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ABSTRACT

R&D is an uncertain activity with highly skewed outcomes. Nonetheless, most recent empirical studies and modeling estimates of the potential of technological change focus on the average returns to research and development (R&D) for a composite technology and contain little or no information about the distribution of returns to R&D—which could be important for capturing the range of costs associated with climate change mitigation policies—by individual technologies. Through an empirical study of patent citation data, this paper adds to the literature on returns to energy R&D by focusing on the behavior of the most successful innovations for six energy technologies, allowing us to determine whether uncertainty or differences in technologies matter most for success. We highlight two key results. First, we compare the results from an aggregate analysis of six energy technologies to technology-by-technology results. Our results show that existing work that assumes diminishing returns but assumes one generic technology is too simplistic and misses important differences between more successful and less successful technologies. Second, we use quantile regression techniques to learn more about patents that have a high positive error term in our regressions – that is, patents that receive many more citations than predicted based on observable characteristics. We find that differences across technologies, rather than differences across quantiles within technologies, are more important. The value of successful technologies persists longer than those of less successful technologies, providing evidence that success is the culmination of several advances building upon one another, rather than resulting from one single breakthrough. Diminishing returns to research efforts appear most problematic during rapid increases of research investment, such as experienced by solar energy in the 1970s.

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I. Introduction

Technological change will play a key role in any attempt to reduce greenhouse gas emissions that lead to climate change. For example, European Union proposals to stabilize global average temperatures at two degrees Celsius over pre-Industrial Revolution levels imply stabilizing atmospheric carbon dioxide (CO_2) concentrations at 450 parts per million (ppm). Current levels already exceed 380 ppm. To meet such targets, annual CO_2 emissions would need to peak at about 9 billion tons of carbon per year by about 2012, and fall to as little as 3.5 billion tons per year by 2100 (Clarke et al., 2007). Meeting emission reduction targets such as these will not be possible without major changes in the way that energy is produced and consumed.

Given the current status of alternative technologies, making such changes will be costly. Generation of electricity and heat is the largest source of carbon emissions, accounting for 41% of carbon emissions worldwide in 2006, followed by transportation at 23% (IEA 2008). In both cases, alternative carbon-free energy sources such as wind, solar, or hydrogen fuels all are priced higher than traditional fossil fuels (IEA 2006). However, technological improvements are likely to occur, leading to lower costs. Much uncertainty surrounds the potential for technological change. In its latest report on climate change, the Intergovernmental Panel on Climate Change (IPCC) summarizes estimates of the costs of stabilizing global carbon concentrations from a variety of climate models. To stabilize concentrations at a level of 550 parts per million (ppm), the estimated costs, in terms of lost GDP in the year 2050, range from a four percent loss to a slight increase in GDP, relative to baseline growth (IPCC 2007). Future technological change is an important driver of this uncertainty, and affects not only the cost of reducing emissions, but also predictions of what emissions levels will occur in the absence of climate policy initiatives.

Despite this uncertainty, most recent empirical studies and modeling estimates of the potential of technological change focus on the average returns to research and development (R&D), but contain little or no information about the distribution of returns to R&D, which is important for capturing the range of costs associated with climate change mitigation policies. The true nature of innovation and the R&D process is inherently uncertain and thus can be best described by a probability distribution (Mansfield, 1968; Evenson and Kislev, 1975). More importantly, this probability distribution is highly skewed (Jaffe and Trajtenberg, 2002; Pakes, 1986), suggesting that models focusing on average returns may severely underestimate the potential for significant innovations. Except for work by Baker (e.g., Baker and Solak, 2011; Baker and Adu-Bonnah, 2008), however, few studies in the climate policy literature have assumed that investment in R&D influences the level of uncertainty associated with the magnitude of the returns to R&D. This is in part due to a lack of empirical support for calibrating R&D models based on anything other than average returns. Due to the highly skewed returns to R&D, deterministic models based on average returns could underestimate the value of R&D investments as part of a strategy to avoid extreme climate impacts in the future. Through an empirical study of patent citation data, this paper adds to the literature on returns to energy R&D by focusing on the behavior of the most successful innovations. Moreover, we are interested in understanding whether this behavior differs across energy technologies. The objective of this work is to provide an empirical basis for better modeling of the uncertain returns to energy R&D.

Our paper builds on existing work using patent citations to study the returns to innovation (e.g., Popp 2002, 2006a, Caballero and Jaffe 1993). A common finding in this literature is that research experiences diminishing returns – it gets more difficult to make additional advances as technology improves.[1] We make two contributions. First, in contrast to Popp (2006a), we compare the results from analyzing an aggregate of six energy technologies to technology-by-technology results. Our results show that existing work that assumes diminishing returns for one generic technology is too simplistic and misses differences between more successful and less successful technologies.

Second, given the importance of differences across technologies, is there any new information we can cull from looking at the most successful patents within each technology? To measure the relative importance of differences across technologies versus the uncertainty of R&D, we apply quantile regression techniques to learn more about patents that have a high positive error term in our regressions – that is, patents that receive many more citations than predicted based on observable characteristics. It is these patents that are the high value patents in the distribution of possible outcomes. While standard regression estimates give the change in the conditional mean of the dependent variable as we change a variable by one unit, quantile regression allows for an examination of inter-variable relationships at various parts of the conditional distribution by allowing estimates of the coefficients to vary based across quantiles of the distribution. Using quantile techniques, we consider the following questions:

- How does the likelihood of receiving a highly cited patent vary with research effort?[2]

[1] Note that claims of diminishing returns to research within a field need not be inconsistent with the more general notion that there are increasing returns to research at the macroeconomic level. As new research makes the technologies in a given field obsolete, research efforts should switch to other, more productive areas. Such a general equilibrium analysis is beyond the scope of this research.

[2] Lanjouw and Schankerman (2004) suggest that the expected value of research is independent of the amount of research spending by a firm. That is, increased firm R&D expenditures do not increase the average value of a firm's patents. Our question is slightly different, as we focus on those patents in the upper tail of the value distribution, as these are the patents that move knowledge forward. Because additional R&D projects increase the likelihood that any one research draw will be high valued, Lanjouw and Schankerman's findings do not rule out the possibility that more R&D effort would increase the probability of observing a single high-valued invention. See, for example, the

- Does it become harder to achieve a highly cited patent over time? I.e., is the distribution of potential ideas replenished over time, or does success become more difficult as high-valued opportunities are depleted?
- Do these results differ across energy technologies?

We find that higher R&D spending does not necessarily lead to highly cited patents ("breakthroughs"). We also find no evidence that highly cited patents or breakthroughs are more difficult to achieve over time. Interestingly, we find that increases in subsequent patents lead to a proportionally higher increase in citations to earlier high quality patents, suggesting that these high quality patents may induce subsequent innovations. Lastly, comparing the results from technology-by-technology regressions to those pooling our six energy technologies, we find that differences across quantiles only hold for select technologies and are smaller in magnitude than differences across technologies. Thus, differences in technologies seem to be more important than R&D uncertainty in explaining patent behavior.

II. Literature Review

A survey of the recent climate policy and energy modeling literature shows that a decade after the work of researchers such as Goulder and Mathai (2000) and Goulder and Schneider (1999), the induced technical change climate policy and energy planning research community still has a long way to go in representing technology-by-technology variation and uncertain returns to R&D in its analyses. Goulder and Mathai (2000) presented a new analytic framework for characterizing optimal carbon emissions abatement and carbon taxes under learning-by-searching technical change. In their simplified framework, they considered a single

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model in Evenson and Kislev (1975). However, if firms invest in the most promising research projects first, one would expect the probability of highly valued research to decrease as research effort increases.

representative emission abating technology affected by R&D investments. Alternatively, Goulder and Schneider (1999) considered multiple technologies in their study of the impact of carbon policy on energy R&D investments, but they too made an important simplifying assumption (for the sake of focusing on their contribution) by assigning their technology groups the same parameter value for R&D program effectiveness. Goulder and Schneider (1999) comment on their decision and perform key sensitivity analyses, citing the lack of available empirical data for doing otherwise. Even today, the majority of researchers in the induced technical change climate policy and energy planning research community continue to make very similar assumptions about R&D-based technical change.

Within a sampling of the last five to seven years of the numerical modeling literature, the same distinct categories of assumptions arise. Bosetti *et al*. (2006) present WITCH, an optimal growth model that endogenously accounts for R&D-based technological learning. However, while retaining the typical technological detail of bottom-up models, WITCH considers a single R&D-influenced technology category (advanced biofuels). Later, Bosetti and Tavoni (2009) use a stochastic version of WITCH to determine optimal investment in an uncertain backstop technology R&D program under stringent carbon policies. They, too, use a single representative carbon-free backstop. Schwoon and Tol (2006) use a formulation of the Goulder and Mathai (2000) model to study the impact of socio-economic inertia in optimal carbon abatement in the presence of induced-technical change. Their model consists of a single learning sector, and therefore one parameter value for the inertia and R&D learning parameters. Moreover, in their future research discussion the authors point to the need to break the economy up into additional sectors, because they can have quite different inertias and parameters. Finally, most recently Bye and Jacobsen (2011) use a numerical energy-climate CGE model to study how to divide

R&D investment dollars between general and emission-saving technologies under various carbon tax magnitudes. However, in doing so, they use a single representative backstop technology (CCS) to differentiate between general R&D and emission saving R&D technology programs.

During this time, other studies considered multiple technology categories, but used essentially the same values and assumptions about the process of innovation across them. In their R&D investment analysis for general versus emission-saving technologies, Bye and Jacobsen (2011) also use identical functional forms and assumptions for decreasing returns to knowledge for the backstop and general technology R&D processes. The authors comment on the general fact that different R&D industries must have important differences, but that they found no empirical research supporting using a different structure or parameter values. Several other important economic models introduced and used within the last decade to study energy technology R&D investment and climate policies, either in the context of the entire energy sector or specific sectors such as electricity, also make similar assumptions. Popp (2006b) uses the same parameters for the innovation possibilities frontier and diminishing returns to research in ENTICE-BR for both types of innovation processes included (energy efficiency and carbon-free backstop technology). Miketa and Schrattenholzer (2004) use the same learning rate for both wind and solar technologies in determining the optimal allocation of R&D funds to the two electricity technologies using a learning-by-searching modified version of the MESSAGE electricity sub-model. Finally, Otto *et. al*. (2008) study cost-effectiveness of climate policy under technology externalities, and use a CGE model to show that it is second-best optimal to subsidize emission intensive R&D when combined with a carbon pricing scheme. However, for their two R&D-affected industries (a non-carbon intensive industry and a carbon-intensive industry), they assume that knowledge accumulates as a deterministic function of investment.

Even studies that allow for uncertain returns to research focus on average returns to R&D during calibration. First, in determining the optimal R&D allocation between three different technologies (fossil, renewables, and CCS) in a climate-energy-economic model under uncertainty (MERGE), Blanford (2009) utilizes the same parameter values for the return on investment, diminishing returns, and limiting probability for the different technologies (although alternate values *are* tested across different model runs). The behavior of all technologies in the analysis are therefore effectively treated the same. Second, Baker and Adu-Bonnah (2008) consider two R&D-affected technology categories (alternative non-fossil and conventional fossil), use different structures to model technical change, and allow for differing probabilities for program riskiness to study the socially optimal level of R&D investment in the two technologies. However, investment in R&D in the model results in one of only three outcomes: a deterministic "target" amount of technical change, total failure, or a "breakthrough." Moreover, a one-to-one relationship between R&D investment dollars and the target amount of technical change is used for both technology groups, and sensitivity analyses are run on important innovation parameters such as the cost coefficient using a wide value range.

In an effort to help close these research gaps, Baker et al. (2008, 2009a, 2009b) perform a comprehensive data collection using expert elicitations for how government funding differentially impacts the probability of success for three key alternative energy technologies: CCS, solar photovoltaic, and nuclear. Their findings allow for technology-specific calibration of induced innovation and technical change in certain types of climate policy assessments, as shown in Baker and Solak (2011). The current paper addresses another key gap in the empirical literature, also with an aim to support calibration in climate policy modeling. Using the historical record on technology-specific knowledge flows as measured via patent data, we examine the variation in the behavior of potential "breakthrough" innovations through time for a wide variety of technologies, focusing both on differences across technologies and between successful and unsuccessful patents within technology groups.

