in a given year is calculated as the difference between the rank of the company with patent quantity as the output variable and the rank of the same company with patent quality as the output variable. A positive value means higher relative efficiency in producing valuable patents than mere patent quantity. Sorted by the relative efficiency in 2010.

patents over a high number of low-valued patents.

And third, patenting strategies can differ vastly even among companies operating within one industry. It is true that the industries do, on average, develop differently. Software companies mostly started with a large emphasis on patent value in the 1990s and then gradually moved towards a more balanced approach. Aerospace companies went through the opposite development and computer companies were always among those which focused the least on patent value production. Semiconductor companies, on the other hand, were the most volatile in terms of their patenting strategies. Nevertheless, judging from the individual relative performance, patenting strategy seems to depend significantly on managerial decisions of individual companies' managers or owners. External factors do probably play a role but are not strong enough to harmonize the divergence in strategies.

6 Concluding Remarks

As we mention in the Introduction, patent right in the form of a royal monopoly privilege was primarily an end in itself: its goal was to improve royal revenues and attract skillful artisans as a favorable side effect. It was mostly during the nineteenth century that countries started to adopt laws focused on protection of intellectual property with the goal of providing a means to innovation. However, the ability of patents to motivate innovation has started to be questioned again in the last years with a broad stream of literature analyzing the concept of strategic patenting. The argument goes that the existing institutions of intellectual property, and especially patents, are becoming ends instead of means, again.

In order to study this phenomenon, we built a data set of more than 208,000 U.S. patents applied for between 1975 and 2010. These patents were granted to 22 companies from aerospace, computer manufacturing, semiconductors and software industries. With the number of received citations as a proxy for patent social value, we use data envelopment analysis (DEA) to estimate the relative importance of strategic versus protective patenting of individual companies between 1980–2010.

We find that there was an almost universal drop in patent social value in the second half of the 1990s, signaling a shift towards the strategic use of patents. But whatever factor may have caused it, it was not strong enough to harmonize the differences in patenting strategies

among companies. The development of strategies continues even after 2000 with semiconductor companies on average increasing their focus on patent value relative to companies from other industries. We further reveal that, on average, aerospace and software companies preferred the production of valuable patents to mere patent quantity. But in general, patenting strategies differ vastly even among companies operating within one industry. They seem to depend on decisions of respective managers or owners.

Interestingly, we find that until 2004 software companies on average focused relatively the most on patent value which is in contradiction to the findings of other authors (Rai, 2013; Graham & Vishnubhakat, 2013). Computer companies, on the other hand, were always among those which focused the least on patent value. And, confirming our expectations, aerospace industry companies do produce valuable patents when taking into account the industry specifics using DEA; even though a mere comparison of the number of citations received by aerospace patents would send them to the very bottom of our sample.

We believe that our method of identifying company-level patenting strategy may be useful not only in the debate about the extent of strategic patenting, but also for authors estimating the efficiency of technological innovation; because up to now, they have focused merely on patent quantity as one of the outputs of innovation process. But as we argue in this paper, the production of a high number of patents may be a result of strategic patenting, rather than socially valuable innovations.

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Appendix

Figure A1: Proportion of patents getting their first citation more than five years from application if cited

