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ABSTRACT

This paper uses patent citation data to study flows of knowledge across time and across institutions in the field of energy research. Popp (2002) finds the level of energy-saving R&D depends not only on energy prices, but also on the quality of the accumulated knowledge available to inventors. Patent citations are used to represent this quality. This paper explores the pattern of citations in these fields more carefully. I find evidence for diminishing returns to research inputs, both across time and within a given year. To check whether government R&D can help alleviate potential diminishing returns, I pay special attention to citations to government patents. Government patents filed in or after 1981 are more likely to be cited. More importantly, descendants of these government patents are 30 percent more likely to be cited by subsequent patents. Earlier government research was more applied in nature and is not cited more frequently.

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How do the returns to research and development (R&D) evolve over time? This fundamental question lies at the heart of several important questions in economics. Several studies have addressed the returns to R&D by looking at the value of the *output* of R&D. They do this either directly, by including R&D expenditures in the production function of a firm, or indirectly, by estimating the value of holding patent rights.[1] Empirical evidence presented in Popp (2002) suggests that the returns to R&D inputs vary over time as well. That paper finds that the level of energy-saving R&D depends not only on energy prices, but also on the quality of the accumulated knowledge available to inventors. It uses stocks of knowledge constructed from previous patents in the same field, weighted by citations to those patents, to proxy for the quality of accumulated knowledge. Moreover, within each field, the likelihood of citations to new patents falls over time, even after for controlling for the number of subsequent patents that could make a citation. Popp (2002) suggests that this is evidence of diminishing returns to research within a field over time.[2]

This paper addresses the issue of knowledge quality more formally. Given that the quality of available knowledge can be important to future inventors, I ask how this quality, as measured by patent citations, varies over time. This contrasts with much of the previous literature using patent citations, which focuses on the flow of knowledge across institutions (such as from universities or government laboratories to private industry), across regions, and across

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[1] Examples of the first type of study include Griliches and Mairesse (1984), Clark and Griliches (1984) and Scherer (1982, 1984). See Griliches (1995) for a survey of this work. Examples of the second type of work include Putnam (1996), Lanjouw (1993), Pakes (1986), and Pakes and Schankerman (1984). See Lanjouw, Pakes, and Putnam (1998) for a review of this literature.

[2] 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. 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 paper.

nations.[3] Most similar in spirit to this paper is Caballero and Jaffe (1993), who use citations in a macro growth model both to study the diffusion and obsolescence of knowledge, and to study the productivity of knowledge. However, this paper takes a more micro-oriented approach by studying citations in several different energy technology areas.

The paper makes use of an updated version of the data set in Popp (2002), which looks at U.S. patenting activity for 11 energy-related technologies. In contrast to Popp (2002), I use a generalized negative binomial regression to look at the likelihood of citation to individual patents. I include two controls for potential diminishing returns. One, the number of other patents granted in a specific field at a given time, tests for diminishing returns to research inputs *within a given year* by asking whether there are less citation per patent as the number of patents granted per year in a given field increases. That is, do new patents contribute less to the knowledge stock as contemporaneous research efforts increase? As a second control, a stock of patents granted within the field in previous years tests for diminishing returns *across time*. That is, do new innovations become less useful (as measured by subsequent patent citations) as the knowledge base within the field grows? Intuitively, such an effect could be seen as the "fishing out" of viable research ideas within a field.

In addition to examining the changing contributions of new patents to the stock of knowledge over time, I also look at the contribution made by patents issued to the U.S. government. I separately identify patents assigned to the U.S. government, as well as privately-assigned patents that cite these government patents. I show that both types of patents are cited more frequently, and that citations to these patents are most likely after policy changes in the 1980s designed to enhance technology transfer. Given the importance of the quality of

[3] Examples include Jaffe, Fogarty, and Banks (1998), Jaffe and Trajtenberg, (1996), and Jaffe, Trajtenberg, and

knowledge to future researchers, these results suggest that government-sponsored research can support future research by providing an enhanced knowledge base on which future inventors can build.

Following the work in Popp (2002), this paper focuses on innovations in energy supply (such as solar energy) or energy efficiency (such as recapturing waste heat from industrial processes). Studying such innovations is of interest because of the insight they provide into the role that technological change can play in alleviating many of today's environmental problems. Many of these, such as global warming, are long-term problems. Technological change is likely to play a key role in alleviating them. In addition, several papers show that policymakers can induce environmentally-friendly innovation with policies such as a carbon tax or a regulation restricting emissions.[4] Understanding how the productivity of such research varies over time is important to understanding just how important a role technological change will play in easing environmental concerns. For example, Popp (2004) simulates the role of technological change in climate policy, and finds that diminishing returns to research limit the potential impact of innovation. Moreover, examining the role that government research can play in improving the productivity of research provides a possible avenue for policy makers concerned about inducing additional energy efficiency R&D.

I. Patent Citations and the Returns to R&D

When a patent is granted, it contains citations to earlier patents related to the current invention. The citations are placed in the patent after consultations among the applicant, his or

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Henderson (1993). A detailed review of the use of patent citations appears in Jaffe and Trajtenberg (2002).

[4] Empirical works demonstrating the effect of prices or regulation on innovation include Popp (2002), Newell, Jaffe and Stavins (1999), Jaffe and Palmer (1997), and Lanjouw and Mody (1996). Theoretical models include Milliman

her patent attorney, and the patent examiner. It is the applicant's responsibility to list any related previous patents of which he or she is aware, and the examiner, who specializes in just a few patent classifications, will add other patents to the citations as well as subtracting any irrelevant patents cited by the inventor. Patent citations narrow the reach of the new patent by placing the patents cited outside the realm of the current patent, so it is important that all relevant patents be included in the citations.[5] For the same reason, inventors have an incentive to make sure that no unnecessary patents are cited. As a result, the previous patents cited by a new patent should be a good indicator of previous knowledge that was utilized by the inventor. In recent years, many economists have made use of patent citation data to track knowledge flows.

This paper looks at the flow of patent citations within a given field across time. The motivation for doing so is to consider how the quality of knowledge available for inventors to build upon changes over time. Citations made by subsequent patents suggest that the previous patent provided technological knowledge upon which the current inventor could build. Frequent citations to a patent provide evidence that the knowledge embodied in that invention has been particularly useful to other inventors.[6]

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and Prince (1989, 1991) and Jung, Krutilla, and Boyd (1996). Jaffe, Newell, and Stavins (2003) provide a review of this literature.

[5] "Outside the realm" means that the patent holder cannot file an infringement suit against someone whose invention infringes on qualities of the patented invention that were also included in patents cited by the patent holder.

[6] Jaffe, *et al.* (1998) examined the relationships between knowledge flows and patent citations. Their research included interviews with scientists, R&D directors, and patent attorneys. They found that, at the level of individual patents, not all citations are indicative of knowledge flows, as other concerns, such as strategically including irrelevant patents to satisfy the patent examiner, affected the citation process. However, on more aggregate levels, such as the patents for an organization or a firm, they found that patent citations are an indicator of knowledge flows, albeit a noisy indicator. Lanjouw and Mark Schankerman (2004) find that forward citations (citations made by future patents to an existing patent) are one of the least noisy indicators of the quality of an existing patent. In this paper, the focus is on the quality of knowledge embodied in a patent, rather than a specific knowledge flow. Thus, while a citation may not indicate a direct knowledge flow, the fact that it provides a measure of quality upon which future inventors are building is sufficient.

The notion that this supply of knowledge, or technological opportunity, matters to inventors can be traced back to early papers by Scherer (1965, 1982) and Schmookler (1966). At the macroeconomic level, Caballero and Jaffe (1993) link patent citations to the returns to R&D over time. They define the stock of knowledge available to an inventor at any given time as the sum of previous ideas, represented by patents. They use patent citations to measure the usefulness of patents from any given time. They find the probability of citation to a patent falls over time, and that changes in this probability coincide with macroeconomic trends such as the productivity slowdown of the 1970s.

At the microeconomic level, Popp (2002) shows that both supply and demand side factors influence energy R&D. Like Caballero and Jaffe (1993), that paper uses patent data to create stocks of knowledge available for inventors to build upon, where the patents in the stock are weighted by their propensity to be cited. Frequent citations to a patent provide evidence that the knowledge embodied in that invention has been particularly useful to other inventors. The paper finds that the weighted patents stocks have a significant positive effect on energy R&D activity. Moreover, regressions using unweighted patent stocks do not provide reliable results. Inventors "stand on the shoulders" of their predecessors. As a result, the quality of the existing knowledge on which an inventor can build is an important, positive contributor to the level of innovative activity in a given year.