III. Estimation Framework

To envision the research process, consider a distribution representing the possible outcomes from a project. We use forward patent citations as a measure of the value of these outcomes. When a patent is granted, it contains citations to earlier patents that are related to the current invention. The citations are placed in the patent after consultations among the applicant, his or her patent attorney, and the patent examiner. Citations received by a patent indicate that the knowledge represented in the patent was utilized in a subsequent invention.[3] Because we are interested in the social value of invention, we prefer the use of citations as a measure of value over alternatives such as patent renewals and stock market returns, both of which focus primarily on the returns of innovation to the inventing firm. Lanjouw & Schankerman (2004) compare numbers of claims, forward citations, backward citations, and patent family size, and find that forward citations are the most reliable measure of patent quality. Moreover, Popp (2002) shows that (a) the likelihood of citation to patents for a given technology and year can be used to measure the quality of the knowledge stock on which future inventors build and (b) that increasing quality of the knowledge stock leads to more inventions in future years. Popp (2006a) suggests that the likelihood of citation falls over time, suggesting that research success does become more difficult as knowledge progresses. This paper also provides evidence that the

[3] The key assumption here is that a citation made to a previous patent indicates a flow of knowledge from the cited patent to the citing patent, so that patents cited more frequently are considered more valuable to future inventors. Jaffe, Fogarty, and Banks (1998) investigate the validity of this assumption, using evidence from citations made to NASA patents. They conclude that, although there is noise in the citation process, aggregate citation patterns represent knowledge spillovers, although the spillover may be indirect.

expected number of citations per patent falls in years when many other patents are granted in the field, suggesting that there are also diminishing returns to research in any given time period. However, neither of these papers considers the uncertainty inherent in the research process, as they focus on average returns within a given year and constrain the results to be the same for all technologies.

We build on this work by considering the entire distribution of research outcomes, focusing on the characteristics of high-value (e.g. highly cited) patents. It is these high-value patents that will have the most impact on climate change. Note, however, that a simple count of patent citations is not sufficient. The number of subsequent citations received by a patent is a function of, among other things, the number of patents that are granted in subsequent years. More citations will be received by patents in active fields. Thus, following the model in Popp (2006a), we estimate the predicted number of citations for each patent. However, whereas Popp (2006a) only focused on mean values and assumed common parameter values across technologies, we (1) allow the results to vary across technologies and (2) use quantile regression to provide additional information on patents that are highly cited. Defining $cites_{i,j,s,t}$ as the number of citations made to patent *i* in technology group *j* with grant year *t*, by patents with application year *s*, and $NCTG_{j,s}$ as the number of successful patent applications pertaining to technology *j* filed by U.S. inventors in year *s*, the predicted total number of citations to each patent/year pair are:

$$cites_{i,j,s,t} = NCTG_{j,s} e^{\lambda_i} = e^{\ln(NCTG_{j,s}) + \boldsymbol{\beta}'\mathbf{X}_{\mathbf{i,j,s,t}} + \varepsilon_{i,j,s,t}} \tag{1}$$

$NCTG_{j,s}$ controls for the opportunities for citation available to each patent. Because our observations are count data, we use negative binomial regression to estimate equation (1).

Following Popp (2006a), the vector of explanatory variables, $\mathbf{X}_{\mathbf{i,j,s,t}}$, controls for features of the citing and cited patent. Most importantly, we include two tests for diminishing returns. First, we ask whether the likelihood of citation falls when more patents are granted within a specific technology group in the same year as the cited patent. This variable, $NCTD_{j,t}$, tests for diminishing returns to research *within a given year*, *t*. A negative coefficient on this variable suggests that any individual patent will receive fewer citations, after controlling for each patent's characteristics, if it is granted in a year with many other patents in the same technology. Diminishing returns here may imply that the additional research done in such years is of lower quality. The assumption is that researchers choose the most fruitful projects first. When the demand for energy R&D increases (for example, when energy prices are higher), marginal projects that weren't viewed as profitable before now appear worthwhile. Alternatively, it may be the case that there are fewer citations per patent because the patents overlap. This suggests that the extra research done in years with many patents is of less social value, since the unique contribution of each patent is smaller.

Second, we ask whether the probability of citation falls as the cumulative number of patents in a field increases. Cumulative patents $K_{j,t}$, defined below, tests for diminishing returns *across time*. Diminishing returns across time could occur if there is a limited pool of potential inventions in a given field. As the technological frontier moves outward, it becomes increasingly difficult to create new inventions that exceed the current standard. To test this, we create a stock of existing patents for each technology, using patent data from 1900-2007. In any year *t*, the stock of existing patents is calculated as:

$$K_{j,t} = \sum_{l=0}^{t} PAT_{j,l} \exp[-\beta_1(t-l)]\{1-\exp[-\beta_2(t-l+1)]\} \qquad (1)$$

In this equation, β_1 represents a rate of decay, and β_2 a rate of diffusion. We choose a decay rate of 0.1 and a rate of diffusion of 0.25. Such rates are commonly found in the literature on technological change, and imply that a patent has its maximum effect on the stock about 4 years after the patent was granted (see, for example, Griliches, 1995). For each technology, the stocks are normalized so that the level of the stock in 1980 equals 100. Thus, a one-unit change in the stock indicates a one percent increase in the knowledge stock for that technology.

In addition to these controls for the returns to research over time, we also consider several variables that control for the characteristics of individual potentially cited patents. In particular, to capture the level and direction of government-sponsored R&D, we include two variables to ascertain the effect of government research on the knowledge stock. The first is a dummy variable set equal to 1 if the cited patent is assigned to the U.S. government. This includes patents assigned to a government laboratory. The second is a dummy variable set equal to 1 if the cited patent is a child of a U.S. government patent. These are defined as patents that are not assigned to the U.S. government, but that cite at least one patent assigned to the U.S. government.[4] In addition, we include controls for patent features such as the number of claims and the number of citations made by the patent. The complete list of explanatory variables appears below:

- $NCTG_{j,s}$ represents the **total number of successful U.S. patent applications per citing year, s:** This controls for opportunities for future citations. Separate counts are made for each technology group, *j*.
- $NCTD_{j,t}$ represents the **total number of patents granted in the technology group in the same year, t, as the cited patent.** As noted, this controls for diminishing returns within a given year.

[4] I label these patents as "children" so as to provide a short label for discussion. It need not be the case, however, that child patents are direct descendants of government research, meaning that they need not result from work directly related to the government's research efforts. Citations may result simply because both patents are in similar areas, so that there is an indirect knowledge spillover, but no intentional technology transfer between the government and the private patent.

- $K_{j,t\text{-}1}$ is the lagged value of the **stock of accumulated patents** granted in technology j by year t, where year t represents the issue year of the cited patent. This controls for diminishing returns across time.
- **ASSIGNEE$_i$** is a set of dummy variables defining the **patent assignee of the cited patent**. Potential assignee types are corporate, individual, government, university, other research institution, and child of a government patent. For each type, we include separate dummy variables for U.S. and foreign assignees (e.g. there is a dummy variable for U.S. corporations and a second for foreign corporations). U.S. corporations are the excluded category.
- $CLAIMS_i$ represents the **number of claims** on each cited patent. Other things equal, patents with more claims should be cited more frequently.
- $CITEMADE_i$ is the **number of citations made by** the cited patent. Patents may generate more subsequent citations simply because they are in more crowded areas. The number of citations made by these patents controls for this.
- $CITELAG_{s,t}$ is the difference between the citing patent's application year, s, and the cited patent's grant year, t. This allows for declining probabilities of citation over time, as the cited patents gradually become obsolete. To allow for non-linear effects, we also include $CITELAG^2_{s,t}$.
- **CITINGYR$_s$** is a vector of year dummies defined based on the application year of the citing patents. 1990 is the excluded year. This captures any fixed effects in

citations common to a grant year. Over time, the number of citations per patent have increased due to changes in citing behavior.[5]

- **TECHNOLOGY$_j$** is a vector of energy technology group dummies. About half of all patent citations are to patents in the same classification (Jaffe *et al.* 1993). However, the technology groups in this paper range from groups with one or two subclassifications to groups with patents from many different broad classifications. Technology groups with broad definitions are more likely to include subclasses that are not strongly related, which means that citations to other patents in the group are less likely in those groups. The excluded group is nuclear power.

We are particularly interested in patents that have a high positive error term from this regression – that is, patents that receive many more citations than predicted based on observable characteristics. It is these patents that are the high value patents in the distribution of possible outcomes. Quantile regression techniques allow us to learn more about these patents. While standard regression estimates give the change in the conditional *mean* of the dependent variable as we change a variable by one unit, quantile regression allows examination of inter-variable relationships at various parts of the conditional distribution by allowing estimates of the coefficients to vary across quantiles of the distribution.[6] Using quantile regression, we can, for example, ask whether additional research effort (measured by the total number of patents in a field) increases the likelihood of highly valuable patents, and whether this likelihood varies over

[5] Changes in citing behavior over time must be accounted for because of institutional changes at the patent office that make patents more likely to cite earlier patents than was previously true, even if all other factors are equal. In particular, two changes have played an important role. First, computerization of patent office records has made it easier for both patent examiners and inventors to locate other patents similar to the current invention. Second, increasing legal pressure has made it more important for examiners to be sure that all relevant patents are cited.
[6] Koenker and Hallock (2001) provide a review of quantile regression techniques.

time. This last question addresses whether the distribution of potential ideas is replenished over time, or if success becomes more difficult as high-valued opportunities are depleted.

In addition we also explore the potential sources of high-valued innovations, asking whether these highly cited patents come from particular institutions, and whether increased government R&D spending can affect the likelihood of discovering high-value inventions. For example, Popp (2006a) finds that government patents are not more likely to be cited than other patents. This result is surprising, as one expects government research to focus on more basic needs, which should be cited more frequently. One possible explanation for this could be that government research projects are more risky. If the government does research that private firms won't do because of greater risk, government research could have a similar expected value to private research, while at the same time resulting in both more high-value innovations and low-value innovations. Quantile regression allows us to identify such differences across high- and low-valued patents.

IV. Data

Our data include all patents for our selected technologies granted by the U.S. Patent and Trademark Office (USPTO) with priority dates ranging from 1971 to 2008.[7] We focus on granted patents because, until 2000, only patents granted by the USPTO were made public.[8] This also ensures that all the patents in our sample have met a minimum quality threshold. To identify patents, we use a combination of the International Patent Classification (IPC) codes on

[7] To calculate the stocks described in section II, we use patents dating back to 1900. However, the citation data needed for the remaining analysis is not available until patents granted in 1975, limiting the citation analysis to patents from the 1970s forward. Note that, because we observe granted patents, patent counts in recent years are truncated, since the average patent takes 2-3 years to go through the examination process. Year effects will account for this truncation bias.

[8] This is different from most countries, where patent applications are published 18 months after they are filed. Even today, while most U.S. applications are published after 18 months, an inventor can request that the application not be published as long as the applicant agrees not to pursue patent protection in other countries.

the patent and keyword searches of the title and abstract. The IPC classes and keyword searches used are listed in Appendix A.[9] We include patents related to six technologies that either provide cleaner energy or reduce energy consumption: wind, solar, fuel cells, nuclear, hybrid autos, and energy efficiency. We obtained the patent data using Delphion, a commercially-available database that allows searching and downloading of patent records from patent offices worldwide.[10]

Patents are sorted by the priority year, which is the year in which the initial application pertaining to this patent was filed. If a patent is granted, protection begins from the priority date. This date corresponds to when the inventive activity took place, as patent applications are usually filed early in the inventive process (see, e.g., Griliches, 1990). Figure 1 shows the trends in each technology across time. Invention in nuclear technologies was strong throughout the 1970s until 1990, at which point patent counts begin to decline. Patent counts in both solar and wind energy have two peaks – one during the 1970s energy crisis and a second in the 21st century as climate policy brings renewed interest to renewable energy. Interestingly, the 1970s peak is larger for solar energy, whereas for wind the more recent peak is larger. The trend for energy efficiency is similar to wind, although the 1970s peak is less notable. Both fuel cells and hybrid vehicle patents remain relatively flat until 1990 and peak around the year 2000.