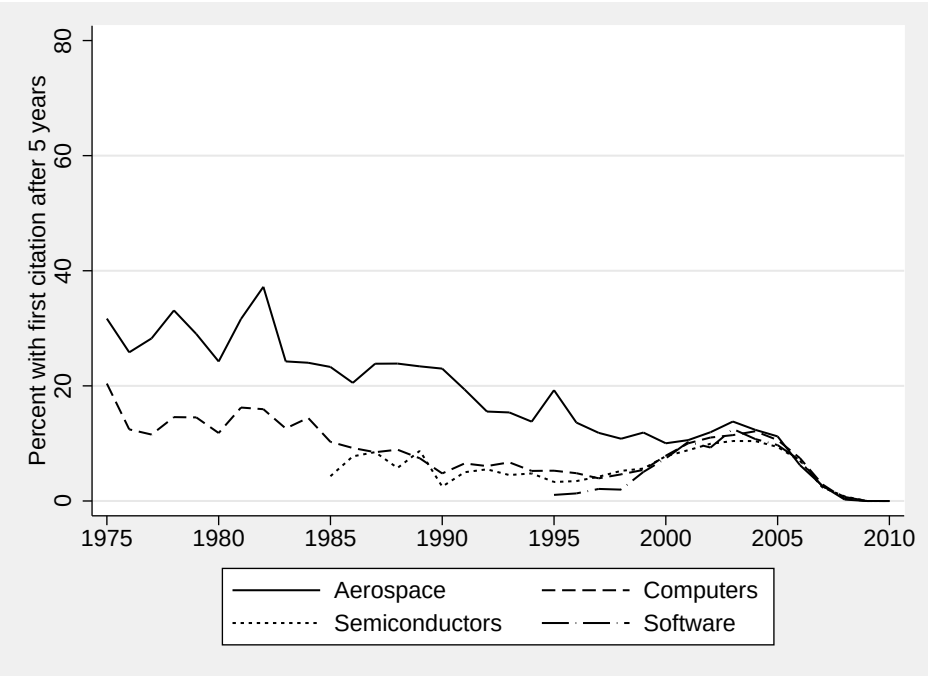
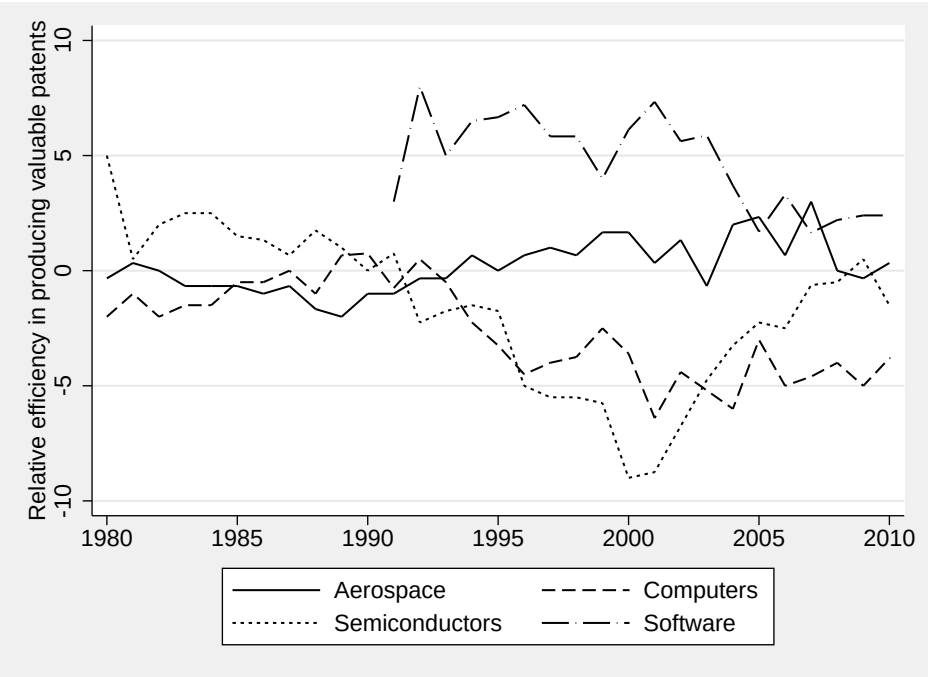
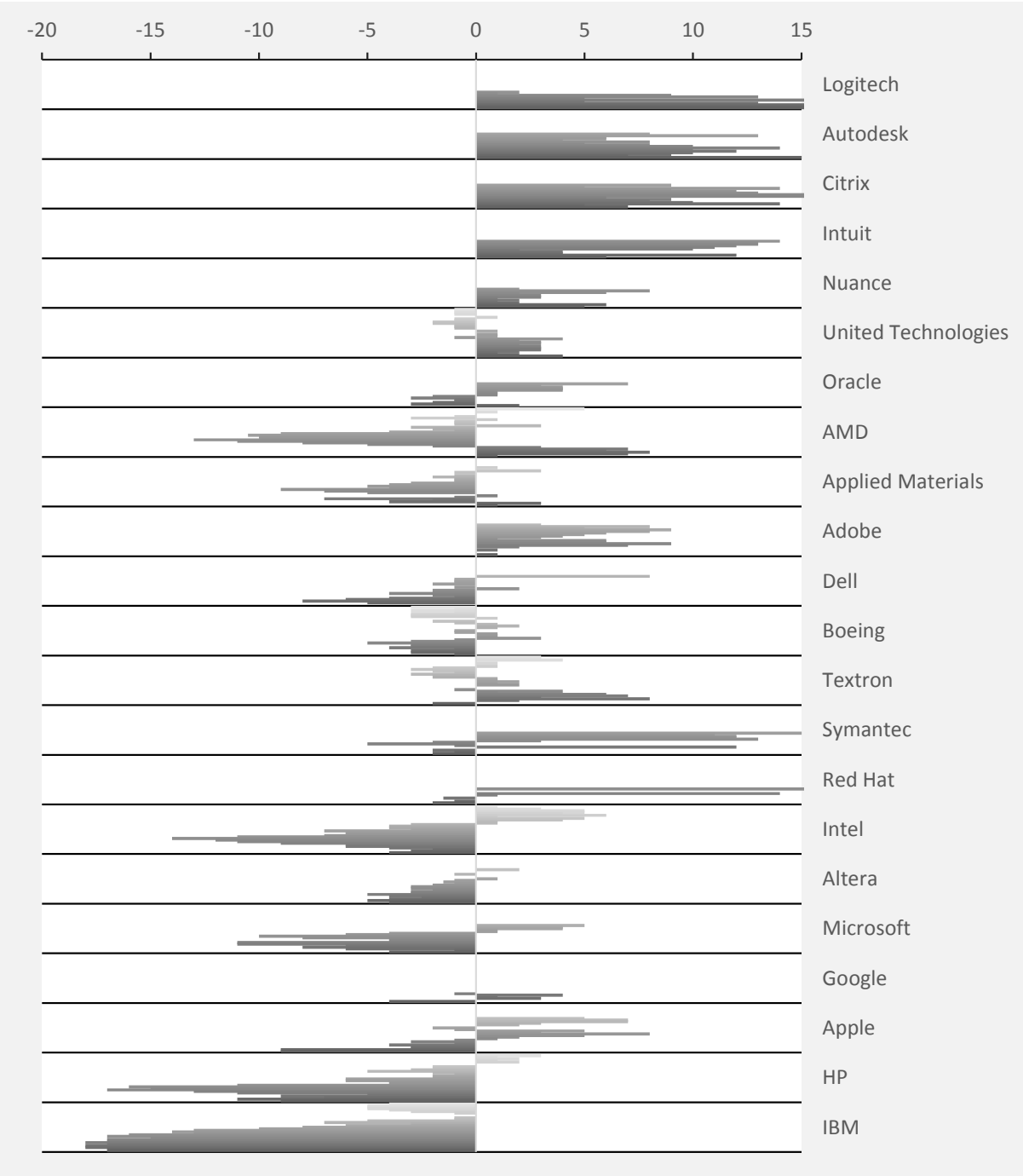