Furthermore, the patterns of citation found in Popp (2002) suggest that diminishing returns to the quality of existing knowledge are important. The likelihood of citations to new energy patents falls over time, suggesting that the quality of knowledge available for inventors to build upon also falls.[7] The intuition here is that, as more and more discoveries are made, it gets harder to develop a new innovation that improves upon the existing technology. Since the quality of the knowledge stock is an important determinant of the level of innovative activity, decreasing quality of the knowledge stock over time means that diminishing returns to R&D investment will result in lower levels of induced R&D over time. This paper examines this claim more closely. I look for changes in the likelihood of future citations to a patent both *across time* – that is, is the additional new knowledge embodied in a patent less valuable when the stock of knowledge is larger – and *within time* – that is, is additional research less valuable when lots of R&D is done at a given time.

The notion that the returns to R&D may fall over time can be linked to other branches in the economic literature. For example, Evenson (1991) offers *invention potential exhaustion* (IPE) as a possible explanation for the fall in patenting activity during the 1970s and 1980s. Using the search model of R&D (Evenson and Kislev 1975) as a starting point, Evenson argues that inventors have a limited pool of possible inventions from which new innovations are drawn. As more inventions are created, fewer possibilities for future success exist. The search for new ideas gets harder and harder. The analysis that follows is similar in nature, as it focuses solely on citations within a group of energy technologies. In addition to being consistent with the data used in Popp (2002), limiting the analysis to patents within a group (say, for example, solar energy patents citing other solar energy patents), is necessary to be able to define the pool of potentially citing and cited patents in a manageable way. As such, citations made outside the group (e.g. citations made by a solar energy patent to a chemistry patent) are not included. Thus, this paper is limited to examining the research trends for a given technology, and does not

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[7] Note that since the probability of a patent being cited depends not only on the quality of the patent, but also on the

explore the possibility that new technologies from outside the field (such as the general purpose technologies discussed in Helpman 1998) may provide new research opportunities, either by providing new options within a technology group (referred to as *recharge* in Evenson, 1991) or by providing completely new areas to explore.

II. Estimation Framework

This paper builds on the work of Popp (2002) by more carefully examining changes in the likelihood of citation to energy patents over time. That paper introduces a database of all patents falling into one of 11 energy technology categories granted in the United States between 1970 and 1994. This paper extends the data through 1999. In addition, while Popp (2002) examined citations using cohorts of patents from individual years, this paper looks at citations to individual energy patents. By doing so, I am able to not only examine changes in the likelihood of a patent receiving citations over time, but can also ask what individual patent characteristics affect the likelihood of citation.

A notable feature of patent citation data is that most patents are rarely cited. Thus, generalized negative binomial estimation of count data is used. The data to be used in this study include potentially cited patents granted between 1975 and 1996, and citing patents with application years between 1976 and 1997. Following Popp (2002), I only consider citations made by patents from U.S. applicants. Thus, the results can be interpreted as examining how the stock of knowledge available to American inventors changes over time.[8] Because citations to

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number of patents that follow, it is important to look at probability of citation, rather than raw citation counts.

[8] Popp (2002) considers the stock of knowledge available to inventors as just one of several factors, such as energy prices and government-sponsored energy R&D, influencing energy research. Since foreign inventors are likely to be influenced by conditions not included in that analysis, that paper focuses on citations made by U.S. assignee patents.

earlier patents as interpreted a proxy for the knowledge available to inventors when the research was carried out, citing patents are sorted by the year of application.[9]

In contrast, the available knowledge upon which inventors may build includes patents from both the U.S. and abroad. Thus, the data for cited patents include both domestic and foreign patents. Cited patents are sorted by the grant year of the patent. Since patent applications were not published in the United States during the time frame of this study, the publication date represents the date in which the invention first entered the public record. Note that only cited patents within the same energy technology group are considered. These patents can be considered as representing the state of knowledge within the technological field.

The dependent variable is a patent/citing year pair.[10] As much research has shown (see, for example, the papers in Jaffe and Trajtenberg 2002), the probability of a patent being cited falls over time, as the ideas embodied in the patent become obsolete. I create a variable **citelag**, defined as the difference between the citing patent's application year and the cited patent's grant year, to control for time effects.[11] That is, for a patent granted in 1993, separate observations occur in the data set for the total number of citations received from patents with application years of 1994, 1995, 1996, and 1997, respectively.

Because in most years, the number of citations will be 0, I use generalized negative binomial regression. Generalized negative binomial regression builds upon the basic Poisson regression framework. In a Poisson regression, the probability of a specific number of

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[9] Several researchers have found that grouping patents by the date of application is a good indicator of R&D activity (for example, see Griliches 1990). Moreover, since, before 2001, information on patents was not made public in the United States until the patent was granted, only *successful* patent applications are included in the data set.

[10] Note that there are a few cases where a patent appears in more than one technology group. When this occurs, only citations within that group are considered, so that for each patent/citing year pair there are two records (one for each technology group).

[11] While negative lags are possible (e.g. a patent granted in 1990, but first filed in 1987, citing a patent granted in 1989), such patents rarely occur in the database. Including the possibility of negative lags greatly expands the set of

occurrences, y, of the dependent variable occurring can be written as:

$$\Pr(Y_i = y_i) = \frac{e^{-\lambda_i}\lambda_i^{y_i}}{y_i!}, \quad y_i = 0,1,2,\ldots \tag{1}$$

Typically, λ_i is specified as a function of a vector of independent variables, so that

$\ln \lambda_i = \boldsymbol{\beta}'\mathbf{X_i}$

One restriction of the Poisson model is that it assumes the mean and variance of the dependent variable are the same:

$$E[y_i \mid \mathbf{X_i}] = \mathrm{Var}[y_i \mid \mathbf{X_i}] = \lambda_i = e^{\boldsymbol{\beta}'\mathbf{X_i}} \tag{2}$$

Typically, this assumption breaks down when the data are overdispersed – that is, when the variance of the dependent variable is greater than the mean. As shown in section III, that is the case here.[12] Negative binomial models extend the Poisson model by including an overdispersion term that allows the variance to increase faster than the mean used (see, for example, Cameron and Trivedi, 1998 and Winkelmann and Zimmermann, 1995):

$$\ln \lambda_i = \boldsymbol{\beta}'\mathbf{X_i} + \varepsilon_i \tag{3}$$

where $\exp(\varepsilon_i)$ has a gamma distribution with mean one and variance α. The generalized negative binomial regression extends this further by allowing α to vary as a linear combination of covariates. In the models that follow, I allow for different α for each of the technology groups. Such a model can be estimated using standard maximum likelihood techniques.[13]

In this model, $\ln \lambda_i$ predicts the number of citations to patent i based on its characteristics. Of course, the number of citations depends not only on these characteristics, but also on the

possibly citing patents set while adding little new information, since few citations occur with negative lags. Thus, such observations are deleted.

[12] Moreover, in each model that follows, hypothesis tests reject the null hypothesis that the Poisson model assuming equal mean and variance is appropriate.

[13] For this paper, estimation is carried out using the **gnbreg** command in Stata.

number of opportunities to be cited. Defining $cites_{i,j,s,t}$ as the number of citations made to patent *i* in technology group *j* and granted in year *s*, by patents with application year *t*, the total number of citations to each patent/year pair are:

$$cites_{i,j,s,t} = NCTG_{j,t}e^{\lambda_i} = e^{\ln(NCTG_{j,t})+\boldsymbol{\beta}'\mathbf{X}_{\mathbf{i,j,s,t}}+\varepsilon_{i,j,s,t}} \quad (4)$$

$NCTG_{j,t}$ represents the number of successful patent applications filed by U.S. inventors in technology *j* in year *t,* which is the application year for the citing patent. This variable controls for the opportunities for citation available to each patent.

The vector **X** controls for other factors that affect the probability of citation to each patent/year pair. Most importantly, I include two tests for diminishing returns. First, I ask whether the likelihood of citation falls when more patents are granted within a specific technology group in a given year. This variable, $NCTD_{j,s}$, tests for diminishing returns to research *within a given year*. A negative coefficient on this variable suggests 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, I ask whether the probability of citation falls as the cumulative number of patents in a field increases. This variable, 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, I create a stock of existing patents for each technology, using patent data from 1900-1997. In any year *s*, the stock of existing patents is calculated as:

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

In this equation, β_1 represents a rate of decay, and β_2 a rate of diffusion. In Popp (2002), I use similar stocks (with patent counts weighted by citations) to represent the supply of knowledge available to inventors. In that paper, I first use citation data to estimate rates of decay and diffusion. The rates found there (β_1 = 0.353483 and β_2 = 0.001991) are used in this paper. That work finds that this supply is important. Thus, the question here is whether it becomes more difficult to add to the stock of knowledge over time. As a sensitivity check, I also calculate stocks using two other sets of rates. One is 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 grant (see, for example, Griliches 1995). Finally, I include a third stock that assumes no decay and instantaneous diffusion, so that the stock is simply the sum of all patents granted in a class between 1900 and year *s*.