The Delphion database includes rich descriptive data for each patent, including patent citations made by each patent and the number of claims. Using this citation data, we are able to

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[9] The IPC system is used by patent offices around the world to classify patents based on their intended use. We begin by using a combination of keyword and IPC class searches to identify patent classes that both include relevant patents and that do not also include irrelevant patents. We prefer to omit classes that contain a mix of relevant and irrelevant patents. While this may cause us to omit some relevant patents, this is preferred to including irrelevant patents that would simply add noise to our data without adding additional information. For most technologies, this resulted in a set of IPC classes that were used to identify relevant technologies. In the case of energy efficiency, we could not identify relevant classes, as these patents are spread throughout various end use technologies. Thus, we instead use a keyword search to identify these patents.

[10] http://www.delphion.com.

obtain forward citations received by each of our energy patents by other patents within the same technology field. Table 1 and Figure 2 provide descriptive statistics on forward citations received by patents in each of our technology groups. Note that the distribution of citations is highly skewed. Many patents are never cited. For every technology, the 25th percentile of citations received is 0. The median for the aggregate of all technologies is just one citation received. Across technologies, the median ranges from 0 for efficiency patents to 3 for wind patents. Even at the 75th percentile, forward citations received range from 1 for energy efficiency to 7 for wind. However, there is a long tail with a select group of highly cited patents, as the maximum number of citations received ranges from 47 in nuclear energy to 210 for energy efficiency and for hybrid vehicle technologies.

The three panels of Figure 2 provide a visual representation of three typical distributions of patent citations. Each shows, on the *y*-axis, the number of patents from a given year and technology that receive a specific number of forward citations. Panel A represents citations received by a successful technology, hybrid vehicles. Here we see the distribution of citations received by hybrid vehicle patents from 1991. Note that while over half of the 80 patents from this year receive five citations or less, there is a very long tail, including one patent that receives 76 citations. The pattern of another successful technology, wind energy patents from 1981, is similar, as shown in panel B. Of particular note here is that, compared to the two other panels, most of these patents receive at least one citation. Only 4 of 76 wind patents from that year receive no citations. Most patents receive a few citations, but the tail is noticeably shorter than for hybrid vehicles. Finally, panel C shows citations received by solar energy patents in 1981. Compared to hybrid vehicles and wind energy, solar energy has received less commercial success. The patent citations received are consistent with these patents having lower social value. Of the 337 solar energy patents from 1981, 193 receive two or fewer citations. Moreover, while the distribution is still skewed, there are no large outliers, unlike the hybrid vehicle case.

Table 2 provides descriptive data by technology for other patent characteristics. The number of claims per patent is relatively stable, with the average ranging from 11.5 for nuclear to 17.0 for fuel cells. The number of cited references to earlier patents ranges from 7.7 for nuclear to 12.3 for efficiency. In both cases, these data suggest that nuclear energy patents are narrower in scope than their counterparts in fields such as fuel cells or energy efficiency. Interestingly, while the greater breadth of fuel cell patents also results in a high average number of future citations received, that is not the case for energy efficiency patents. Finally, note that the size of each technology group does vary, as there are only 47.5 wind patents per year on average, compared to 469.5 energy efficiency patents per year. Nonetheless, wind patents are very likely to receive citations from future wind patents, whereas energy efficiency patents are less likely than our other technologies to receive a future citation from a patent within the same group. This suggests that it is not just the size of each group that matters, but the quality of the innovations that influence future usefulness.

To consider whether patents from some institutions are more valuable than others, we use data from the NBER patent database to identify the type of assignee for each patent (e.g., corporate, individual, government, university, other research institution, and child of a government patent, as well as foreign or domestic).[11] Table 3 shows the percentage of patents from various assignees. The first rows show these data for the overall sample, followed by percentages for selected single years. Overall, nuclear and solar are most likely to have patents

[11] We used an updated version of the NBER database that includes data on assignees for all patents granted through 2006, available at https://sites.google.com/site/patentdataproject/Home. For patents from 2007 onward, we matched assignee characteristics with patents from the same assignee from earlier years when possible and then manually coded patents for which the assignee did not appear in the NBER database.

assigned to government. Except for hybrid vehicles, about 40% of patents come from foreign inventors. Largely due to innovation from Japanese auto manufacturers, over two-thirds of hybrid vehicle patents granted in the U.S. go to foreign inventors. Looking across time, government patents were more prevalent in the 1970s and 1980s, and the share of foreign patents is growing for every technology.

Finally, the right-hand columns of Table 3 show the average number of citations received by patents with different assignees. Except for wind, children of government patents receive the most citations. There is variation in the quality of government patents across technologies. Government wind patents receive, on average, more citations than any other type of wind patent. However, just 1.44% of wind patents are assigned to the government. Government patents also receive more citations than the average patent for fuel cells and solar energy. For the remaining technologies, government patents receive fewer citations than average. In all cases, foreign patents receive fewer citations.

V. Estimation

Because most patents are never cited, we use count data regression techniques. For the quantile regressions, we use a method suggested by Machado and Santos Silva (2005) and developed for Stata by Miranda (2006, 2008).[12] To overcome the problem of having a discrete dependent variable when doing the quantile regression, this method smooths the data by adding a uniform random variable to each dependent variable. With appropriate assumptions (discussed in Machado and Santos Silva 2005), standard quantile regression techniques can be applied to a monotonic transformation of this smoothed variable. Because the "jitters" to the data are

[12] QCOUNT, the Stata software for quantile regressions using count data is available from http://ideas.repec.org/c/boc/bocode/s456714.html.

randomly added, 100 draws of the random variable *u* are taken and an average of the jittered sample is created.

Our regressions include patents granted in the U.S. for six technologies (wind, solar, fuel cells, nuclear, hybrid autos, and energy efficiency). We consider cited patents with initial priority dates from 1971 to 2004, and citing patents with priority dates ranging from 1972 to 2008.

Table 4 presents regression results pooling all technologies. Except for the coefficient for ln(# of citing patents), results are shown as incidence rate ratios, e^{β}. Moreover, to aid interpretation and make comparisons across technologies, the number of patents, the number of claims, and the number of citations made by each patent are normalized so that a one-unit change equals a ten percent deviation from the mean.[13] For example, an incidence rate ratio of 1.2 implies that a ten percent deviation from the mean for that variable results in 20 percent more citations to the patent. The first four columns present the 25th, 50th, 75th, and 90th quantiles, and the final column presents the results from a standard generalized negative binomial regression. Our primary focus is on the behavior of patents in the higher quantiles. Indeed, descriptive data suggest that the mean number of citations falls near the 75th quantile for most technologies, as most patents are never cited. The interpretation for each quantile is that these represent patents with unobserved characteristics in quantile *x*. Intuitively, this can be thought of as the unobserved quality of each patent, so that patents in higher quantiles have higher unobserved quality.

Note that ln(# of citing patents) controls for the number of opportunities for a patent to be cited. In a standard count model, this coefficient should equal 1. Indeed, it is not significantly

[13] The normalization first divides each continuous variable by its mean, multiplies by 10, and then takes deviations from the mean by subtracting 10. This procedure is introduced in Kerr and Newell (2003), and results in normalized variables that have a mean of 0.

different from 1 in column 5. Interestingly, its value grows in the quantile models, with a value of 1.493 for the 90^{th} quantile, indicating that increases in subsequent patents more than proportionally increase citations to high quality patents. This suggests that high quality patents may be the *cause* of these subsequent patents – that is, the value of high quality knowledge leads to additional patents in subsequent years. Also interesting is that the cite lag, or the time that passes between the cited and citing patents, is twice as short for high quality patents, suggesting that the value of these patents is revealed quickly. While statistically significant due to the large number of observations, the squared term for the cite lag has almost no meaningful effect, with a value of 0.999 or 1.0 in all cases.

The accumulated stock of past patents ("stock of patents") and the number of patents granted in the same year as the cited patent ("# of patents in cited year") are important for calibration of climate models, as they control for potential diminishing returns to innovation. The only evidence for diminishing returns is in a given year, as suggested by the significant value of 0.962 associated with "# of patents in cited year" in the last column. Thus, as more patent applications are filed in a given year, the probability of any one patent receiving a citation falls (by 3.8% for a 10% increase in patent applications). This effect is twice as large for the highest quality patents (i.e., a 10% increase in the number of patents in the cited year reduces the probability of citation by 6.2% in the 90^{th} quantile, compared to just 3.3% in the 25^{th} quantile), suggesting that additional research effort is applied to marginal projects with less potential value. Thus, the pooled regression results suggest that large increases in research spending do not necessarily make it easier to obtain breakthrough results, as the most promising projects are pursued first.

Finally, we control for several possible patent assignee characteristics. While the effect of most characteristics is similar across quantiles, we do find that patents assigned to government agencies are less likely to receive citations in the highest quality quantile. Moreover, as in Popp (2006a), children of government patents are the most valuable. This suggests that the value of government research is enhanced once acted upon by the private sector. Moreover, while the differences are small, nearly all assignee effects are smallest in the 90th quantile. Since corporate patents are the excluded category, this suggests that those patents are most likely to result in high value outcomes.

While we find some differences across quantiles, the results in Table 4 constrain the effects to be the same across all technologies. However, our data include a range of technologies. Some, such as wind and hybrid vehicles, have moved from experimental technologies to (at least limited) commercial success. Solar, in contrast, remains a high-cost niche technology. Others, such as energy efficiency and nuclear, have been mature for some time. Therefore, we also estimate separate regressions for each individual technology.[14] Table 5 presents results for the generalized negative binomial regression by technology. This suggests that there are important differences across technologies. Of particular note is the effect of the cite lag variable. Using coefficient estimates for citelag and citelag^2 from the individual technology regressions, Figure 3 shows how the probability of citation changes after *x* years. As shown in panel A of Figure 3, the probability of citation trends downward monotonically over time for most technologies. However, for wind and hybrid vehicles, the probability of citation initially increases, peaking after six years for wind and three years for hybrids. Indeed, the combined effect of the cite lag variables for wind does not become negative until year 12. As

[14] We drop the variable *NCTGt* from these regressions, as it is perfectly collinear with the individual year dummies for citing patents.

these two technologies are the most successful of our six energy technologies, this suggests that the value of patents last longer for successful technologies. For instance, evidence from a history of wind technology innovation (Dykes, 2010a; Dykes, 2010b) demonstrates that success in wind is cumulative. There is not a single breakthrough invention, but rather a series of successful innovations that build on the last major improvement. At each step, innovations such as variable speed, improved power electronics, better materials for rotors, and the ability to "feather" rotors required success of the previous innovation. The persistent value of wind patents over time is consistent with such behavior.

Regarding diminishing returns, once again the only meaningful evidence is found within a given year. Wind, solar, and fuel cells all experience diminishing returns within a given year, as suggested by the significant <1 coefficient associated with "# of patents in cited year" in Table 5. A ten percent increase in patents in the cited year reduces the probability of receiving a citation by 2.6% for wind, 4.3% for solar and 2.1% for fuel cells. In contrast, both hybrids and energy efficiency show evidence of positive spillovers within a given year, as the probability of citation increases for patents from years with higher patenting activity. There are few noticeable differences for assignee types across technologies, except that the low value of U.S. government patents found in the pooled regression appears to be almost entirely a result of nuclear energy patents, as this is the only technology for which this coefficient is significant.

To help reconcile the differences regarding diminishing returns across different technologies, Table 6 includes the results of an additional regression adding a squared term for the number of patents in the cited year.[15] To be able to interpret the squared term, we do not normalize the data in this regression, and thus only use this approach for single technology

[15] Results for other coefficients remain the same and are not reported.

regressions.[16] As shown in Table 6, diminishing returns are an issue for all technologies when the level of innovation is high enough, as the squared term is negative for all technologies in which the linear term is not negative. This holds true for wind, nuclear, and hybrid vehicles. Moreover, for all three of these technologies, the turning point at which increased patenting leads to diminishing returns occurs at reasonable values, either slightly above or slightly below the average number of patents per year for these technologies. Figure 4 shows the patent counts for each technology, with years affected by diminishing returns represented by dashed lines. These dashed lines represent years where the number of patents is above the turning point calculated in Table 6. In each case, it is the years of peak patenting activity that experience diminishing returns within a given year.