Figure A2: Relative efficiency of industries in producing patent value vs. patent quantity – CRS



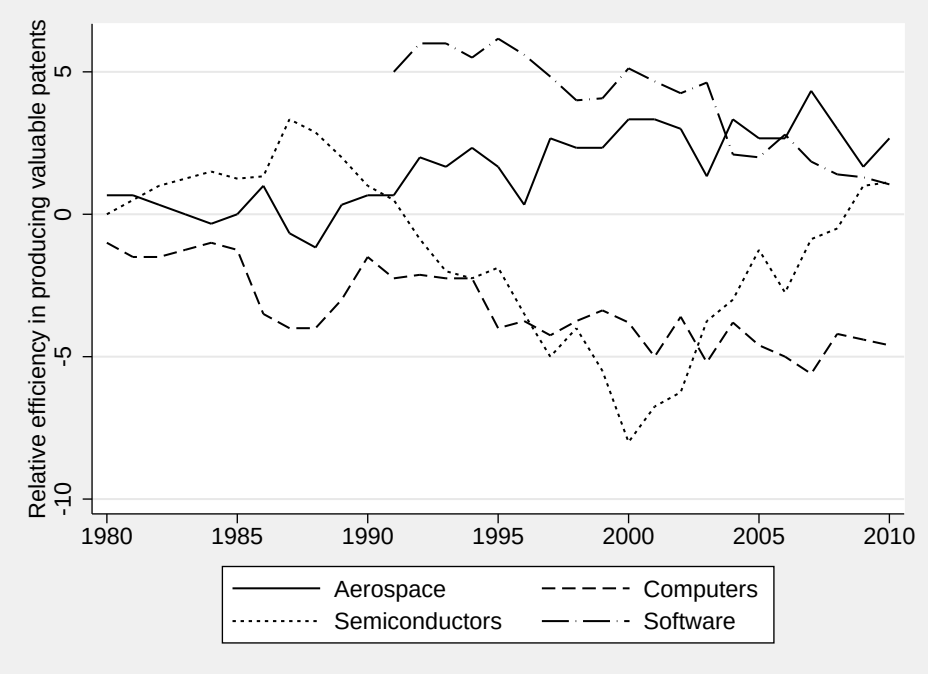
Notes: See Figure 8. Estimated using constant returns to scale assumption.