In addition to these controls for the returns to research over time, I also consider several variables that control for the characteristics of individual potentially cited patents. In particular, as one variable over which policy makers have control is the level and direction of government-sponsored R&D, I 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 patents. 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.[14] In addition, I 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:

- $NCTG_{j,t}$ represents the **total number of successful U.S. patent applications per citing year:** This controls for opportunities for future citations. Separate counts are made for each technology group, *j*.
- $NCTD_{j,s}$ represents the **total number of patents granted in the technology group in the same year as the cited patent.** As noted, this controls for diminishing returns within a given year.
- $K_{j,s-1}$ is the lagged value of the **stock of accumulated patents** granted in technology *j* by year *s*, where year *s* represents the issue year of the cited patent. This controls for diminishing returns across time.
- $GOVTPAT_i$ is a dummy variable equal to one if the cited patent is **assigned to the US government (including government laboratories).**
- $GOVT\_CHILD_i$ is a dummy variable equal to one if the cited patent is a **child of a government patent**, as defined above.
- $CLAIMS_i$ represents the **number of claims** on each cited patent. Other things equal, patents with more claims should be cited more frequently.

[14] 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.

- $CITEMADE_i$ 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, t, and the cited patent's grant year, s. This allows for declining probabilities of citation over time, as the cited patents gradually become obsolete.
- $ORIG_i$ is a measure of **originality** of the cited patent. I use the index on originality contained in the NBER Patent-Citations Data File (Hall *et al*. 2002). This measure is a Herfindahl concentration index of whether the patent cites other patents from a wide range of technology classes, or from only a select group of technologies. It is defined as:

$$Originality_i = 1 - \sum_{k}^{n_i} s_{ik}^2$$

  where s_{ij} denotes the percentage of citations made by patent i to patents in patent class k, out of a total of n_i patent classes.
- **$CTRY_i$** is a vector of dummy variables for the **country of origin** of the cited patents. Cited patents are assigned to one of eight country groups – United States, Japan, Germany, France, United Kingdom, Canada, Other member states of the European Patent Organization, or Other countries. This control is important, as most patent citations are between patents originating from the same country (Jaffe and Trajtenberg 1996)

- $\mathbf{CITEDYR_i}$ is a vector of year dummies defined based on the year of grant of the cited patent. 1975 is the excluded year. This captures any fixed effects in citations common to a grant year.
- $\mathbf{CITINGYR_s}$ is a vector of year dummies defined based on the application year of the citing patents. 1975 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.[15]
- $\mathbf{TECHGRP_j}$ 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 continuous casting.

Using these variables, ln λ_i becomes:

$$\ln \lambda_{i,j,s,t} = \beta_1 \ln(NCTG_{j,t}) + \beta_2 NCTD_{j,s} + \beta_3 K_{j,s\text{-}1} + \beta_4 GOVTPAT_i + \beta_5 GOVT\_CHILD_i + \beta_6 CLAIMS_i + \beta_7 CITEMADE\mathrm{i} + \beta_8 ORIGINAL_i + \beta_9 CITELAG_{s,t} + \boldsymbol{\beta_{10}}\mathbf{CTRY_i} + \boldsymbol{\beta_{11}}\mathbf{CITEDYR_i} + \boldsymbol{\beta_{12}}\mathbf{CITINGYR_s} + \boldsymbol{\beta_{13}}\mathbf{TECHGRP_j} + \varepsilon_i \tag{6}$$

Referring back to equation (4), note that the estimated coefficient on $\ln(NCTG_{i,t})$ should equal 1.

[15] 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.

III. Data

This paper extends the database of energy patents created in Popp (2002) by including addition years of data and additional descriptive information on each cited patent. Descriptive data on these patents comes from the NBER Patent-Citations Data File (Hall *et al*. 2002). Below I discuss both the creation of the original data set and the modifications added for this paper.

Creation of the data set begins by identifying patents in relevant energy technology fields. All patents granted in the United States are given a U.S. classification number. There are currently over 300 main classification groups and over 50,000 subclassifications. In order to identify subclassifications pertaining to energy efficiency, I used resources from the Department of Energy and from the academic sciences to identify several areas of research in the energy field. Descriptions of these technologies were then matched with U.S. patent subclassifications, and those technologies for which no clear subclassification existed were eliminated. The resulting set of subclassifications was then sorted into 11 distinct technology groups, including 6 groups pertaining to energy supply, such as solar energy, and 5 groups relating to energy demand, such as methods of reusing industrial waste heat. Table 1 lists the 11 technology groups and shows the number of patent applications from each year. The appendix provides a complete list of subclassifications included in each technology group.[16]

Having identified the relevant subclassifications for each energy technology group, I next obtain information on the individual patents in these groups. Using data from the MicroPatent CD-ROM database of patent abstracts and additional data from the U.S. Patent and Trademark Office, I identified all patents in the 11 technology groups that were granted in the United States

[16] Interested readers may download a more thorough description of the technologies chosen, as well as additional data on these technology groups, at http://faculty.maxwell.syr.edu/dcpopp/papers/patdata.PDF.

between 1900 and 1999.[17] The additional descriptive data on these patents needed for the regression, described in section II, comes from the NBER patent database (Hall *et al*., 2002).[18] The time frame of the study is determined by the availability of these data. In particular, data on citations are only available for patents granted since 1975.

Table 2 presents descriptive data for the subsequent citations made to each patent. Data are presented by technology for the entire sample, as well as for the years 1975, 1980, and 1990. The table shows the number of patents granted in each group, the percentage assigned to the government, the percentage that are children of government patents, and the average number of citations received by these patents.[19] Note that the percentage of patents assigned to the government is highest in 1975. In general, government patents receive more subsequent citations. Within a given year, the number of citations received by child patents is also high. However, this is not true for the sample as a whole, as there are few child patents in the early years of the data.

Table 3 presents descriptive data for the other variables. Overall, patents receive an average of 1.8 subsequent citations. The average number of subsequent citations varies from 0.968 for waste heat patents to 2.8 for solar energy patents. Note that this result is not solely a function of the size of each group, as the number of potentially citing patents per year for solar energy is only the fourth highest among the eleven energy technology groups. The average

[17] While the cited patents used in the regression only go back to 1975, data extending back to 1900 are used to construct the patent stocks described in section II.
[18] In addition to data taken from the NBER data file, I also use additional data on the type of assignee made available to the author. Unlike the other data, this variable is only complete through 1996. I thank Adam Jaffe for making these data available.
[19] Note that in this paper, self-citations are included. Self-citations are when the citing and cited patent have the same assignee. Many papers on knowledge flows across space (e.g. across countries or institutions) do not include self-citations. However, in this paper, the concern is the usefulness of past research to current inventors. Whether research was done by one firm or by two separate firms should not matter for the question of whether or not there are diminishing returns to research over time. As such, it seems theoretically correct to include self-citations.

number of claims ranges from 10.5 for waste heat to 13.7 for coal liquefaction. The number of citations made by these patents ranges from 5.2 for continuous casting to 9.0 for coal liquefaction. The combination of high claims and citations for coal liquefaction suggests that patents in this group are broader than other groups. Originality ranges from a low of 0.234 for continuous casting to a high of 0.459 for using waste as fuel. For the entire sample, 60% of patents are American. This ranges from 39% for continuous casting to 80% for coal liquefaction. Note that solar energy patents are also predominantly American, which is a likely explanation for the high number of citations for this group. Note also that the size of each group, defined by the average number of patents per year, varies, with heat exchange being the largest, and coal gasification, heat pumps, and Stirling engines the smallest.

IV. Results

I use the data described above to estimate equation (6). Because the data include repeated observations for each potentially cited patent, I calculate robust standard errors using clustering based on the various cited patents. Moreover, as can be seen from Table 3, the magnitudes of several key variables vary across groups. For example, 132 patents granted in a year has a very different interpretation for coal liquefaction, where that is the maximum number granted in the sample, than in solar energy, where the average number of patents granted per year is 283. Thus, to aid interpretation, I normalize the stock of patents, number of patents granted in the cited year, number of claims and citations made, and originality so that a one unit change in the normalized variable is equivalent to a ten percent change from the mean value for

Nonetheless, the results which follow are essentially the same if self-citations are dropped from the data. Results are available from the author by request.

each technology group.[20] Table 4 presents the base regression results, using patent stocks calculated with the rates of decay and diffusion in Popp (2002). Except where noted, results are shown as incidence rate ratios, e^{β}. For example, an incidence rate ratio of 1.2 says that a ten percent deviation from the mean for that variable results in 20 percent more citations to the patent.