The other notable change in Table 6 is that the coefficient on cite lag increases for hybrid patents. As a result, while hybrid and wind patents are still the only two technologies for which the probability of citation does not decay immediately, it is now hybrid patents that see the probability of citation increase more strongly over time. This is shown in panel B of Figure 3, where the combined effect of the cite lag variables for hybrid patents does not become negative until year 19. As we will show below, this result is driven by the most successful hybrid patents.

Tables 7 and 8 present the quantile results for each technology. Table 7 includes patent characteristics (including our tests for diminishing returns) and Table 8 includes assignee characteristics. Comparisons across technologies can be seen by reading across, and comparisons across quantiles for a given technology can be seen by reading downward. What is notable here is that the differences across quantiles found in the pooled regression only hold up in select technologies and are generally of a smaller magnitude. The most notable difference is that the cite lag for hybrids only increases the probability of citation in the 90th quantile,

[16] However, we do divide the number of patents by 10 to obtain reasonable magnitudes on the coefficients.

suggesting that the result found for hybrids in Table 6 is driven by the highest quality patents. Similarly, for three less successful technologies – solar, fuel cells, and nuclear – patents in the 90^{th} percentile decay more quickly. However, it is clear that the major differences are driven by technology, rather than by quantiles. For example, for the three technologies in which the effect of number of patents in the cited year is positive, the coefficient is positive across all quantiles. Moreover, for each of these three technologies, the turning point of the net effect of number of patents in the cited year is similar across all quantiles. The largest spread is for hybrids, where the turning point ranges from 271.9 patents in the 50^{th} quantile to 302.9 patents in the 90^{th} quantile. Thus, it is not that more valuable wind patents behave differently than less valuable wind technologies, but rather that patents from successful technologies such as wind and hybrids behave differently than other technologies.

VI. Discussion

Reducing carbon emissions will require a diverse set of energy technologies. As the costs of many alternative technologies are high, innovation will play an important role in efforts to reduce carbon emissions. While climate models are beginning to reflect the diverse nature of the technologies required to reduce emissions, efforts to calibrate R&D-driven innovation on these technologies lag behind. Most empirical papers on energy innovation pool technologies together, and to our knowledge, all existing work focuses on the average returns to innovation on alternative energy technologies. By estimating separate equations for each technology and using quantile regression techniques to focus on the characteristics of high-value energy patents, we are able to determine whether R&D uncertainty or differences in technologies matter most for patent success.

By testing for the impact of patent characteristics on patent value by technology, we find that there are differences between successful and less successful technologies. In particular, the value of successful technologies persists longer than those of less successful technologies, providing evidence that success is the culmination of several advances building upon one another, rather than resulting from one big hit. Our evidence on diminishing returns suggests that diminishing returns within a given year are an issue when inventive activity is particularly high. However, at low levels of activity, some technologies, such as hybrid vehicles, experience increasing returns, suggesting benefits to positive spillovers are possible with just moderate levels of research investment.

By using quantile regression techniques, we explore whether high value patents have different observable characteristics than other patents. When pooled across technologies, we do find evidence that the magnitude of diminishing returns within a given year is larger for the most successful innovations. However, using quantile regressions for individual technologies, this result only holds for solar energy. While this may suggest that solar energy innovation was hurt by moving too quickly in the 1970s, the biggest takeaway point from this research is that it is differences across technologies, rather than among high and low impact innovations within a technology, that are most important.

Our results suggest that allowing for different behavior across technologies is important when modeling R&D-based innovation in climate models, and we provide empirical evidence for such calibration. In particular, it would be useful to classify technologies based on their likelihood of success, with knowledge based on technologies perceived to be successful decaying more slowly. Such technologies are also likely to have slow, steady improvement over time, rather than large discrete jumps in knowledge. The results on diminishing returns by quantiles and technology suggest that diminishing returns will be most problematic during rapid increases of research investment, such as experienced by solar energy in the 1970s, but that it need not be universal. Finally, that decay rates fall monotonically for less successful technologies suggests that data patent citations received just a few years after a patent's initial filing data could provide researchers and policymakers information on the research avenues most likely to be successful.

Our results also provide qualitative insights for policy. Diminishing returns within a given year but not necessarily over time, as in the wind and hybrid cases, suggest that long-term sustained incentives to innovate may be more effective than short bursts of support. Moving advanced technologies to large-scale commercial deployment will likely require a sequence of innovations over a number of years. This sequence suggests that research prizes, which offer large rewards for a single technological breakthrough, will be less effective, as they do not provide incentives for the series of incremental gains needed to make successful energy technologies possible. The differences between technologies also supports economic theory, which would indicate that technology neutral policy instruments be used where possible. In the 1970s it would have been difficult to predict that wind and hybrid technologies would evolve differently from solar and fuel cells. Technology-specific support can lead to spending on low-value innovations, as in the case of federal support for nuclear. Finally, as suggested above, some evidence of which technologies are higher-value can sometimes be apparent after several years, and policies that can adjust to new information will lead to more efficient outcomes.

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Table 1 – Descriptive data: number of citations per patent, 1971-2008

		No. of Citations			*No. of Citations*			*No. of Citations*
Efficiency	Mean	1.212	**Hybrid**	Mean	4.928	**Solar**	Mean	3.830
	SD	4.473		SD	10.219		SD	5.761
	Max	210		Max	210		Max	69
	Min	0		Min	0		Min	0
	5_percentile	0		5_percentile	0		5_percentile	0
	25_percentile	0		25_percentile	0		25_percentile	0
	50_percentile	0		50_percentile	1		50_percentile	2
	75_percentile	1		75_percentile	5		75_percentile	5
	95_percentile	5		95_percentile	22		95_percentile	15
	99_percentile	15		99_percentile	46		99_percentile	29
Fuel Cells	Mean	5.378	**Nuclear**	Mean	3.187	**Wind**	Mean	4.912
	SD	10.325		SD	4.367		SD	6.492
	Max	119		Max	47		Max	62
	Min	0		Min	0		Min	0
	5_percentile	0		5_percentile	0		5_percentile	0
	25_percentile	0		25_percentile	0		25_percentile	0
	50_percentile	1		50_percentile	2		50_percentile	3
	75_percentile	6		75_percentile	4		75_percentile	7
	95_percentile	25		95_percentile	12		95_percentile	18
	99_percentile	49		99_percentile	20		99_percentile	31
Total	Mean	2.967						
	SD	6.673						
	Max	210						
	Min	0						
	5_percentile	0						
	25_percentile	0						
	50_percentile	1						
	75_percentile	3						
	95_percentile	14						
	99_percentile	31						

Table 2 – Other descriptive data, 1971-2008

		Citations	*Claims*	*Cited References*	*Patents Per Year*
Efficiency	Mean	1.212	15.731	12.322	469.510
	SD	4.473	13.672	21.037	424.155
	Max	210	318	641	1421
	Min	0	1	0	1
Fuel Cells	Mean	5.378	16.957	11.481	172.020
	SD	10.325	14.661	19.337	233.436
	Max	119	300	479	912
	Min	0	0	0	2
Hybrid	Mean	4.928	14.371	11.501	81.596
	SD	10.219	11.937	18.050	109.167
	Max	210	167	395	379
	Min	0	1	0	1
Nuclear	Mean	3.187	11.536	7.702	176.542
	SD	4.367	10.531	8.615	119.899
	Max	47	499	201	330
	Min	0	0	0	1
Solar	Mean	3.830	14.135	8.118	151.365
	SD	5.761	13.030	8.707	150.767
	Max	69	236	140	542
	Min	0	0	0	1
Wind	Mean	4.912	14.067	11.483	47.523
	SD	6.492	11.558	15.426	38.885
	Max	62	138	327	145
	Min	0	1	0	1
Total	Mean	2.967	14.823	10.711	134.689
	SD	6.673	13.182	17.437	227.498
	Max	210	499	641	1421
	Min	0	0	0	1

Table 3 – Descriptive data: granted patents and citations by assignee

	% of granted patents by assignee						Average number of cites received by assignee					
	N	*% private*	*% gov*	*% other public*	*% foreign*	*% gov child*	*average cites*	*Private*	*Government*	*Other Public*	*Foreign*	*Child*
Entire Sample												
Efficiency	23005	96.03	1.05	2.91	42.97	0.76	1.21	1.22	0.76	1.26	1.15	7.25
Fuel Cells	8429	89.54	2.64	7.88	49.63	16.41	5.38	5.24	8.82	5.71	4.29	9.32
Hybrid	3835	95.56	0.54	3.84	67.57	3.68	4.93	5.03	4.10	2.61	4.76	12.24
Nuclear	10416	84.65	12.09	3.31	46.47	28.82	3.19	3.28	2.96	1.58	2.58	3.76
Solar	7871	92.12	3.84	3.97	39.82	15.48	3.19	3.81	4.63	3.49	2.42	4.81
Wind	2091	96.04	1.44	2.67	41.47	9.20	4.91	4.87	7.21	4.83	3.12	5.25
1971												
Efficiency	66	98.48	0.00	1.52	34.85	0.00	1.08	1.06	0.00	2.00	0.48	0.00
Fuel Cells	32	88.00	10.00	2.00	34.00	0.00	6.16	6.52	3.60	3.00	7.94	0.00
Hybrid	30	100.00	0.00	0.00	43.33	3.33	5.70	5.70	0.00	0.00	6.92	0.00
Nuclear	12	67.44	27.91	4.65	43.41	16.28	5.05	5.83	3.50	3.00	3.81	4.76
Solar	27	75.00	25.00	0.00	37.50	25.00	8.63	6.25	15.75	0.00	13.33	9.50
Wind	72	100.00	0.00	0.00	33.33	0.00	10.33	10.33	0.00	0.00	5.00	0.00
1981												
Efficiency	558	96.95	1.25	1.79	36.02	0.18	1.12	1.14	1.00	0.20	1.18	0.00
Fuel Cells	73	76.00	9.33	14.67	22.67	13.33	9.75	9.77	8.43	10.45	9.06	9.44
Hybrid	22	96.15	3.85	0.00	26.92	3.85	5.46	5.24	11.00	0.00	1.86	8.00
Nuclear	247	80.59	18.32	1.10	58.24	37.00	3.84	4.00	2.92	7.00	3.00	4.01
Solar	542	93.18	5.04	2.08	33.23	14.84	3.03	2.97	3.18	5.57	2.35	3.39
Wind	36	96.05	0.00	3.95	30.26	5.26	5.93	6.11	0.00	1.67	2.87	9.00

(continued on next page)

	% of granted patents by assignee						Average number of cites received by assignee					
	N	*% private*	*% gov*	*% other public*	*% foreign*	*% gov child*	*average cites*	*Private*	*Government*	*Other Public*	*Foreign*	*Child of government patent*
1991												
Efficiency	567	93.47	2.12	4.41	42.33	0.71	1.63	1.63	0.17	2.36	2.09	38.67
Fuel Cells	150	89.06	5.47	5.47	55.47	37.50	15.21	14.33	15.71	29.00	15.49	23.74
Hybrid	130	97.50	0.00	2.50	71.25	8.75	9.06	8.86	0.00	17.00	9.33	19.00
Nuclear	241	92.53	6.17	1.30	44.81	30.19	2.63	2.71	1.79	1.25	1.90	2.63
Solar	130	90.50	5.03	4.47	49.72	16.20	3.13	3.24	1.67	2.50	2.60	3.67
Wind	30	100.00	0.00	0.00	34.38	12.50	9.53	9.53	0.00	0.00	4.27	13.25
2001												
Efficiency	1360	95.59	0.81	3.90	47.21	1.10	0.65	0.65	0.27	0.79	0.42	1.33
Fuel Cells	904	94.30	0.99	4.82	58.99	11.29	0.95	0.94	1.78	0.98	0.65	1.34
Hybrid	346	97.31	0.00	2.69	73.12	1.61	1.74	1.76	0.00	0.80	1.44	1.00
Nuclear	310	76.97	2.81	20.79	61.24	17.98	0.29	0.21	0.00	0.62	0.16	0.17
Solar	222	93.58	1.89	4.53	52.08	15.47	0.65	0.69	0.00	0.08	0.41	0.89
Wind	64	96.55	0.69	2.76	64.14	11.72	1.49	1.48	3.00	1.50	0.95	1.56