Figure A3: Relative efficiency of companies in producing patent value vs. patent quantity – CRS



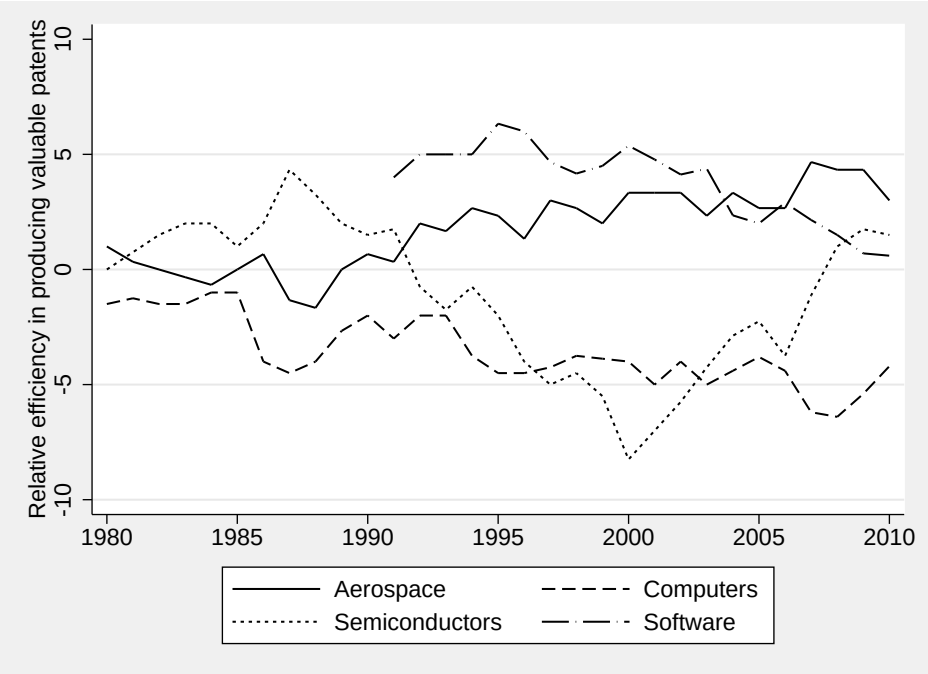
Notes: See Figure 9. Estimated using constant returns to scale assumption.

Figure A4: Relative efficiency of industries in producing patent value vs. patent quantity – window 2