The results of the base model are as expected. As a test of the theoretical consistency of the results, note that the coefficient on $\ln(NCTG_{i,t})$ is not statistically significantly different from 1. Both tests for diminishing returns yield statistically significant results. A 10 percent increase in the number of patents granted *within a given year* reduces the number of citations to a patent by 1.4 percent. A 10 percent increase in the stock of existing patents reduces the number of patents by 3.4 percent. To help interpret these results, Tables 5 and 6 calculate the range of change in citations for each technology, based on the maximum and minimum values of the stock and number of patent grants in a year, respectively. In general, changes in the stocks have more effect on citations received by a patent. These changes are most significant for the coal and solar technologies. For example, the highest value of the solar energy knowledge stock is 16 times larger than the smallest value. As such, the effect of changes in the stock of solar energy patent range from increasing citations by 37% to decreasing them by 23%. The smallest effect is for heat exchange, for which the stock does not vary much over the data period. There, changes in the stock affect citations by just a couple of percentage points. Of particular note is that solar energy was a particularly fast growing technology in the mid-1970s. Referring to Table 1, note

[20] The normalization first divides each continuous variable by its mean, multiplies by 10, and then takes deviations from the mean by subtracting 10, which results in normalized variables that have a mean of 0. The variables are normalized to control for differences in the magnitudes across technologies. The number of potentially citing patents is not normalized because it serves as controls for the number of opportunities for citation that a patent has. Since the dependent variable is a level, rather than a normalized variable, the level of the number of opportunities is what matters.

that solar energy patents doubled between 1974 and 1975, and continued to increase rapidly until 1977. In contrast, growth in heat exchange patents in response to higher energy prices was more gradual. These results suggest that when rapid spikes occur, such as with solar energy in the mid-1970s, the potential for diminishing returns to research will be greater.

In comparison, the potential for diminishing returns within a year is smaller. Even for solar energy, citations only fall by 10% when patenting peaks in 1977. While there are some technologies for which the range of the number of other patents granted in year s, $NCTD_{j,s}$, is larger than the range of the stock, the smaller coefficient on this variable causes the effect of diminishing returns to be less important. The highest value of patents per year lowers citations by 3 to 11 percent, whereas the lowest value of patents per year raises citations from 3 to 13 percent.

Turning to patent characteristics, most have small effects. Interestingly, government patents are not significantly more likely to receive future citations than other patents. However, the children of government patents are 13 percent more likely to receive citations. Traditionally, government research is thought to be more basic. In this sense, the lack of additional citations to government patents is a surprise. One possibility is that the nature of government R&D changed during this period. This result is examined more closely in section V.

Most important for determining citations is the number of claims. A 10 percent increase in the number of claims increases citations by just one percent. There is much variation in this variable, however, so that a one standard deviation change in the number of claims leads to a 10 percent change in the number of subsequent citations received. The number of citations made by a patent has no effect on future citations. Finally, one surprising result is that originality decreases the number of citations. However, this magnitude is small (only one-half of one percent). Even for the patent with the maximum originality score in the data (0.91), the number of citations received falls just 6.7 percent as a result of the originality of the patent. Moreover, it is important to remember that this regression only looks at citations within an energy technology group. Patents with higher originality indices are patents that cite other patents from a broader range of classifications. Thus, these patents themselves are likely relevant to a broader range of future patents. It may very well be the case that such patents receive more citations *overall*, but simply do not receive more citations from other energy patents than do other patents in the same field.

For the dummy variables, I find more citations within groups that are more narrowly defined, such as the coal technologies, as opposed to broader classifications such as heat exchange.[21] Also, as expected, patent citations are less likely to be made to patents of foreign origin, with German patents receiving the fewest citations from American inventors. Finally, to save space, Figure 1 presents the time trend dummies over time. As expected, the number of citations increases over time. Compared to the base year of 1975, citations are between 20 and 40 percent more likely from patent applications in the mid-to-late 1990s.

A. Sensitivity Analysis: Alternative Knowledge Stocks

Because tests for diminishing returns may be sensitive to the parameters chosen to construct the stock variable, Table 7 presents results for two alternative stocks, as defined in section II.[22] Note that the results are consistent across specifications, suggesting that the key results are not sensitive to how the stock is defined. One result of note is that the coefficient on

[21] The heat exchange technology group includes all of patent class 165, while each of the coal technologies include only a few subclasses.
[22] The table presents results for the individual patent characteristics. Results for the dummy variables are consistent across specifications, and are available from the author by request.

ln($NCTG_{i,t}$) is significantly different from one when no decay of knowledge is assumed, suggesting that such a specification may be inconsistent with theory. Note also that the log-likelihood value is lowest for that specification.

Tables 5 and 6 examine the diminishing returns estimates for all three knowledge stock assumptions. There is little difference between the results using the *AER* rates and results with a decay rate of 10 percent and rate of diffusion of 25 percent. Assuming no decay rate and instantaneous diffusion causes the knowledge stocks to have slightly less impact. In particular, there is less variation in the effect of the knowledge stock in this case, because the timing of patents matter less. Because knowledge never decays, once a patent is in the knowledge stock, its effect is permanent. In the other specifications, the effect of a new patent is strongest close to the date of grant. As a result, the increase in citations from the minimum stock value with no decay ranges from 8 to 26 percent, compared to 4 to 37 percent for the *AER* rates.

B. Alternative Specifications

Having shown that the base results are not sensitive to how the knowledge stock is defined, I continue by addressing the sensitivity of key results to alternative model specifications.[23] Table 8 shows the base results, along with five regressions omitting various variables. Omitting the control for other patents granted in the same year (column 2), which tests for diminishing returns to citations in a given year, has little impact on other variables. In general, the same is true when omitting the knowledge stock, which controls for diminishing returns to citations over time. However, while other coefficients are not drastically effected (either when omitting only the stock in column 3 or omitting both controls for diminishing returns in column 4), the coefficient on $ln(NCTG_{i,t})$ is now significantly higher than 1. This suggests that a model omitting the stocks is misspecified.

One surprising results above was the negative coefficient on originality. Columns 5 and 6 Table 8 includes two regressions to test the robustness of this result. First, one may be concerned about correlation between originality and the government patents – perhaps government patents are more basic, and thus more original. However, as column (5) shows, there is little change to the other variables when the government patent controls are excluded. Similarly, omitting originality from the model (column 6) has little effect on the other estimates.

V. The Effect of Government Patents

One interesting finding is that government patents are not cited more frequently than other patents. Traditionally, government R&D is thought of as more basic than private R&D, suggesting that government patents should generate more citations. One reason for this surprising result may be that the nature of government R&D has changed over time.

Before President Reagan took office in 1981, federal energy R&D policy included the goal of accelerating the development of new marketable technologies. Support was given to large research projects, such as a program aimed at creating synthetic fuels from coal. When supporting research aimed at marketable technologies, federally funded energy R&D could be a substitute for private innovation, rather than as a source of basic knowledge. If this is the case, we would not expect private patents to cite government patents more frequently. After Reagan's election, government funding for energy R&D was cut significantly. Department of Energy (DOE) support for research was limited to long-term, high-risk projects (Cohen and Noll 1991).

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[23] Given that the results are not sensitive to how the stock is calculated, all regressions in this section use stocks

The DOE focused its efforts on the early stages of research and development – basic research to promote general knowledge and the early stages of applied R&D designed to test the feasibility of new ideas. It was expected that private firms would continue the R&D process by developing commercially acceptable products (U.S. Department of Energy 1987). If these goals were achieved, we should see more citations to government energy patents filed since 1981.[24]

In addition to changes in the type of R&D supported, there were also additional policy changes intended to encourage the transfer of technologies from the public to the private sector. These include the Stevenson-Wylder Technology Innovation Act of 1980 (P.L. 96-480), the Bayh-Dole Act of 1980 (P.L. 96-517), and the Federal Technology Transfer Act of 1986 (P.L. 99-502). The Technology Innovation Act declared technology transfer a mission of all federal laboratories, and required all major federal laboratories to establish a technology transfer office. The Bayh-Dole Act, best known for facilitating patenting of federally funded university R&D, also gave government laboratories permission to grant exclusive licenses to government-owned patents. The hope was that exclusive licenses would entice firms to be more willing to partner with government laboratories. Finally, the Technology Transfer Act of 1986 established cooperative R&D arrangements (CRADAs) between government-run laboratories and private industry. Thus, at the same time that energy R&D policy was shifting to focus on more basic research, broader policy initiatives were established to encourage the transfer of government research results to the private sector.

To examine the effect of these policy shifts, I rerun the basic regression (using the *AER* rates of decay and diffusion) with an additional variable interacting the government patent dummy with a dummy variable for patents applied for in 1981 or later. These results are shown

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calculated with the *AER* decay and diffusion rates. As above, results using alternative specifications are similar.

in column 2 of Table 9. I find that pre-1981 patents are no more or less likely to be cited than other patents. However, post-1981 patents are 12.5 percent more likely to be cited.[25] This is consistent with results in Jaffe and Lerner (2001), who find that both patenting and the number of citations received per patent increased at DOE laboratories since the policy shifts of the 1980s.[26] Children of government patents remain important, as they generate 13 percent more citations.

That children of government patents are cited more often than government patents may suggest that transferring technology to the private sector is important. Although government patents may represent more basic scientific knowledge, the results may not be appropriate for commercialization. It may be that the child patents, which are held by the private sector, provide more commercial value by developing applications for knowledge generated in the government sector. While a complete examination of such a hypothesis is beyond the scope of this paper, I include a couple of regressions that suggest the technology transfer intended by the policy shifts in the 1980s may indeed be taking place.