Table 4 – Pooled Technology Results

Pooled	**q25**	**q 50**	**q75**	**q90**	**gnbreg**
ln(# of citing patents)	0.907***	0.914***	1.147***	1.493***	0.998***
	(0.011)	(0.010)	(0.011)	(0.013)	(0.034)
Cite lag	0.974***	0.976***	0.969***	0.914***	0.964***
	(0.003)	(0.002)	(0.003)	(0.003)	(0.003)
Cite lag^2	0.999***	0.999***	0.999***	1.000	0.999***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Stock of patents	0.999***	0.999***	0.998***	0.999***	0.999***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
# of patents in cited yr.	0.967***	0.967***	0.968***	0.938***	0.962***
	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)
# of claims made	1.008***	1.010***	1.013***	1.018***	1.012***
	(0.001)	(0.000)	(0.001)	(0.001)	(0.001)
# of cited references	0.996***	0.996***	0.996***	0.997***	0.997***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)
Foreign corporation assignee	0.759***	0.757***	0.717***	0.683***	0.722***
	(0.008)	(0.008)	(0.009)	(0.010)	(0.014)
US individual assignee	0.867***	0.866***	0.862***	0.822***	0.829***
	(0.012)	(0.012)	(0.013)	(0.015)	(0.022)
Foreign individual assignee	0.570***	0.573***	0.519***	0.463***	0.534***
	(0.014)	(0.013)	(0.014)	(0.015)	(0.021)
US government assignee	0.852***	0.852***	0.810***	0.726***	0.799***
	(0.023)	(0.022)	(0.022)	(0.026)	(0.041)
Foreign government assignee	0.708***	0.717***	0.688***	0.619***	0.693***
	(0.021)	(0.020)	(0.020)	(0.026)	(0.037)
US university assignee	0.863***	0.860***	0.895**	0.845***	0.903*
	(0.032)	(0.031)	(0.037)	(0.038)	(0.056)
Foreign university assignee	0.451	0.492***	0.451***	0.426***	0.564***
	(0.392)	(0.047)	(0.048)	(0.063)	(0.100)
US institution assignee	0.852***	0.848***	0.838***	0.766***	0.812**
	(0.042)	(0.040)	(0.044)	(0.044)	(0.069)
Foreign institution assignee	0.524***	0.557***	0.511***	0.452***	0.538***
	(0.032)	(0.027)	(0.028)	(0.032)	(0.044)
Child of US govt. patent	1.392***	1.413***	1.450***	1.372***	1.279***
	(0.021)	(0.021)	(0.025)	(0.027)	(0.032)
Child of Foreign govt patent	1.274***	1.270***	1.337***	1.410***	1.267***
	(0.022)	(0.021)	(0.025)	(0.033)	(0.035)
Number of obs.	831678	831678	831678	831678	831678
Predicted quantile	0.26242	0.52377	0.78349	0.95075	
log likelihood					-303570.7

NOTES: Standard errors in parentheses; * p<0.1, ** p<0.05, *** p<0.01.
Except for the coefficient for ln(# of citing patents), results are shown as incidence rate ratios, *e(beta)*. Moreover, to aid interpretation and make comparisons across technologies, the number of patents, the number of claims, and the number of citations made by each patent are normalized so that a one-unit change equals a ten percent deviation from the mean (Kerr and Newell, 2003).

Table 5 – Generalized Negative Binomial Results by Technology

	wind	solar	fuelcell	nuclear	hybrid	eff	overall
ln(# of citing patents)							0.998***
							(0.034)
Cite lag	1.017*	0.975***	0.940***	0.984*	1.018	0.926***	0.964***
	(0.010)	(0.006)	(0.009)	(0.008)	(0.017)	(0.015)	(0.003)
Cite lag^2	0.999***	0.999***	0.999***	0.999***	0.997***	1.000	0.999***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Stock of patents	0.996***	0.997***	0.994***	1.000	0.998***	0.997***	0.999***
	(0.001)	(0.001)	(0.001)	(0.003)	(0.000)	(0.001)	(0.000)
# of patents in cited yr.	0.974***	0.957***	0.979***	0.986	1.027**	1.035***	0.962***
	(0.006)	(0.004)	(0.005)	(0.012)	(0.011)	(0.009)	(0.002)
# of claims made	1.016***	1.011***	1.015***	1.009***	1.016***	1.012***	1.012***
	(0.003)	(0.002)	(0.002)	(0.002)	(0.004)	(0.002)	(0.001)
# of cited references	1.000	0.991***	0.993***	1.000	1.002	1.001	0.997***
	(0.002)	(0.002)	(0.002)	(0.001)	(0.002)	(0.001)	(0.001)
Foreign corporation assignee	0.584***	0.708***	0.654***	0.635***	1.112	0.914*	0.722***
	(0.056)	(0.032)	(0.027)	(0.020)	(0.084)	(0.043)	(0.014)
US individual assignee	0.790***	0.800***	0.592***	0.763***	1.054	1.183***	0.829***
	(0.058)	(0.029)	(0.061)	(0.067)	(0.152)	(0.077)	(0.022)
Foreign individual assignee	0.636***	0.543***	0.446***	0.493***	0.617**	0.622***	0.534***
	(0.056)	(0.032)	(0.080)	(0.060)	(0.130)	(0.054)	(0.021)
US government assignee	1.176	1.077	1.030	0.528***	1.244	0.646	0.799***
	(0.209)	(0.114)	(0.123)	(0.030)	(0.501)	(0.215)	(0.041)
Foreign government assignee	0.804	0.733***	0.567**	0.642***	0.931	0.636*	0.693***
	(0.221)	(0.076)	(0.143)	(0.039)	(0.358)	(0.168)	(0.037)
US university assignee	0.526**	0.926	0.904	0.543***	1.367	1.072	0.903*
	(0.168)	(0.094)	(0.084)	(0.112)	(0.420)	(0.197)	(0.056)
Foreign university assignee	0.793	0.754	0.462**	0.203***	0.000***	0.267*	0.564***
	(0.255)	(0.179)	(0.149)	(0.067)	(0.000)	(0.188)	(0.100)
US institution assignee	0.765	0.919	0.744***	0.557***	1.002	0.838	0.812**
	(0.221)	(0.266)	(0.079)	(0.096)	(0.372)	(0.167)	(0.069)
Foreign institution assignee	0.345**	0.420***	0.494***	0.577***	0.680	1.080	0.538***
	(0.153)	(0.082)	(0.059)	(0.077)	(0.277)	(0.253)	(0.044)
Child of US govt. patent	1.285***	1.395***	1.447***	1.028	1.356**	2.454***	1.279***
	(0.119)	(0.073)	(0.064)	(0.040)	(0.200)	(0.553)	(0.032)
Child of Foreign govt. patent	1.622***	1.397***	1.595***	1.202***	1.232	0.791	1.267***
	(0.200)	(0.075)	(0.131)	(0.044)	(0.255)	(0.169)	(0.035)
Number of obs.	31981	160773	86196	179506	39684	333538	831678
log likelihood	-20032.1	-64944.1	-59450.9	-69914.5	-24580.2	-61275.2	-303570.7

NOTES: Standard errors in parentheses; * p<0.1, ** p<0.05, *** p<0.01; All e(beta) except ln_nctg

Table 6 – Impact of High Patenting Activity

	wind	solar	fuel cells	nuclear	hybrid	efficiency
ln(# of citing patents)						
Cite lag	1.009	0.975***	0.941***	0.970***	1.061***	0.917***
	(0.010)	(0.006)	(0.010)	(0.010)	(0.018)	(0.019)
Cite lag^2	0.999***	0.999***	0.999***	0.999***	0.997***	1.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Stock of patents	0.996***	0.997***	0.994***	0.996	0.999*	0.997***
	(0.001)	(0.001)	(0.001)	(0.004)	(0.000)	(0.001)
# of patents in cited yr. X10	1.045	0.984***	0.994	1.153***	1.082***	1.002
	(0.038)	(0.006)	(0.005)	(0.060)	(0.019)	(0.005)
(# of patents in cited yr. X10)^2	0.994**	1.000	1.000	0.997***	0.999***	1.000
	(0.002)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)
# of claims made	1.013***	1.009***	1.009***	1.009***	1.012***	1.008***
	(0.002)	(0.001)	(0.002)	(0.002)	(0.003)	(0.002)
# of cited references	1.001	0.988***	0.992***	0.999	1.002	1.001
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)
Turning point for n_{CTD} effect	36.6			260.5	268.1	
Average patents/year	55.8	208.4	212.7	232.8	101.1	617.5
Number of obs.	31981	160773	86196	179506	39684	333538
log likelihood	-20022.82	-64943.38	-59450.88	-69904.75	-24543.49	-61274.15

NOTES: Standard errors in parentheses; * p<0.1, ** p<0.05, *** p<0.01; All e(beta) except ln_nctg

Table 7 – Patent Characteristic Quantile Results by Technology

90th quantile	**wind**	**solar**	**fuel cells**	**nuclear**	**hybrid**	**efficiency**
Cite lag	1.005	0.921***	0.899***	0.904***	1.068***	0.884***
	(0.012)	(0.009)	(0.011)	(0.011)	(0.020)	(0.008)
Cite lag^2	0.999**	0.999	0.999**	0.999*	0.996***	1.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)
Stock of patents	0.996***	0.998***	0.990***	0.990**	0.999***	0.994***
	(0.001)	(0.001)	(0.001)	(0.004)	(0.000)	(0.001)
# of patents in cited yr.	1.083**	0.963***	0.993	1.473***	1.100***	0.994**
	(0.033)	(0.005)	(0.005)	(0.083)	(0.014)	(0.002)
# of patents in cited yr.^2	0.992***	1.000***	1.000	0.993***	0.998***	1.000***
	(0.002)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)
# of claims made	1.016***	1.015***	1.011***	1.017***	1.014***	1.009***
	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)
# of cited references	1.002	0.983***	0.991***	0.998	1.003	1.001
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)
75th quantile						
Cite lag	1.020	0.982***	0.931***	0.965***	0.987	0.881***
	(0.011)	(0.005)	(0.010)	(0.007)	(0.016)	(0.008)
Cite lag^2	0.998***	0.999***	0.998***	0.999***	0.999**	1.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)
Stock of patents	0.995***	0.997***	0.994***	0.992***	0.998***	0.994***
	(0.001)	(0.000)	(0.001)	(0.002)	(0.000)	(0.001)
# of patents in cited yr.	1.105***	0.989**	0.995	1.179***	1.132***	0.993**
	(0.031)	(0.004)	(0.004)	(0.042)	(0.013)	(0.002)
# of patents in cited yr.^2	0.989***	1.000	1.000*	0.997***	0.998***	1.000***
	(0.002)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)
# of claims made	1.017***	1.009***	1.010***	1.011***	1.012***	1.006***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)
# of cited references	1.002	0.989***	0.986***	0.999	1.000	1.000
	(0.002)	(0.002)	(0.001)	(0.001)	(0.002)	(0.000)
50th quantile						
Cite lag	1.016	0.984**	0.950***	0.963***	1.015	0.884***
	(0.009)	(0.005)	(0.008)	(0.007)	(0.013)	(0.010)
Cite lag^2	0.998***	0.999***	0.998***	0.999***	0.998***	1.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Stock of patents	0.995***	0.997***	0.995***	0.991***	0.999**	0.994***
	(0.001)	(0.000)	(0.001)	(0.002)	(0.000)	(0.001)
# of patents in cited yr.	1.079***	0.998	0.996	1.199***	1.072***	0.993**
	(0.024)	(0.004)	(0.004)	(0.044)	(0.009)	(0.002)
# of patents in cited yr.^2	0.991***	1.000*	1.000	0.997***	0.999***	1.000***
	(0.002)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)
# of claims made	1.013***	1.006***	1.007***	1.008***	1.006***	1.006***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
# of cited references	1.001	0.990***	0.989***	1.000	0.999	0.999
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)

Table 7 – Patent Characteristic Quantile Results by Technology (continued)