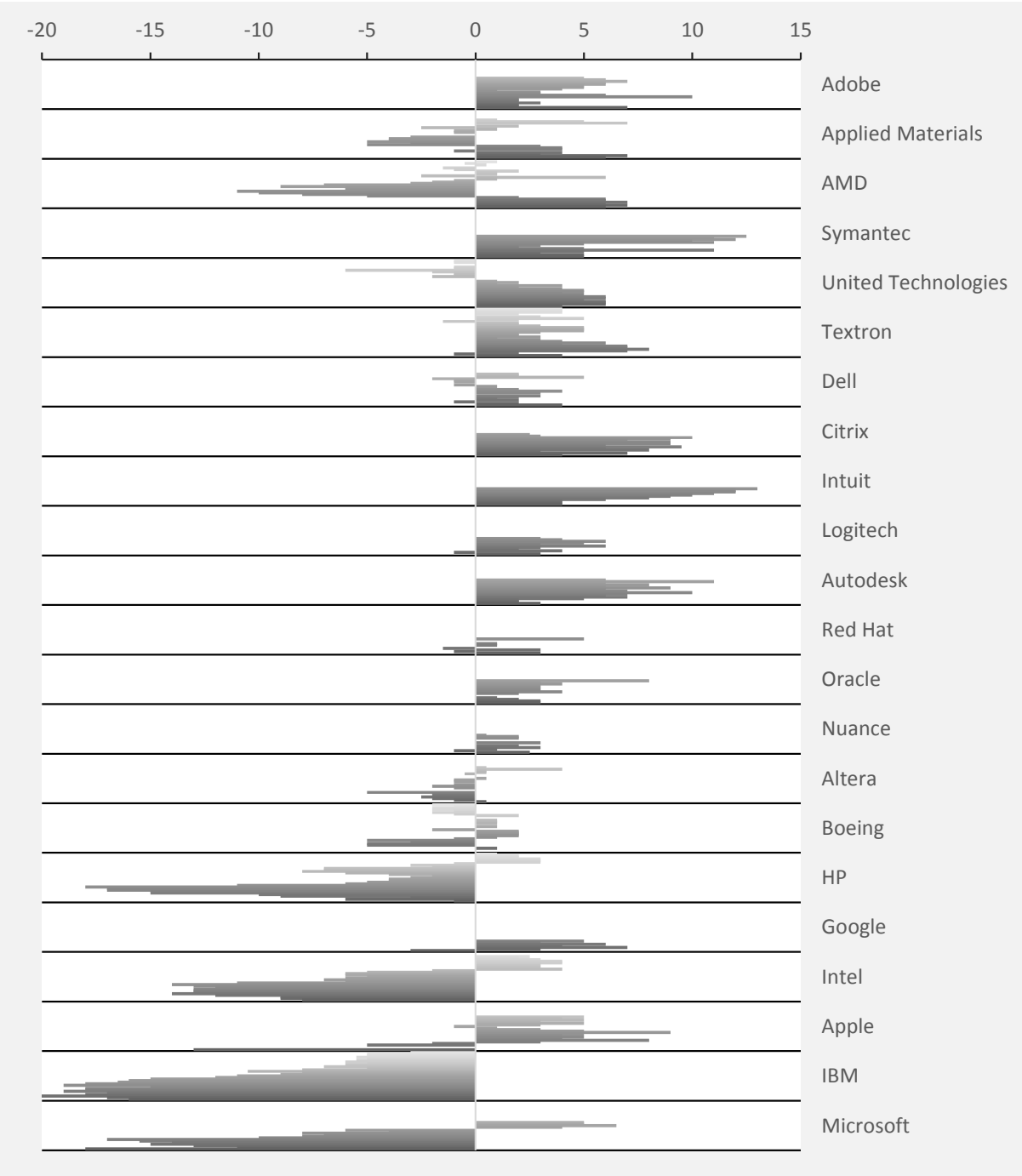
Notes: See Figure 8. Estimated using window length of 2 years.

Figure A5: Relative efficiency of industries in producing patent value vs. patent quantity – window 4