First, in column 3, I interact the child patent dummy with a dummy for patents assigned to U.S. inventors. If technology transfer is important, we would expect that U.S. inventors should be generating particularly useful results from government patents, but should not expect that to be the case for foreign patents. That is not the case in column 3, as US children are no more

[24] Additional support for the change in the nature of government R&D comes from Popp (2002), which finds that government-sponsored energy R&D substitutes private energy R&D before 1981, but is a complement afterwards.
[25] The combined effect equals $\exp(\beta_{gov} + \beta_{interact})$.
[26] Their database differs from the data in this paper in two respects. First, it contains both patents assigned directly to the laboratories and patents assigned to private contractors who collaborated on research at the DOE labs. In this paper, such patents are assigned to the private sector. Second, Jaffe and Lerner do not limit their study to a subset of energy technologies, as is the case here. Thus, this paper focuses on how the usefulness of R&D within a specific technology changes, whereas in Jaffe and Lerner's work, the types of R&D performed at the laboratories may also be changing. For example, federal R&D spending on renewable energy fell during this period.

likely to be cited than other patents. This also holds true in column 4, where I include both the interaction for US children and the interaction for post-1981 government patents.

Finally, column 5 includes three interactions. As before, I consider pre- and post-1981 government patents, as well as U.S. and foreign child patents. I also include interact a dummy variable for child patents based on whether the patent is a child of a government patent that filed its application since 1981. These results suggest that technology transfer may be important, *but not until the policy shift that occurred in 1981*. As before, government patents granted since 1981 are more frequently cited, with such patents receiving 13 percent more citations. Overall, child patents are cited 10 percent more frequently. Of particular note, however, are the results for patents that are children of government patents filed since 1981. Here, we find that foreign children of such patents are just two percent more likely to be cited than other patents. However, U.S. children of these government patents are 29 percent more likely to be cited. The finding that only U.S. children of government patents generate more citations after the shift in U.S. energy R&D policy suggests that technology transfer, rather than indirect knowledge spillovers, may be a driving force behind the importance of child patents. While these results are only suggestive, they do imply a fruitful avenue for future research. It also supports evidence provided in Jaffe and Lerner (2001), who supplement the patent citation analysis discussed above with case studies of two DOE laboratories, Lawrence Livermore National Laboratory and Idaho National Engineering and Environmental Laboratory, where technology transfer efforts increased in the 1980s and 1990s.

VI. Conclusion

This paper examines trends in citations to energy patents granted between 1975 and 1996. In previous work (Popp 2002), I demonstrate that accumulated patent stocks, weighted by the frequency of citation to these patents, can serve as a proxy for the supply of knowledge available to inventors. Moreover, this supply of knowledge is an important determinant of the level of innovative activity in a given year. As such, understanding changes in the number of citations received by a patent can provide insight into how the quality of the stock of knowledge on which inventors build changes over time.

Using generalized negative binomial regression, I find evidence of diminishing returns to the usefulness of new patents to subsequent inventors. Across time, I find that a 10 percent increase in the stock of previous patents reduces subsequent citations from 3 to 5 percent. Given the variation in the size of stocks observed in the data, this can lead to variations in citation rates of up to 60 percent. Within a given year, I find that patents are less likely to be cited, and thus contribute less to the knowledge stock, when the number of other patents granted in the field is high. However, the magnitude of this effect is about half that of the effect of stocks on citation rates.

Given the importance of the quality of knowledge for future R&D found in Popp (2002), this result may leave policy makers discouraged, as it suggests that successful energy R&D (or R&D programs concentrated in other specific fields) will become less productive over time. This paper suggests that government sponsored R&D can help offset these declines. I find that government patents filed since 1981 are 12 percent more likely to be cited than other patents. Notably, this is not true for government patents applied for before 1981, when government sponsored R&D focused more on applied, rather than basic, research. This result suggests that government sponsored R&D can best contribute to the knowledge stock, and thus best induce future R&D, if it focuses on more basic research that is unlikely to be done elsewhere. Moreover, I find that private patents that cite these government patents are themselves cited 30%

more often. This evidence suggests that technology transfer, or at least indirect flows of knowledge, from government research programs to the private sector are needed to fully realize the benefits of government research.

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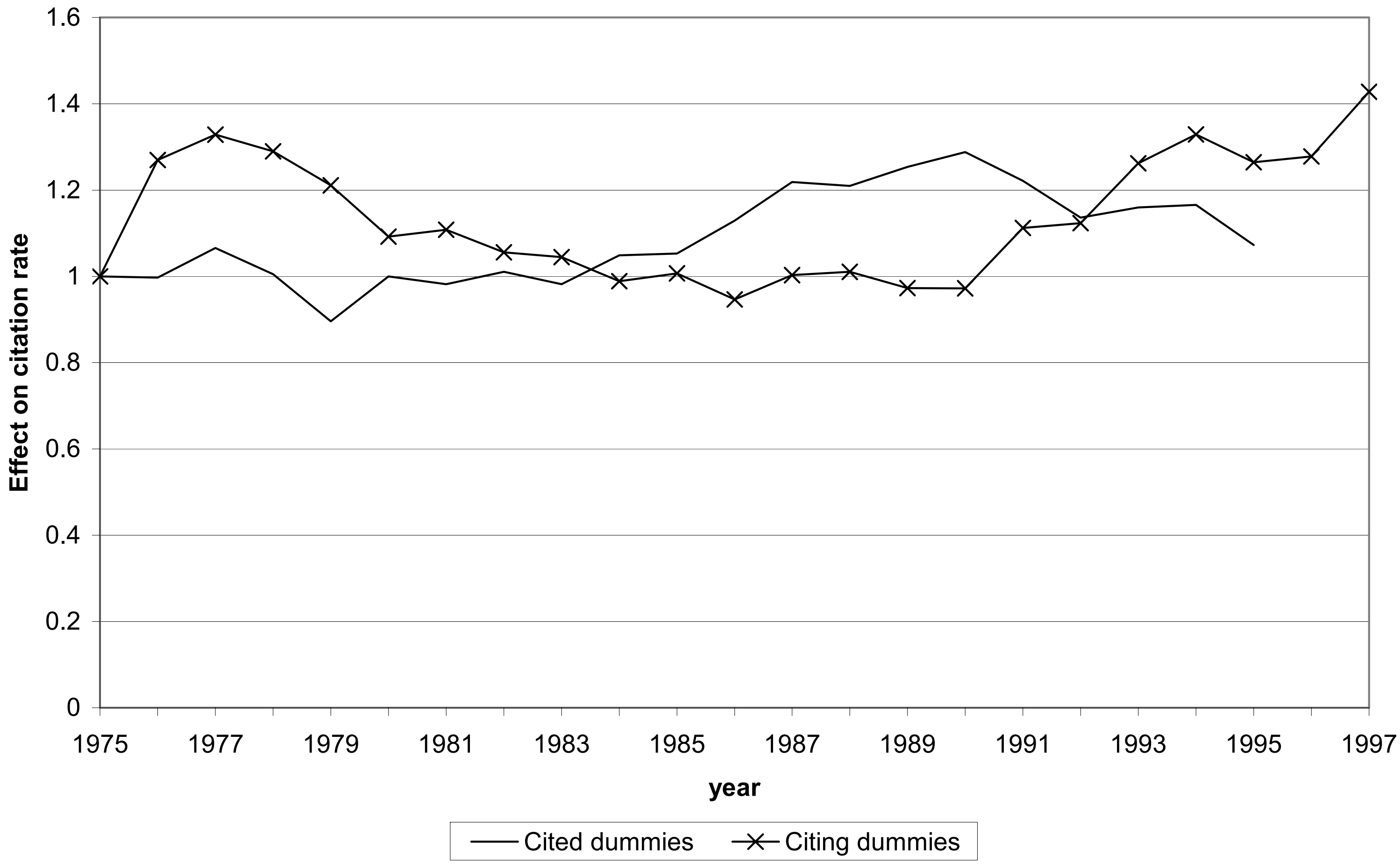
Figure 1 – Citing and Cited Year Fixed Effects



The figure plots citing year and cited year fixed effects. 1975 is the excluded year in the regressions. In addition, because all patents granted in 1996 are cited in 1997 in this data, the cited year 1996 dummy is also excluded.