25th quantile					
Cite lag	1.015	0.976***	0.948***	0.953***	0.994
	(0.009)	(0.006)	(0.008)	(0.007)	(0.014)
Cite lag^2	0.998***	0.999***	0.999***	0.999**	0.999**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)
Stock of patents	0.996***	0.998***	0.995***	0.992***	0.999***
	(0.001)	(0.000)	(0.001)	(0.002)	(0.000)
# of patents in cited yr.	1.075**	0.998	0.996	1.210***	1.065***
	(0.025)	(0.004)	(0.004)	(0.052)	(0.010)
# of patents in cited yr.^2	0.992***	1.000*	1.000	0.997***	0.999***
	(0.002)	(0.000)	(0.000)	(0.001)	(0.000)
# of claims made	1.013***	1.005***	1.006***	1.006***	1.005***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
# of cited references	1.000	0.991***	0.990***	0.999	0.999
	(0.002)	(0.002)	(0.001)	(0.002)	(0.001)

Table 8 – Assignee Characteristic Results by Technology

90th quantile	**wind**	**solar**	**fuel cells**	**nuclear**	**hybrid**	**efficiency**
Foreign corp. assignee	0.466***	0.608***	0.567***	0.517***	1.022	0.929**
	(0.041)	(0.025)	(0.017)	(0.016)	(0.051)	(0.021)
US individual assignee	0.737***	0.747***	0.505***	0.650***	1.130	1.188***
	(0.038)	(0.024)	(0.036)	(0.053)	(0.095)	(0.033)
Foreign individual	0.573***	0.461***	0.342***	0.290***	0.516***	0.707***
	(0.040)	(0.026)	(0.057)	(0.046)	(0.077)	(0.038)
US government assignee	1.123	1.245*	0.956	0.371***	1.463	0.613**
	(0.148)	(0.130)	(0.063)	(0.024)	(0.569)	(0.105)
Foreign government	0.862	0.685***	0.427***	0.520***	0.689	0.623*
	(0.157)	(0.058)	(0.082)	(0.031)	(0.243)	(0.136)
US university assignee	0.334***	0.942	0.890	0.328***	1.519*	0.974
	(0.083)	(0.085)	(0.055)	(0.092)	(0.323)	(0.093)
Foreign university	0.905	0.506**	0.425***	0.086	0.000	0.331
	(0.203)	(0.134)	(0.110)	(172.546)	(5.778)	(0.305)
US institution assignee	0.582**	0.865	0.693***	0.383***	0.945	0.937
	(0.097)	(0.133)	(0.050)	(0.072)	(0.276)	(0.142)
Foreign institution	0.243**	0.306***	0.409***	0.437***	0.654	0.927
	(0.107)	(0.070)	(0.045)	(0.079)	(0.214)	(0.098)
Child of US govt. patent	1.259**	1.754***	1.432***	1.065	1.330**	4.942***
	(0.105)	(0.092)	(0.043)	(0.039)	(0.121)	(1.048)
Child of For. govt. patent	1.680***	1.768***	1.624***	1.332***	1.361	0.909
	(0.193)	(0.096)	(0.075)	(0.045)	(0.223)	(0.239)

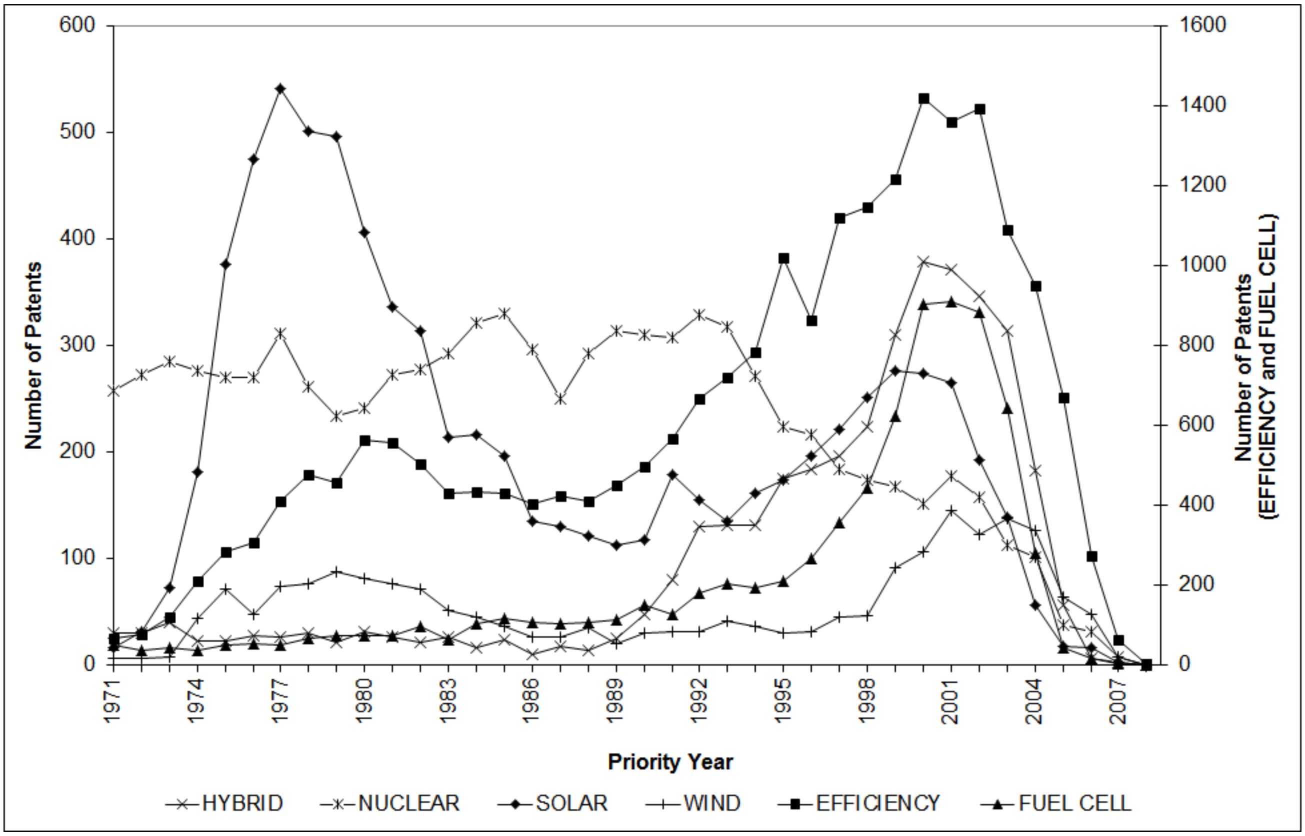
Table 8 – Assignee Characteristic Results by Technology (continued)

75th quantile						
Foreign corporation	0.454***	0.707***	0.575***	0.639***	1.232***	0.922***
	(0.034)	(0.020)	(0.017)	(0.013)	(0.062)	(0.021)
US individual assignee	0.774***	0.843***	0.448***	0.717***	1.035	1.170***
	(0.038)	(0.019)	(0.032)	(0.037)	(0.096)	(0.032)
Foreign individual	0.581***	0.574***	0.303***	0.465***	0.574***	0.685***
	(0.039)	(0.024)	(0.046)	(0.035)	(0.068)	(0.039)
US government	1.457*	1.138*	1.209**	0.551***	1.205	0.562
	(0.224)	(0.068)	(0.083)	(0.020)	(0.506)	(0.284)
Foreign government	0.898	0.756***	0.415***	0.660***	0.887	0.580
	(0.206)	(0.047)	(0.048)	(0.023)	(0.259)	(0.184)
US university assignee	0.340***	0.929	0.790***	0.492***	1.893	0.985
	(0.070)	(0.068)	(0.056)	(0.090)	(0.678)	(0.098)
Foreign university	0.763	0.570**	0.362***	0.061	0.000	0.240
	(0.163)	(0.108)	(0.093)	(20115.22)	(209.060)	(2.86e+05)
US institution assignee	0.782	0.800	0.712***	0.571***	1.377	0.811
	(0.171)	(0.108)	(0.065)	(0.063)	(0.411)	(0.227)
Foreign institution	0.222	0.407***	0.438***	0.609***	0.481**	0.862
	(59330.6)	(0.061)	(0.046)	(0.053)	(0.116)	(0.123)
Child of US govt. patent	1.505***	1.474***	2.009***	1.033	1.593***	2.435***
	(0.124)	(0.049)	(0.067)	(0.026)	(0.193)	(0.267)
Child of For. govt. patent	1.974***	1.391***	1.819***	1.268***	1.484**	0.832
	(0.198)	(0.046)	(0.106)	(0.032)	(0.218)	(0.241)
50th quantile						
Foreign corporation	0.555***	0.703***	0.678***	0.644***	1.171***	0.913***
	(0.033)	(0.019)	(0.016)	(0.013)	(0.043)	(0.023)
US individual assignee	0.821***	0.857***	0.542***	0.739***	0.945	1.174***
	(0.034)	(0.019)	(0.030)	(0.038)	(0.057)	(0.034)
Foreign individual	0.665***	0.598***	0.429***	0.483***	0.703***	0.683***
	(0.034)	(0.024)	(0.050)	(0.037)	(0.058)	(0.064)
US government assignee	1.397*	1.164*	1.157*	0.559***	0.957	0.441
	(0.212)	(0.069)	(0.067)	(0.021)	(0.761)	(1.13e+05)
Foreign government	0.810	0.748***	0.521***	0.664***	0.871	0.558
	(0.165)	(0.048)	(0.048)	(0.024)	(1.201)	(0.488)
US university assignee	0.403***	0.929	0.781***	0.295	1.068	0.749
	(0.108)	(0.065)	(0.045)	(69439.18)	(0.219)	(2.57e+05)
Foreign university	0.785	0.456	0.418***	0.019	0.000	0.227
	(0.178)	(67961.09)	(0.083)	(25929.77)	(19382.3)	(3.01e+05)
US institution assignee	0.793	0.766*	0.719***	0.567***	1.278	0.785
	(0.186)	(0.099)	(0.054)	(0.073)	(0.457)	(40.803)
Foreign institution	0.119	0.377	0.542***	0.611***	0.609	0.780
	(7.9e+05)	(0.263)	(0.049)	(0.058)	(0.206)	(90533.9)
Child of US govt. patent	1.362***	1.438***	1.946***	1.032	1.404***	2.322***
	(0.097)	(0.046)	(0.060)	(0.025)	(0.124)	(0.291)
Child of For. govt. patent	1.968***	1.327***	1.745***	1.238***	1.184	0.829
	(0.181)	(0.041)	(0.092)	(0.028)	(0.132)	(0.837)

Table 8 – Assignee Characteristic Results by Technology (continued)

25th quantile					
Foreign corporation	0.557***	0.714***	0.697***	0.646***	1.148***
	(0.035)	(0.020)	(0.016)	(0.013)	(0.043)
US individual assignee	0.832***	0.860***	0.556***	0.749***	0.961
	(0.036)	(0.020)	(0.031)	(0.042)	(0.059)
Foreign individual	0.670***	0.635***	0.478***	0.419	0.726***
	(0.036)	(0.026)	(0.058)	(5136.148)	(0.065)
US government assignee	1.421*	1.158*	1.136*	0.571***	0.544
	(0.235)	(0.073)	(0.063)	(0.023)	(1.37e+06)
Foreign government	0.786	0.732***	0.555***	0.649***	0.572
	(0.203)	(0.058)	(0.055)	(0.026)	(2.62e+05)
US university assignee	0.206	0.930	0.794***	0.334	0.936
	(7.79e+05)	(0.069)	(0.043)	(99672.705)	(1.152)
Foreign university	0.329	0.360	0.367	0.019	0.002
	(1.23e+06)	(2.05e+05)	(1.08e+05)	(43248.828)	(1.06e+05)
US institution assignee	0.768	0.679	0.747***	0.542***	0.522
	(0.246)	(1.91e+05)	(0.053)	(0.086)	(3.55e+06)
Foreign institution	0.027	0.230	0.532**	0.592***	0.733
	(1.92e+05)	(68282.460)	(0.129)	(0.076)	(0.133)
Child of US govt. patent	1.358***	1.414***	1.822***	1.042	1.397***
	(0.102)	(0.047)	(0.052)	(0.027)	(0.125)
Child of For. govt. patent	1.923***	1.298***	1.691***	1.213***	1.214
	(0.190)	(0.042)	(0.084)	(0.030)	(0.139)