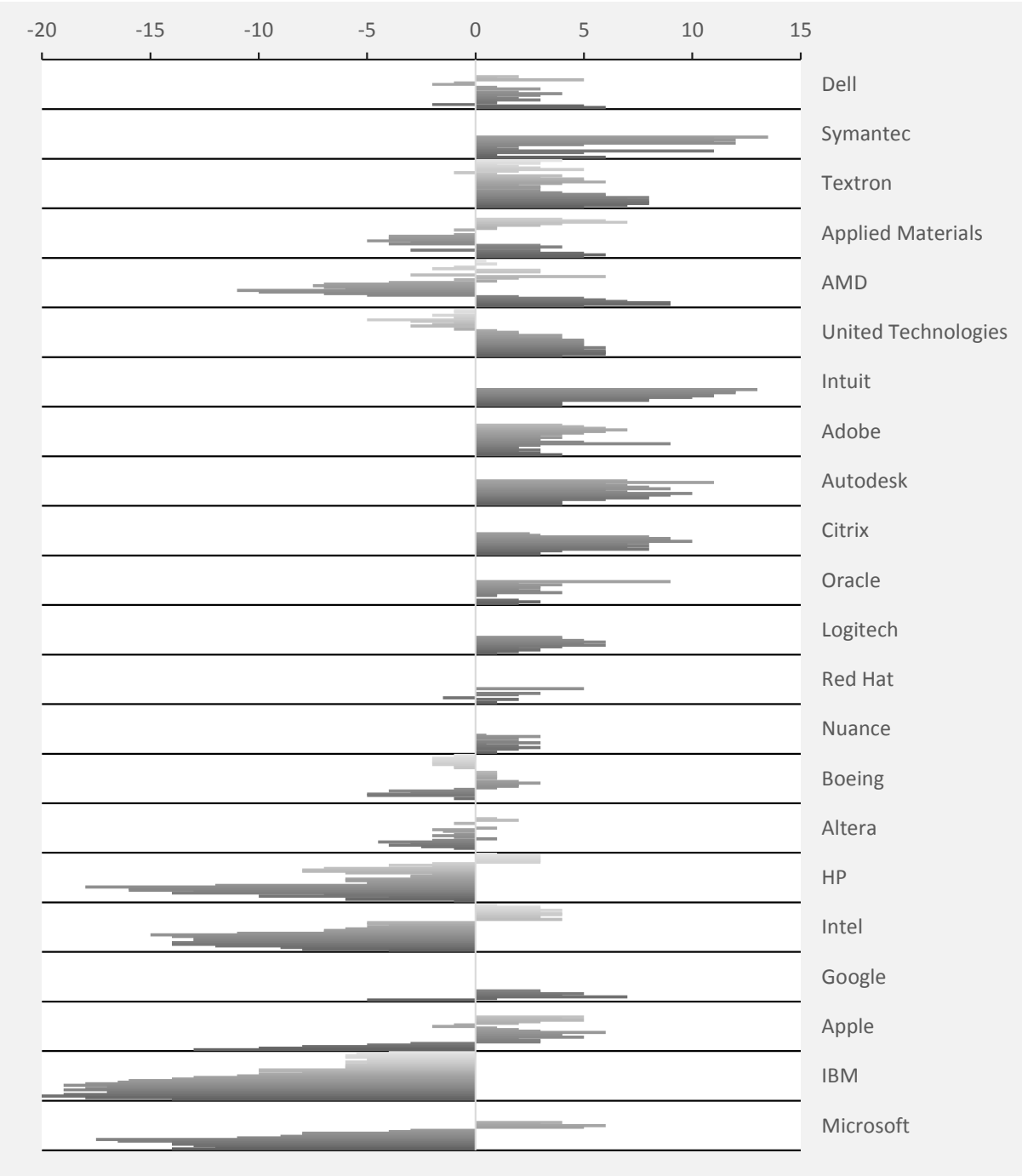
Notes: See Figure 8. Estimated using window length of 4 years.

Figure A6: Relative efficiency of companies in producing patent value vs. patent quantity – window 2



Notes: See Figure 9. Estimated using window length of 2 years.

Figure A7: Relative efficiency of companies in producing patent value vs. patent quantity – window 4



Notes: See Figure 9. Estimated using window length of 4 years.

Table A1: Descriptive statistics

Assignee	Industry	Data coverage	# of patents	Citations per year (mean)	Citations per year (SD)	Employees (thousands)	Real R&D expense (USD millions)
AMD	Semiconductors	1978–2010	9878	0.97	1.43	13.52	677.33
Adobe	Software	1990–2010	1842	0.60	1.07	5.76	449.36
Altera	Semiconductors	1987–2010	4417	0.59	1.28	2.24	199.33
Apple	Computers	1988–2010	5966	1.05	2.17	26.12	873.14
Applied Materials	Semiconductors	1985–2010	6130	1.03	1.56	13.63	880.91
Autodesk	Software	1992–2010	489	0.51	1.03	4.49	285.85
Boeing	Aerospace	1975–2010	9374	0.51	0.72	150.19	2261.38
Citrix	Software	1995–2010	418	0.95	1.69	4.01	189.92
Dell	Computers	1989–2010	2652	0.88	1.65	53.49	405.77
Google	Software	1999–2010	2530	0.50	0.97	16.31	2100.80
HP	Computers	1975–2010	25370	0.80	1.72	137.39	2987.87
IBM	Computers	1975–2010	76952	0.92	1.71	334.12	4703.85
Intel	Semiconductors	1978–2010	23208	0.89	1.79	76.54	4086.81
Intuit	Software	1999–2010	486	0.26	0.57	7.77	458.56
Logitech	Computers	1990–2010	281	0.52	0.65	6.51	79.08
Microsoft	Software	1990–2010	22646	0.99	2.11	62.06	6039.54
Nuance	Software	1998–2010	451	0.36	0.81	3.47	74.01
Oracle	Software	1995–2010	4751	0.63	1.36	68.62	2122.06
Red Hat	Software	2000–2010	735	0.16	0.37	2.70	112.37
Symantec	Software	1996–2010	1887	0.61	1.13	14.10	684.29
Textron	Aerospace	1975–2010	2321	0.51	0.65	53.46	250.62
United Technologies	Aerospace	1975–2010	6178	0.52	0.66	187.16	1215.57