Table 1 – Successful U.S. Patent Applications by Year

year	Coal Liquefaction	Coal Gasification	Solar Energy	Solar Batteries	Fuel Cells	Waste as Fuel	Waste Heat	Heat Exchange	Heat Pumps	Stirling Engines	Continuous Casting
1974	52	41	106	36	28	49	27	382	8	18	50
1975	44	36	225	73	40	28	25	415	8	13	44
1976	107	42	324	97	34	30	35	450	20	17	44
1977	92	45	375	131	56	35	29	504	17	11	38
1978	117	56	340	149	44	42	16	488	33	13	41
1979	84	35	305	129	44	44	28	476	24	12	45
1980	100	40	283	119	57	50	26	456	23	18	44
1981	105	31	220	125	62	44	23	399	30	22	43
1982	83	29	165	105	82	59	31	399	18	35	49
1983	75	25	104	85	59	53	22	322	11	21	61
1984	73	18	106	92	49	43	26	350	8	20	64
1985	35	19	87	87	61	47	17	293	14	13	46
1986	23	11	45	79	81	62	13	330	15	13	83
1987	13	17	38	55	68	84	13	307	11	19	41
1988	17	12	46	66	65	70	26	327	5	11	60
1989	23	14	33	46	58	84	24	318	14	12	39
1990	19	10	28	46	60	101	24	344	19	18	35
1991	10	5	34	52	52	95	19	391	22	12	38
1992	10	5	29	52	58	85	21	413	12	11	30
1993	10	6	33	43	66	72	28	410	18	8	39
1994	10	11	32	56	67	76	24	360	15	14	32
1995	10	6	33	53	91	67	22	367	16	4	38
1996	8	6	32	46	75	57	25	340	13	18	29
1997	10	2	13	34	86	32	22	307	17	14	15

The table shows the number of successful U.S. patent applications in each of the 11 energy technology groups. Only applications made by domestic inventors are included. The data contain all patents granted through the end of 1999.

Table 2 – Descriptive Data: Granted Patents and Citations

Entire Sample					*mean cites by type*		
	N	% gov	% child	ave cites	Private	Govt.	Child
Coal liquefaction	1,369	3.73%	18.92%	2.41	2.47	3.33	2.02
Coal gasification	776	5.03%	15.34%	1.05	1.05	1.21	1.03
Solar Energy	3,850	2.96%	16.78%	2.81	2.92	3.56	2.15
Solar Batteries	2,694	6.01%	20.16%	2.03	1.95	2.03	2.30
Fuel Cells	2,061	6.11%	22.46%	2.71	2.66	4.02	2.50
Waste Fuel	2,110	1.33%	10.33%	2.38	2.31	1.54	3.10
Waste Heat	1,240	0.81%	2.66%	0.97	0.98	0.60	0.48
Heat Exchange	13,798	1.84%	9.00%	1.58	1.54	2.03	1.80
Heat Pump	572	1.05%	3.50%	1.09	1.12	0.67	0.55
Stirling Engines	585	2.91%	16.24%	1.34	1.22	3.71	1.52
Continuous Casting	2,558	0.55%	3.09%	0.97	0.97	1.36	1.04
1975							
Coal liquefaction	29	13.79%	0.00%	6.41	5.24	13.75	0.00
Coal gasification	26	3.85%	0.00%	2.77	2.80	2.00	0.00
Solar Energy	50	4.00%	0.00%	14.88	14.94	13.50	0.00
Solar Batteries	37	18.92%	0.00%	5.65	6.00	4.14	0.00
Fuel Cells	72	8.33%	0.00%	2.40	2.47	1.67	0.00
Waste Fuel	93	1.08%	0.00%	3.54	3.45	12.00	0.00
Waste Heat	28	3.57%	0.00%	1.79	1.85	0.00	0.00
Heat Exchange	531	3.39%	0.00%	2.10	2.08	2.78	0.00
Heat Pump	7	0.00%	0.00%	4.00	4.00	0.00	0.00
Stirling Engines	23	0.00%	0.00%	1.78	1.78	0.00	0.00
Continuous Casting	137	0.00%	0.00%	1.61	1.61	0.00	0.00
1980							
Coal liquefaction	99	4.04%	20.20%	3.30	3.35	0.50	3.70
Coal gasification	61	3.28%	16.39%	0.93	0.86	1.00	1.30
Solar Energy	370	3.24%	20.00%	2.76	2.70	3.42	2.86
Solar Batteries	150	6.67%	25.33%	2.71	2.57	2.10	3.24
Fuel Cells	67	4.48%	5.97%	4.19	4.35	3.00	2.75
Waste Fuel	64	3.13%	15.63%	3.86	3.23	3.50	7.20
Waste Heat	48	0.00%	2.08%	1.25	1.28	0.00	0.00
Heat Exchange	696	2.16%	10.06%	1.94	1.91	1.67	2.24
Heat Pump	33	3.03%	3.03%	1.06	1.06	1.00	1.00
Stirling Engines	23	4.35%	0.00%	2.26	1.95	9.00	0.00
Continuous Casting	109	0.00%	0.00%	1.65	1.65	0.00	0.00
1990							
Coal liquefaction	20	5.00%	25.00%	0.35	0.29	0.00	0.60
Coal gasification	29	0.00%	13.79%	0.45	0.52	0.00	0.00
Solar Energy	75	0.00%	18.67%	0.45	0.41	0.00	0.64
Solar Batteries	98	4.08%	18.37%	1.21	1.03	1.00	2.06
Fuel Cells	98	12.24%	29.59%	2.62	1.79	3.25	4.00
Waste Fuel	136	0.00%	8.82%	2.58	2.49	0.00	3.50
Waste Heat	61	0.00%	0.00%	1.00	1.00	0.00	0.00
Heat Exchange	620	2.26%	8.23%	1.57	1.52	0.71	2.27
Heat Pump	24	0.00%	0.00%	1.00	1.00	0.00	0.00
Stirling Engines	20	0.00%	15.00%	1.20	1.35	0.00	0.33
Continuous Casting	133	1.50%	1.50%	0.93	0.86	6.50	0.00

Table 3 – Other Descriptive Data

		Citations	Claims	Cites Made	Original	US dummy	# citing pats per year	# cited pats per year
Coal liquefaction	mean	2.414	13.747	9.023	0.329	0.807	26.551	92.139
	sd	3.398	10.398	6.968	0.266	0.395	28.622	37.897
	max	29	108	103	0.889	1	117	132
	min	0	1	1	0	0	8	9
Coal Gasification	mean	1.052	11.451	7.153	0.419	0.653	12.693	47.012
	sd	1.644	9.013	5.676	0.265	0.476	10.336	16.277
	max	11	67	103	0.860	1	56	66
	min	0	1	1	0	0	2	7
Solar Energy	mean	2.806	11.332	7.650	0.345	0.760	61.189	283.024
	sd	4.518	10.050	5.217	0.266	0.427	66.510	133.064
	max	46	184	120	0.885	1	375	504
	min	0	1	1	0	0	13	41
Solar Batteries	mean	2.026	14.008	6.128	0.407	0.634	57.349	137.524
	sd	3.208	12.273	5.754	0.277	0.482	21.539	31.655
	max	62	164	120	0.909	1	149	184
	min	0	1	1	0	0	34	41
Fuel Cells	mean	2.709	14.008	6.611	0.291	0.605	70.410	101.606
	sd	3.998	10.818	6.167	0.277	0.489	12.867	24.784
	max	60	110	83	0.887	1	91	141
	min	0	1	1	0	0	34	57
Waste Fuel	mean	2.383	13.396	8.625	0.459	0.605	66.111	107.349
	sd	3.617	13.035	6.967	0.262	0.489	19.737	28.662
	max	35	279	80	0.886	1	101	142
	min	0	1	1	0	0	28	44
Waste Heat	mean	0.968	10.502	6.229	0.302	0.397	22.734	66.591
	sd	1.535	8.785	5.763	0.272	0.489	3.815	22.938
	max	16	103	126	0.862	1	35	121
	min	0	1	1	0	0	13	31
Heat Exchange	mean	1.577	10.736	7.663	0.411	0.595	356.379	660.036
	sd	2.436	8.807	5.877	0.274	0.491	42.421	65.192
	max	32	184	95	0.905	1	504	816
	min	0	1	1	0	0	293	517

Table continued on next page

Table 3 – Other Descriptive Data (continued)

		Citations	Claims	Cites Made	Original	US dummy	# citing pats per year	# cited pats per year
Heat Pump	mean	1.093	10.731	7.316	0.274	0.596	15.114	29.042
	sd	2.018	7.816	4.877	0.259	0.491	4.058	7.786
	max	17	51	34	0.864	1	30	41
	min	0	1	1	0	0	5	7
Stirling Engines	mean	1.340	11.670	5.588	0.272	0.556	13.410	30.465
	sd	2.119	11.133	6.278	0.264	0.497	5.334	9.300
	max	25	92	52	0.833	1	35	47
	min	0	1	1	0	0	4	12
Continuous Casting	mean	0.974	11.251	5.220	0.234	0.387	37.646	134.397
	sd	2.195	9.834	4.203	0.274	0.487	13.986	33.328
	max	39	111	45	0.880	1	83	192
	min	0	1	1	0	0	15	63
Total	mean	1.830	11.676	7.274	0.371	0.605	182.810	367.780
	sd	3.070	10.027	5.884	0.279	0.489	158.110	272.318
	max	62	279	126	0.909	1	504	816
	min	0	1	1	0	0	2	7