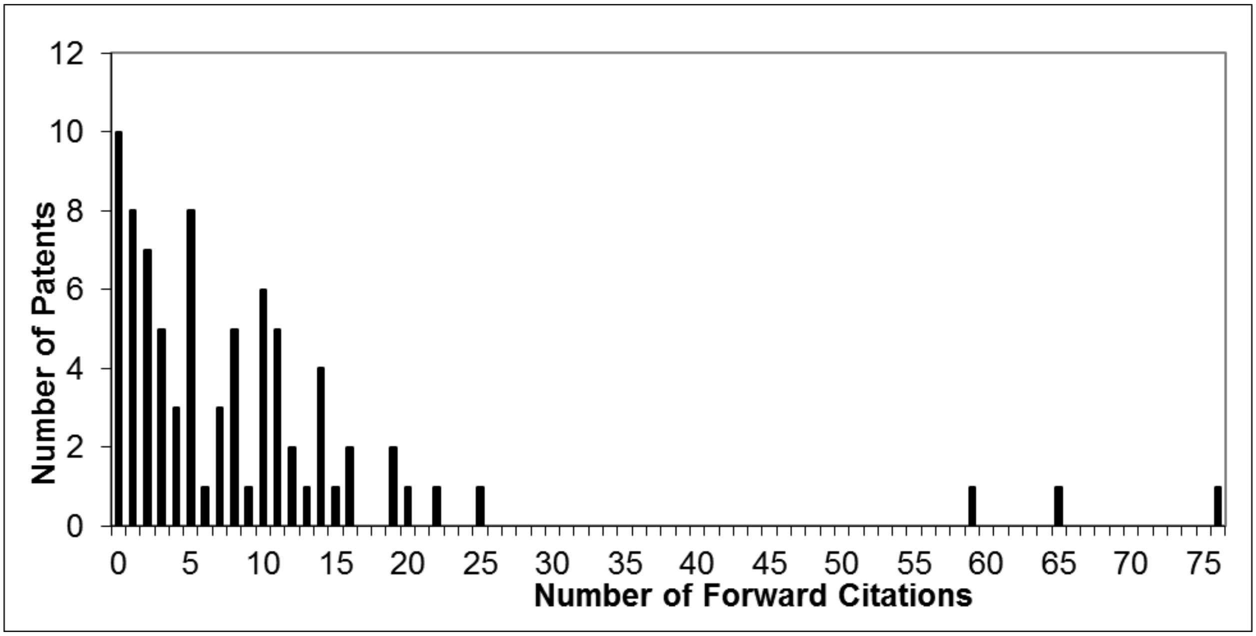
Figure 1 – Successful U.S. Patent Applications by Priority Year



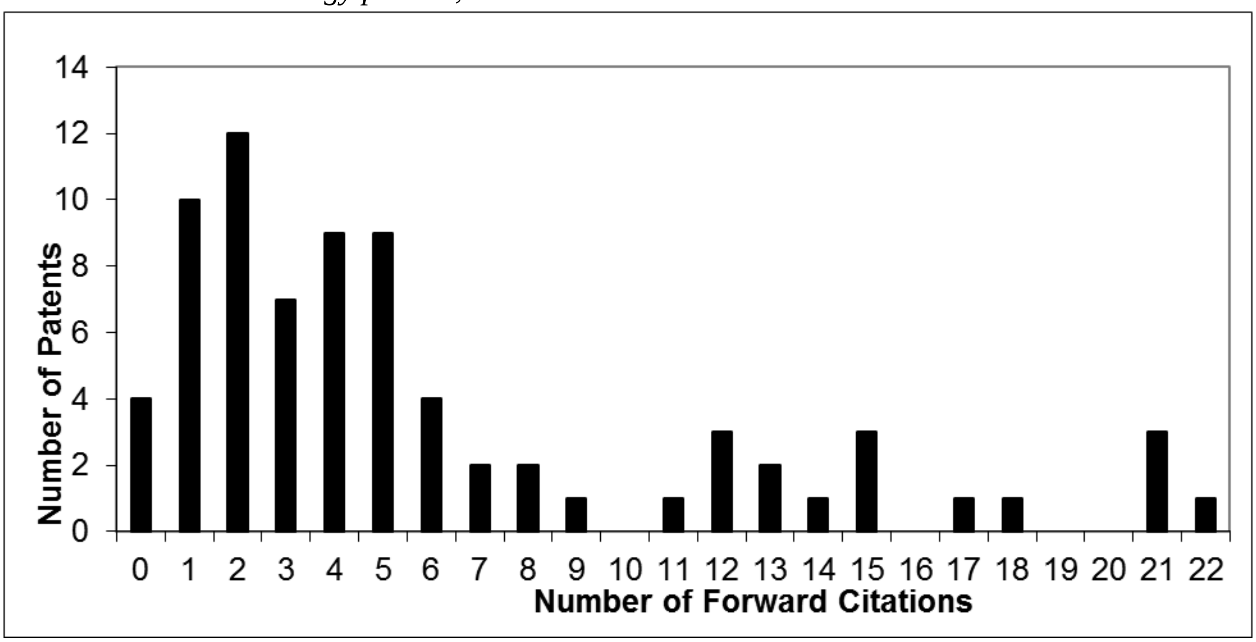
The figure shows successful U.S. patent applications for each of our six technologies, sorted by priority date. Note that our data only include granted patents. Thus, patent counts in the last years of the sample are truncated, as some patent applications from these years have yet to be processed.

Figure 2 – Sample Citation Frequency Distributions

A. Citations to hybrid patents,1991

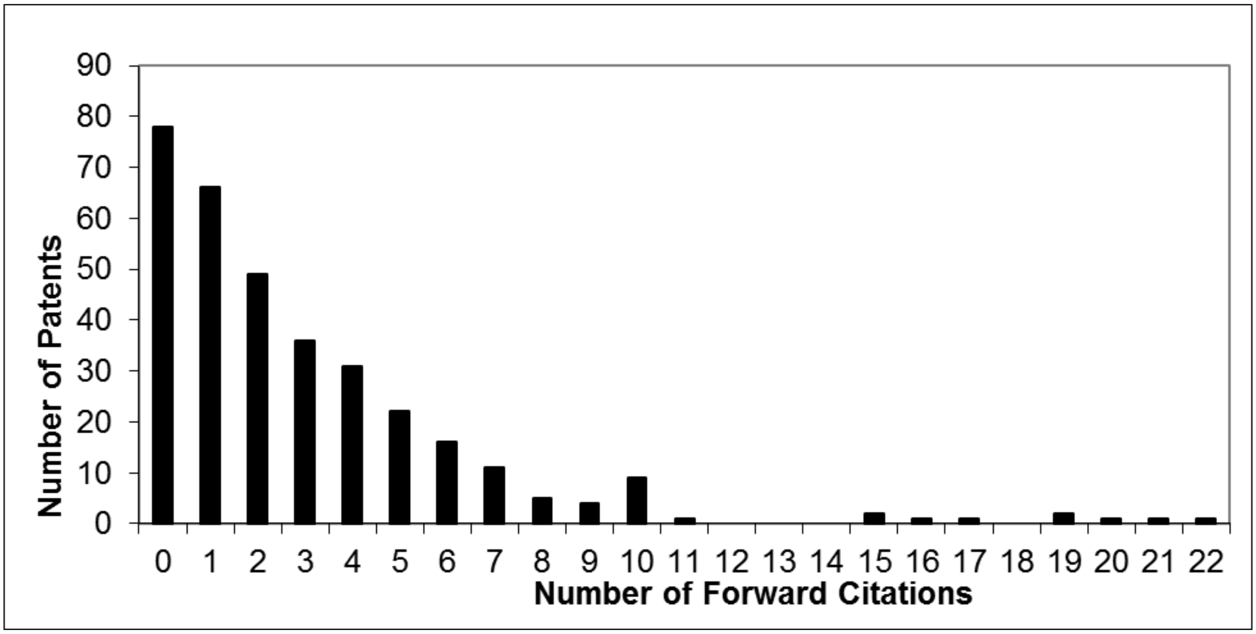


B. Citations to wind energy patents,1981



(continued on next page)

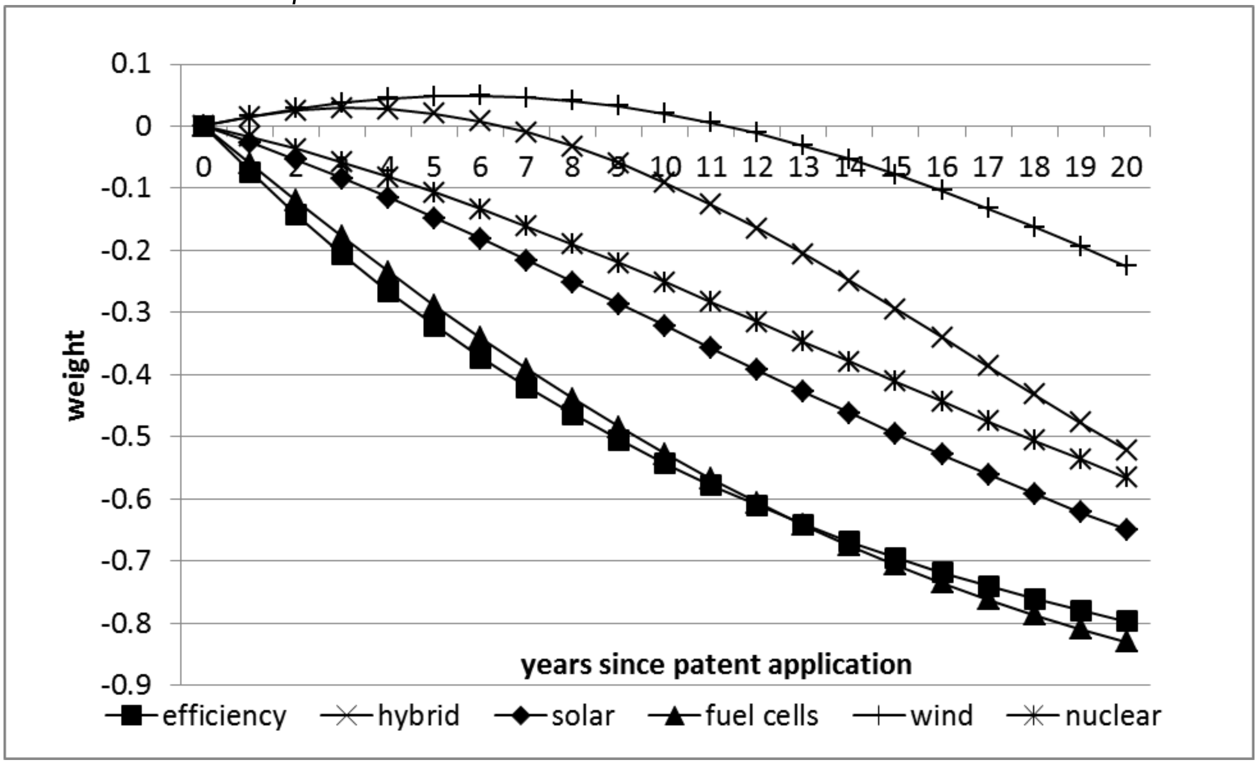
C. Citations to solar energy patents,1981



Each figure shows the distribution of forward citations received by patents from a given priority year and for a given technology. The *x*-axis shows the number of forward citations received, and the *y*-axis shows the number of patents receiving that many forward citations.

Figure 3 – Effect of cite lag by technology

A. Based on estimates from Table 5



B. Based on estimates from Table 6

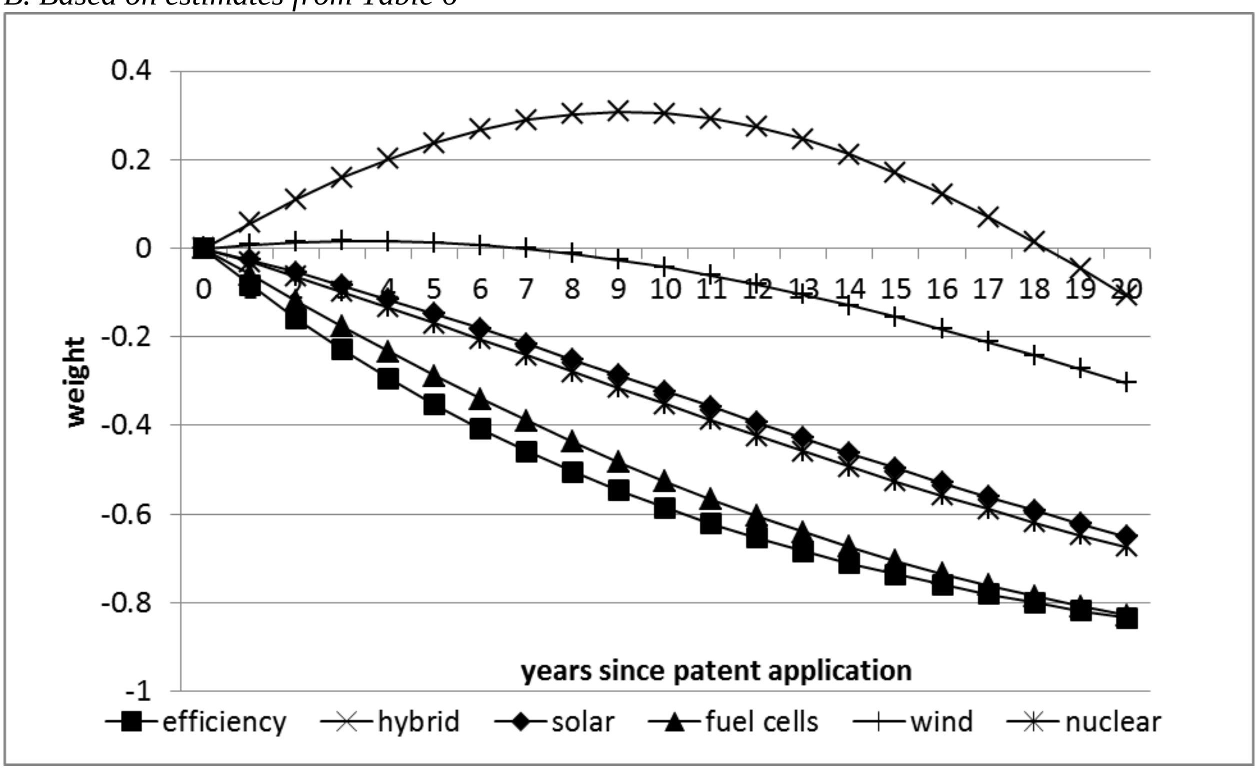
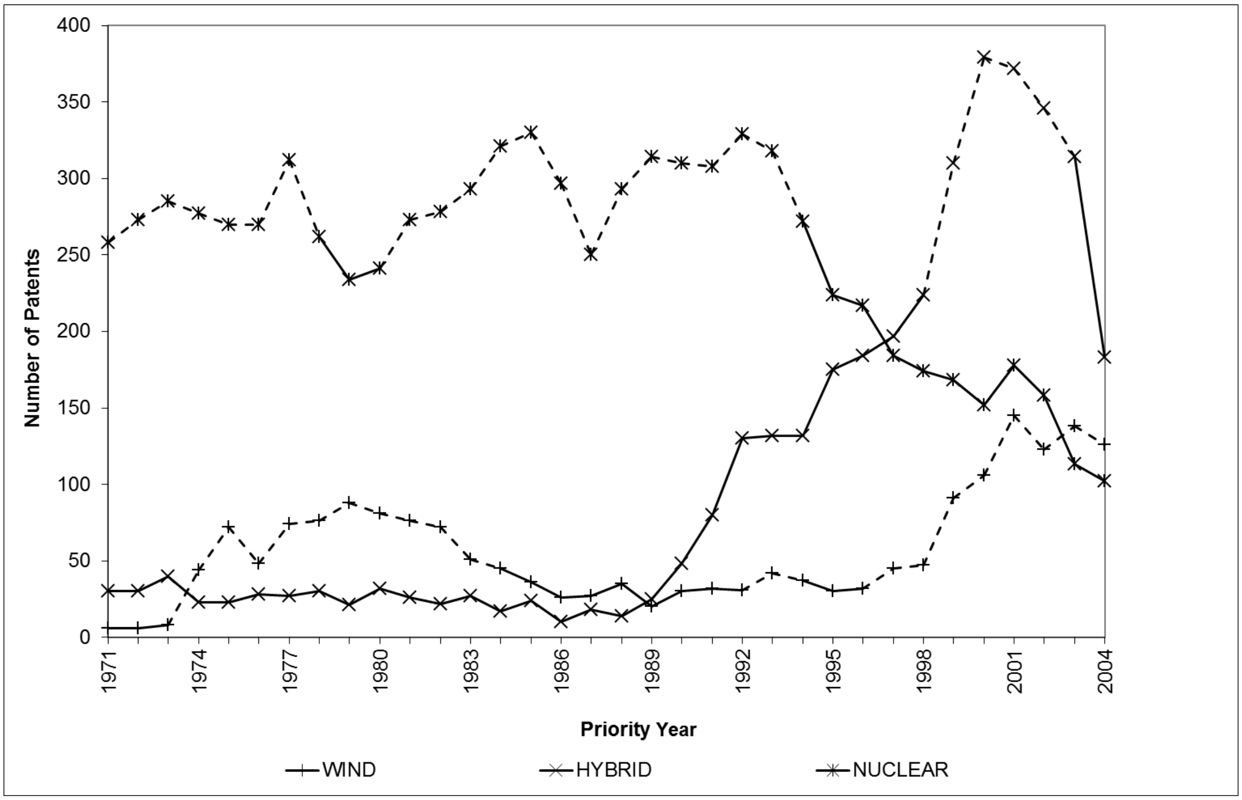


Figure 4 – Years affected by diminishing returns



The figure shows patent counts sorted by priority year for the three technologies where diminishing returns varies depending on the number of patents. Years affected by diminishing returns are shown with dashed lines.

Appendix A – List of IPC Classes Used

Electric/Hybrid Vehicles

B60W 20	VEHICLES IN GENERAL/CONJOINT CONTROL OF VEHICLE SUB-UNITS OF DIFFERENT TYPE OR DIFFERENT FUNCTION; CONTROL SYSTEMS SPECIALLY ADAPTED FOR HYBRID VEHICLES; ROAD VEHICLE DRIVE CONTROL SYSTEMS FOR PURPOSES NOT RELATED TO THE CONTROL OF A PARTICULAR SUB-UNIT /Control systems specially adapted for hybrid vehicles, i.e. vehicles having two or more prime movers of more than one type, e.g. electrical and internal combustion motors, all used for propulsion of the vehicle
B60L 7	VEHICLES IN GENERAL/ELECTRIC EQUIPMENT OR PROPULSION OF ELECTRICALLY-PROPELLED VEHICLES; MAGNETIC SUSPENSION OR LEVITATION FOR VEHICLES; ELECTRODYNAMIC BRAKE SYSTEMS FOR VEHICLES, IN GENERAL/ Electrodynamic brake systems for vehicles in general
B60L 8	VEHICLES IN GENERAL/ELECTRIC EQUIPMENT OR PROPULSION OF ELECTRICALLY-PROPELLED VEHICLES; MAGNETIC SUSPENSION OR LEVITATION FOR VEHICLES; ELECTRODYNAMIC BRAKE SYSTEMS FOR VEHICLES, IN GENERAL/ Electric propulsion with power supply from force of nature, e.g. sun, wind
B60L 11	VEHICLES IN GENERAL/ELECTRIC EQUIPMENT OR PROPULSION OF ELECTRICALLY-PROPELLED VEHICLES; MAGNETIC SUSPENSION OR LEVITATION FOR VEHICLES; ELECTRODYNAMIC BRAKE SYSTEMS FOR VEHICLES, IN GENERAL/ Electric propulsion with power supplied within the vehicle
NOT B60L 7/28	VEHICLES IN GENERAL/ELECTRIC EQUIPMENT OR PROPULSION OF ELECTRICALLY-PROPELLED VEHICLES; MAGNETIC SUSPENSION OR LEVITATION FOR VEHICLES; ELECTRODYNAMIC BRAKE SYSTEMS FOR VEHICLES, IN GENERAL/ Electrodynamic brake systems for vehicles in general/Eddy-current braking

Energy efficiency

keywords only:	((((((energy OR fuel OR gas* OR electric* OR petrol*) <near/1> (consum* OR use OR using OR usage OR burn*)) <near/3> (reduc* OR less OR lower)) <in> (AB, TI, BACKGROUND)) OR ((((energy OR fuel OR gas*) <near/1> (efficien* OR economy OR mileage OR productivity)) <near/3> (improv* OR increas* OR better OR greater)) <in> (AB, TI, BACKGROUND)))

Fuel cells

H01M 8	PROCESSES OR MEANS, e.g. BATTERIES, FOR THE DIRECT CONVERSION OF CHEMICAL ENERGY INTO ELECTRICAL ENERGY/Fuel cells; Manufacture thereof

Nuclear Energy

G21B	NUCLEONICS/NUCLEAR PHYSICS; NUCLEAR ENGINEERING/ FUSION REACTORS
G21C	NUCLEONICS/NUCLEAR PHYSICS; NUCLEAR ENGINEERING/ NUCLEAR REACTORS
G21D	NUCLEONICS/NUCLEAR PHYSICS; NUCLEAR ENGINEERING/ NUCLEAR POWER PLANT

Solar energy

F03G 6	MACHINES OR ENGINES FOR LIQUIDS; WIND, SPRING, OR WEIGHT MOTORS; PRODUCING MECHANICAL POWER OR A REACTIVE PROPULSIVE THRUST, NOT OTHERWISE PROVIDED FOR/ SPRING, WEIGHT, INERTIA, OR LIKE MOTORS; MECHANICAL-POWER-PRODUCING DEVICES OR MECHANISMS, NOT OTHERWISE PROVIDED FOR OR USING ENERGY SOURCES NOT OTHERWISE PROVIDED FOR /Devices for producing mechanical power from solar energy
F24J 2	MECHANICAL ENGINEERING; LIGHTING; HEATING; WEAPONS; BLASTING/HEATING, RANGES, VENTILATING/PRODUCTION OR USE OF HEAT NOT OTHERWISE PROVIDED FOR/Use of solar heat, e.g. solar heat collectors
H01L 27/142	ELECTRICITY/BASIC ELECTRIC ELEMENTS/ SEMICONDUCTOR DEVICES; ELECTRIC SOLID STATE DEVICES NOT OTHERWISE PROVIDED FOR/ Devices consisting of a plurality of semiconductor or other solid-state components formed in or on a common substrate/including semiconductor components specially adapted for rectifying, oscillating, amplifying or switching and having at least one potential-jump barrier or surface barrier; including integrated passive circuit elements with at least one potential-jump barrier or surface barrier/energy conversion devices
H01L 31/04-058	ELECTRICITY/BASIC ELECTRIC ELEMENTS/ SEMICONDUCTOR DEVICES; ELECTRIC SOLID STATE DEVICES NOT OTHERWISE PROVIDED FOR/ Semiconductor devices sensitive to infra-red radiation, light, electromagnetic radiation of shorter wavelength, or corpuscular radiation and specially adapted either for the conversion of the energy of such radiation into electrical energy or for the control of electrical energy by such radiation; Processes or apparatus specially adapted for the manufacture or treatment thereof or of parts thereof; Details

	thereof/Adapted as conversion devices/ including a panel or array of photoelectric cells, e.g. solar cells
H02N 6	ELECTRICITY/ GENERATION, CONVERSION, OR DISTRIBUTION OF ELECTRIC POWER/ELECTRIC MACHINES NOT OTHERWISE PROVIDED FOR/ Generators in which light radiation is directly converted into electrical energy

Wind

F03D	MACHINES OR ENGINES FOR LIQUIDS; WIND, SPRING, OR WEIGHT MOTORS; PRODUCING MECHANICAL POWER OR A REACTIVE PROPULSIVE THRUST, NOT OTHERWISE PROVIDED FOR/Wind Motors