Table 4 – Base Regression Results

Patent characteristics		*Cited country dummies*	
ln(# of citing patents)*	1.024	United States	N/A
	1.282†		
# of patents in cited yr.	0.986	Japan	0.686
	-3.552		-12.906
Stock of patents	0.966	Germany	0.520
	-9.527		-17.754
Government patent	1.038	France	0.584
	0.778		-11.438
Government child	1.131	United Kingdom	0.595
	4.757		-8.244
# of claims	1.011	Canada	0.712
	11.928		-5.595
# of citations made	1.001	Other EPO	0.571
	1.358		-14.298
Originality	0.995	Other	0.653
	-4.315		-7.193
Cite lag	0.937	Constant	0.003
	-15.612		-44.670
Technology dummies		*Dispersion coefficients**	
Coal liquefaction	2.078	Coal liquefaction	0.461
	13.206		-6.700
Coal gasification	2.217	Coal gasification	0.460
	11.172		-3.783
Solar energy	0.849	Solar energy	0.158
	-3.328		-16.992
Solar batteries	1.079	Solar batteries	0.373
	1.469		-8.564
Fuel cells	1.563	Fuel cells	0.455
	8.322		-7.122
Waste as fuel	1.470	Waste as fuel	0.413
	7.306		-7.840
Waste heat	1.870	Waste heat	0.731
	10.322		-2.124
Heat exchange	0.157	Heat exchange	0.469
	-30.913		-7.772
Heat pumps	2.748	Heat pumps	0.502
	11.994		-3.467
Stirling engines	3.713	Stirling engines	0.605
	17.317		-2.713
Continuous casting	N/A	Continuous casting	N/A
		Constant	4.586
			16.481
		num. of obs.	404497
		log-likelihood	-156031.51

* For these parameters, actual values, rather than exponential values, are presented.
†: null hypothesis for this coefficient is that the coefficient equals 1.

Table 5 – The Effect of Knowledge Stocks

AER Rates	Mean	Std. Dev.	Min	Max	Max/ Min	% Dev from Mean: Min Value	% Dev from Mean: Max Value	% change in citations from min value	% change in citations from max value
Coal liquefaction	1.474	0.530	0.780	2.296	2.94	-47%	56%	118%	82%
Coal gasification	0.800	0.275	0.250	1.147	4.58	-69%	43%	127%	86%
Solar Energy	3.696	2.018	0.399	6.414	16.07	-89%	74%	137%	77%
Solar Batteries	2.382	0.939	0.744	3.393	4.56	-69%	42%	127%	86%
Fuel Cells	2.002	0.250	1.659	2.500	1.51	-17%	25%	106%	92%
Waste Fuel	1.802	0.540	1.151	2.748	2.39	-36%	53%	113%	83%
Waste Heat	1.173	0.372	0.646	1.600	2.48	-45%	36%	117%	88%
Heat Exchange	14.224	0.897	12.526	15.177	1.21	-12%	7%	104%	98%
Heat Pump	0.486	0.166	0.220	0.647	2.95	-55%	33%	121%	89%
Stirling Engines	0.614	0.077	0.459	0.730	1.59	-25%	19%	109%	94%
Continuous Casting	2.907	0.235	2.428	3.243	1.34	-16%	12%	106%	96%
Decay = 0.1, Diffusion = 0.25									
Coal liquefaction	414.17	131.8	185.01	565.75	3.06	-55%	37%	121%	87%
Coal gasification	211.95	78.9	54.64	285.46	5.22	-74%	35%	130%	88%
Solar Energy	973.92	471.5	171.37	1465.4	8.55	-82%	50%	133%	83%
Solar Batteries	604.23	272.6	195.03	906.24	4.65	-68%	50%	127%	83%
Fuel Cells	597.01	67.9	501.75	742.34	1.48	-16%	24%	106%	91%
Waste Fuel	470.15	153.6	250.87	753.48	3.00	-47%	60%	118%	80%
Waste Heat	334.72	95.4	214.44	463.62	2.16	-36%	39%	113%	87%
Heat Exchange	4499.3	438.0	3701.1	4990.1	1.35	-18%	11%	106%	96%
Heat Pump	146.44	37.31	97.01	195.64	2.02	-34%	34%	113%	88%
Stirling Engines	173.06	35.82	102.14	212.92	2.08	-41%	23%	115%	92%
Continuous Casting	848.04	112.2	609.45	985.05	1.62	-28%	16%	110%	94%
No Decay									
Coal liquefaction	1695.3	495.7	855	2235	2.61	-50%	32%	119%	86%
Coal gasification	1059.4	268.9	571	1366	2.39	-46%	29%	117%	87%
Solar Energy	4159.3	1405	1710	5605	3.28	-59%	35%	123%	84%
Solar Batteries	2026.8	913.8	685	3382	4.94	-66%	67%	126%	72%
Fuel Cells	2176.0	600.2	1314	3271	2.49	-40%	50%	115%	78%
Waste Fuel	2235.5	639.3	1379	3411	2.47	-38%	53%	114%	77%
Waste Heat	2101.2	428.0	1502	2775	1.85	-29%	32%	110%	86%
Heat Exchange	32409	4337	25545	39302	1.54	-21%	21%	108%	90%
Heat Pump	759.4	182.1	499	1052	2.11	-34%	39%	113%	83%
Stirling Engines	709.6	190.0	415	1002	2.41	-42%	41%	116%	82%
Continuous Casting	3417.7	842.4	2096	4748	2.27	-39%	39%	114%	83%

The table includes descriptive statistics for the knowledge stock, for each of the three alternative combinations of decay and diffusion used in the paper. The last two columns present the change in citations based on either the highest and lowest value of each stock, compared to the number of citations received when the stock is at its mean value for the respective technology.

Table 6 – The Effect of Other Patents in a Given Year

# patents/cited year	mean	min	max	% Dev from Mean: Min Value	% Dev from Mean: Max Value	% change in citations: min value (*AER* rates)	% change in citations: max value (*AER* rates)	% change in citations: min value (β_1=0.1; β_2=0.25)	% change in citations: max value (β_1=0.1; β_2=0.25)	% change in citations: min value (no decay)	% change in citations: max value (no decay)
Coal liquefaction	92.14	9	132	-90%	43%	113%	94%	122%	91%	118%	92%
Coal gasification	47.01	7	66	-85%	40%	112%	95%	121%	91%	117%	93%
Solar Energy	283.0	41	504	-86%	78%	113%	90%	121%	84%	117%	87%
Solar Batteries	137.5	41	184	-70%	34%	110%	95%	117%	93%	114%	94%
Fuel Cells	101.6	57	141	-44%	39%	106%	95%	110%	92%	108%	93%
Waste Fuel	107.4	44	142	-59%	32%	109%	96%	114%	93%	111%	94%
Waste Heat	66.59	31	121	-53%	82%	108%	89%	113%	83%	110%	86%
Heat Exchange	660.0	517	816	-22%	24%	103%	97%	105%	95%	104%	96%
Heat Pump	29.04	7	41	-76%	41%	111%	94%	119%	91%	115%	93%
Stirling Engines	30.46	12	47	-61%	54%	109%	93%	115%	89%	112%	91%
Continuous Casting	134.4	63	192	-53%	43%	108%	94%	113%	91%	110%	93%

The table provides descriptive statistics for the number of patents granted in each technology per year, along with the range of results pertaining to diminishing returns within a year. These results are presented for each alternative stock of patents. These results are the change in citations based on either the highest and lowest value of patents granted each year, compared to the number of citations received when the number of patents granted is at its mean value for the respective technology.

Table 7 – Sensitivity to Rates of Decay and Diffusion

Variable	*AER Rates*	*Decay 0.1; Diff. 0.25*	*No Decay*
ln(# of citing patents)*	1.024	1.018	1.047
	1.282†	0.935†	2.502†
# of patents in cited yr.	0.986	0.978	0.982
	-3.552	-5.673	-4.628
Stock of patents	0.966	0.963	0.952
	-9.527	-9.295	-7.028
Government patent	1.038	1.040	1.041
	0.778	0.812	0.840
Government child	1.131	1.132	1.135
	4.757	4.786	4.891
# of claims	1.011	1.011	1.012
	11.928	11.963	12.022
# of citations made	1.001	1.002	1.001
	1.358	1.390	1.345
Originality	0.995	0.995	0.995
	-4.315	-4.367	-4.448
Cite lag	0.937	0.932	0.953
	-15.612	-16.366	-9.829
Num. of obs.	404497	404497	404497
log-likelihood	-156031.5	-156039.9	-156075.6

* For this parameter, actual values, rather than exponential values, are presented.
†: null hypothesis for this coefficient is that the coefficient equals 1.

Table 8 – Sensitivity to Model Specification

Variable	*(1) Base Model*	*(2) Omit NCTD*	*(3) Omit Stock*	*(4) No Dim. Returns*	*(5) Omit Govt. Patents*	*(6) Omit Originality*
ln(# of citing patents)*	1.024	1.008	1.113	1.097	1.022	1.024
	1.282†	0.442†	6.301†	5.547†	1.188†	1.266†
# of patents in cited yr.	0.986		0.980		0.987	0.986
	-3.552		-5.060		-3.389	-3.545
Stock of patents	0.966	0.963			0.965	0.966
	-9.527	-10.088			-9.591	-9.527
Government patent	1.038	1.040	1.048	1.052		1.038
	0.778	0.826	0.975	1.066		0.772
Government child	1.131	1.127	1.134	1.129		1.127
	4.757	4.629	4.840	4.663		4.640
# of claims	1.011	1.011	1.011	1.011	1.012	1.011
	11.928	11.902	11.960	11.926	11.991	11.910
# of citations made	1.001	1.001	1.001	1.001	1.002	1.000
	1.358	1.351	1.217	1.190	2.204	0.028
Originality	0.995	0.995	0.995	0.995	0.995	
	-4.315	-4.306	-4.303	-4.290	-4.177	
Cite lag	0.937	0.938	0.943	0.946	0.937	0.938
	-15.612	-15.326	-14.172	-13.527	-15.742	-15.553
Num. of obs.	404497	404497	404497	404497	404497	404497
log-likelihood	-156032	-156048	-156139	-156174	-156062	-156056

* For this parameter, actual values, rather than exponential values, are presented.
†: null hypothesis for this coefficient is that the coefficient equals 1.

Table 9 – Government Patents

Variable	(1) *Base*	(2) *1981 Interact*	(3) *US Children*	(4) *US Child and 1981*	(5) *US Child Post 1981*
ln(# of citing patents)*	1.024	1.024	1.024	1.024	1.025
	1.282(a)	1.297(a)	1.286(a)	1.301(a)	1.315(a)
# of patents in cited yr.	0.986	0.986	0.986	0.986	0.986
	-3.552	-3.561	-3.551	-3.561	-3.524
Stock of patents	0.966	0.966	0.966	0.966	0.966
	-9.527	-9.548	-9.527	-9.548	-9.532
Government patent	1.038	0.978	1.038	0.978	0.977
	0.778	-0.359	0.790	-0.351	-0.377
Govt. pat 1981 or later		1.151		1.151	1.157
		1.497		1.499	1.556
Government child	1.131	1.132	1.112	1.113	1.145
	4.757	4.790	2.163	2.175	2.418
Govt. child 1981 or later					0.890
					-1.127
Child with US assignee			1.022	1.022	0.965
			0.383	0.391	-0.550
US child 1981 or later					1.312
					2.273
# of claims	1.011	1.011	1.011	1.011	1.011
	11.928	11.925	11.928	11.925	11.927
# of citations made	1.001	1.001	1.001	1.001	1.001
	1.358	1.339	1.350	1.330	1.272
Originality	0.995	0.995	0.995	0.995	0.995
	-4.315	-4.309	-4.312	-4.307	-4.280
Cite lag	0.937	0.938	0.937	0.938	0.938
	-15.612	-15.574	-15.612	-15.574	-15.410
Num. of obs.	404497	404497	404497	404497	404497
log-likelihood	-156032	-156028	-156031	-156028	-156020

APPENDIX: U.S. patent classifications related to energy

Guide to definitions: The first phrase is the main classification. For example, class 208 contains patents for Mineral Oils: Processes and Products. These are followed by the various subclassifications, listed in descending order of precedence.

***Supply Technologies**:*
Coal Liquefaction:

208/400-435	Mineral Oils: Processes and Products/By treatment of solid material (e.g. coal liquefaction)

Coal Gasification:

48/200	Gas: Heating and Illuminating/Processes/Coal, oil and water
48/201	Gas: Heating and Illuminating/Processes/Coal and oil
48/202	Gas: Heating and Illuminating/Processes/Coal and water
48/210	Gas: Heating and Illuminating/Processes/Coal
48/71	Gas: Heating and Illuminating/Generators/Cupola/Coal, oil and water
48/72	Gas: Heating and Illuminating/Generators/Cupola/Coal and oil
48/73	Gas: Heating and Illuminating/Generators/Cupola/Coal and water
48/77	Gas: Heating and Illuminating/Generators/Cupola/Producers/Coal
48/98	Gas: Heating and Illuminating/Generators/Retort/Coal, oil and water
48/99	Gas: Heating and Illuminating/Generators/Retort/Coal and water
48/100	Gas: Heating and Illuminating/Generators/Retort/Coal and oil
48/101	Gas: Heating and Illuminating/Generators/Retort/Coal

Solar Energy:

60/641.8-641.15	Power Plants/Utilizing natural heat/Solar
62/235.1	Refrigeration/Utilizing solar energy
126/561-568	Stoves and Furnaces/Solar heat collector for pond or pool
126/569-713	Stoves and Furnaces/Solar heat collector
126/903	Stoves and Furnaces/Cross-Reference Art/Solar collector cleaning device
126/904	Stoves and Furnaces/Cross-Reference Art/Arrangements for sealing solar collector
126/905	Stoves and Furnaces/Cross-Reference Art/Preventing condensing of moisture in solar collector
126/906	Stoves and Furnaces/Cross-Reference Art/Connecting plural solar collectors in a circuit
126/910	Stoves and Furnaces/Cross-Reference Art/Heat storage liquid

Solar Energy – Batteries:

136/206	Batteries: Thermoelectric and Photoelectric/Thermoelectric/Electric power generator/ Solar energy type
136/243	Batteries: Thermoelectric and Photoelectric/Photoelectric
136/244-251	Batteries: Thermoelectric and Photoelectric/Photoelectric/Panel
136/252-265	Batteries: Thermoelectric and Photoelectric/Photoelectric/Cells

Fuel Cells:

429/12-46	Chemistry: Electrical Current Producing Apparatus, Product, and Process/Fuel cell, subcombination thereof or method of operating

Using waste as fuel:

110/235-259	Furnaces/Refuse incinerator
110/346	Furnaces/Incinerating refuse

Demand Technologies:

Waste heat:

122/7R	Liquid Heaters and Vaporizers/Industrial/Waste heat
7A	Liquid Heaters and Vaporizers/Industrial/Waste heat/Steel converter
7B	Liquid Heaters and Vaporizers/Industrial/Waste heat/Additional burner
7C	Liquid Heaters and Vaporizers/Industrial/Waste heat/Waste sulfate
7D	Liquid Heaters and Vaporizers/Industrial/Waste heat/Carbon monoxide
60/597-624	Power Plants/Fluid motor means driven by waste heat or by exhaust energy from internal combustion engine

Heat exchange:

165	Heat Exchange

Heat pumps:

62/238.7	Refrigeration/Disparate apparatus utilized as heat source or absorber/With vapor compression system/Reversible, i.e. heat pump
62/324.1-325	Refrigeration/Reversible, i.e., heat pump

Stirling engine:

60/517-526	Power Plants/Motor operated by expansion and/or contraction of a unit of mass of motivating medium/Unit of mass is a gas which is heated or cooled in one of a plurality of constantly communicating expansible chambers and freely transferable therebetween

Continuous casting:

148/541	Metal Treatment/Process of modifying of maintaining internal physical structure (i.e. microstructure) or chemical properties of metal, process of reactive coating of metal and process of chemical-heat removing (e.g., flame-cutting, etc.) or burning of metal/With casting or solidifying from melt/Iron(Fe) or iron base alloy/Continuous casting
148/551	Metal Treatment/Process of modifying of maintaining internal physical structure (i.e. microstructure) or chemical properties of metal, process of reactive coating of metal and process of chemical-heat removing (e.g., flame-cutting, etc.) or burning of metal/With casting or solidifying from melt/Aluminum (Al) or aluminum base alloy/Continuous casting
164/263	Metal Founding/With product severing or trimming means/Associated with continuous casting means
164/268	Metal Founding/With coating means/associated with a continuous or semicontinuous casting means
164/415	Metal Founding/Means providing inert or reducing atmosphere/In continuous casting apparatus
164/416	Metal Founding/Including vibrator means/In continuous casting mold
164/417	Metal Founding/Combined/Including continuous casting apparatus
164/418-444	Metal Founding/Means to shape metallic material/Continuous or semicontinuous casting
164/445-446	Metal Founding/Starter bar
164/447-448	Metal Founding/Product supporting or withdrawal means for continuous casting apparatus
164/449.1-450.5	Metal Founding/Control means responsive to or actuated by means sensing or measuring a condition or variable (i.e., automatic control)/Control of feed material enroute to shaping area/Responsive to material level/In continuous casting apparatus
164/451-455	Metal Founding/Process/With measuring, testing, inspecting, or condition determination/Of continuous or semicontinuous casting
164/459-491	Metal Founding/Process/Shaping liquid metal against a forming surface/Continuous or semicontinuous casting
164/502-504	Metal Founding/Including means to directly apply magnetic force to work or to manipulate or hold shaping means/In continuous casting apparatus
164/505-509	Metal Founding/Means to directly apply electrical or wave energy to work/In continuous casting apparatus
164/154.4	Metal Founding/Control means responsive to or actuated by means sensing or measuring a condition or variable (i.e., automatic control)/Responsive to position or spatial dimension/Responsive to rate of change/Continuous casting
164/154.5	Metal Founding/Control means responsive to or actuated by means sensing or measuring a condition or variable (i.e., automatic control)/Responsive to position or spatial dimension/Continuous casting