# Recombinant innovation and the boundaries of the firm

Rachel Griffith
Sokbae Lee
Bas Straathof

The Institute for Fiscal Studies
Department of Economics, UCL

**cemmap** working paper CWP40/14

# Recombinant innovation and the boundaries of the firm

Rachel Griffith, Sokbae Lee and Bas Straathof*

August 2014

**Abstract**

There is considerable interest in understanding how important market frictions are in stifling the transmission of ideas from one firm to another. Although the theoretical literature emphasizes the importance of these frictions, direct empirical evidence on them is limited. We use comprehensive patent data from the European Patent Office and a multiple spells duration model to provide estimates that suggest that they are substantial. It is around 30% more costly to successfully discover and utilize new ideas created in another firm than in your own. This compares to the increased costs of accessing new ideas across national borders of around 5%, and across technologies of around 20%. These result point towards substantial imperfections in the market for technology.

**Keywords:** recombinant innovation, multinational firms, patent policy

**JEL classification: F23, O32, O33**

**Acknowledgements:** The authors gratefully acknowledge financial support from the Economic and Social Research Council (ESRC) under the Centre for the Microeconomic Analysis of Public Policy (CPP), grant number RES-544-28-0001, from the European Research Council (ERC) grant ERC-2009-AdG-249529-MAPFAN, and from the European Research Council (ERC) grant ERC-2009-StG-240910-ROMETA.

*Griffith is at the Institute for Fiscal Studies and University of Manchester, Lee is at the Institute for Fiscal Studies and Seoul National University, and Straathof is at CPB Netherlands Bureau for Economic Policy Analysis. **Correspondence:** rgriffith@ifs.org.uk, sokbae@snu.ac.kr, s.m.straathof@cpb.nl.

# 1 Introduction

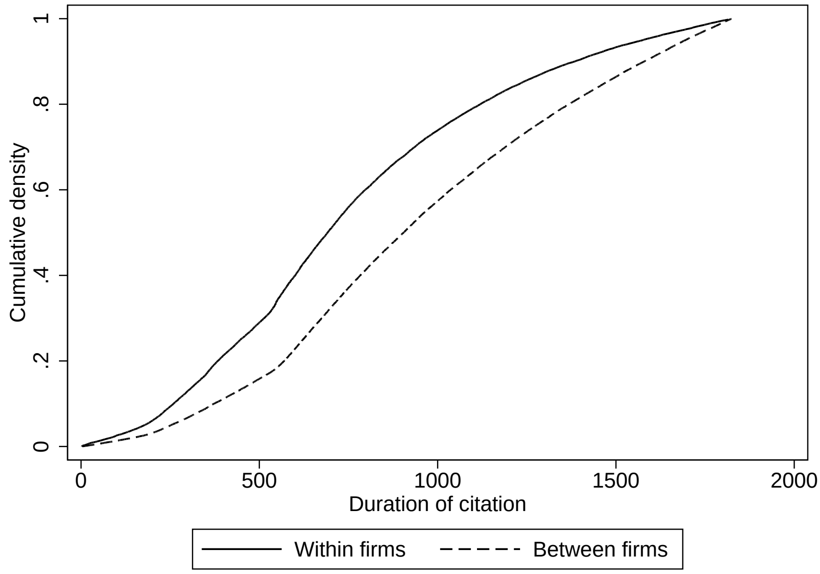
Innovation is reliant on the recombination of existing ideas, now more than ever (Jones (2009), Wuchty et al. (2007), Henderson and Clark (1990), Henderson and Cockburn (1990) and Weitzman (1998)). Firms combine prior art with their own ideas to form new patentable technologies. There is an extensive theoretical literature that details the ways by which market frictions, such as incomplete contracts, transactions costs and intellectual property rights, might stifle the transmission and use of ideas across firms, leading to less research than is socially desirable (Scotchmer (1991), Green and Scotchmer (1995), Bessen (2004), Boldrin and Levine (2013)).

Our contribution in this paper is to develop an empirically tractable model of search and innovation that we can take to data to learn about the size of these market frictions. We estimate the increase in effort that is required to successfully develop a new technology when it relies on transactions in the market, as opposed to internal to the firm. We use data on all patents applications made at the European patent office, matched to firm structures, to consider the length of time it takes a firm to build on an idea published in a patent held by a different firm, relative to an idea published in a patent held within the same firm.

In our data we see that on average it takes around 200 days longer for the first citation of a patent to occur when that citation is by a different firm than when it is by the same firm, see Figure 1 (data described below). Of course this could be due to a large number of potentially confounding factors; we use a multiple-spell duration model (Griffith et al. (2011)) to try to control for these. Our empirical approach controls for characteristics of the cited and citing patent; our identification strategy relies on variation between the time it takes for the first and second citation. Our central estimate suggests that successful discovery and use of information that leads to a new idea is around 30% more costly cross-firm than within-firm.

We compare this to the costs of search across geographic space, to which the empirical literature has paid a lot of attention, and to the costs of search across technological space. This compares to a 5% increase in costs when it is across national borders rather than within-country, and around 20% more costly across (4-digit) technology classes. These results suggest

Figure 1: Cumulative density of time to first citation in days if cited within 5 years




that the empirical magnitude of market frictions are substantial, and we interpret our evidence as pointing towards substantial imperfections in the market for technology.

Our paper is related to several relevant literatures. The patent system grants a firm monopoly rights over an idea for a fixed period, with the aim to provide monopoly rents to improve incentive to innovate (Schumpeter (1943), Nordhaus (1969) and Tirole (1988)), because there will be under-investment due to the public goods nature of ideas (Nelson (1959), Arrow (1962), Shapiro (2007)). Some argue that patents facilitate technology transfer (Acemoglu et al. (2008)), while others argue that they create a barrier to technology transfer (Bessen and Maskin (2009)). When new inventions build on old ones it is not clear what impact intellectual property rights such as patents will have on total innovation (Scotchmer (1991), Gallini and Scotchmer (2002), Boldrin and Levine (2008), and Boldrin and Levine (2013)).

A separate literature emphasises that firms have incentives to make it costly for other firms to build on their technology and effectively develop new recombinant technologies (Chang (1995), Horstmann et al. (2004), Arundel (2001)). Williams (2013) provides empirical evidence on the impact of intellectual property rights in stifling technology transer by looking at one technology; she provides evidence that patents on the human genome hindered subsequent scientific research and product development.

Also related to our work is the large literature that has considered the nature and boundaries of the firm, and when technology transactions will occur in the market or within the firm (Coase (1937), Williamson (1971), Williamson (1975), Williamson (1979), Arrow (1962), Grossman and Hart (1986), Davidson and McFetridge (1984) and more recently Irarrazabal et al. (2013), Mansfield and Romeo (1980), Bessen (2004) and Ponzetto (2012), Costinot et al. (2011)).

The paper proceeds as follows. In the next section we lay out a simple model of search and discovery of ideas for recombination to create new patentable technologies. In section 3 we layout our econometric approach to estimating the cost of search, discovery and use. In section 4 we describe the data, and in section 5 present our estimates. A final section summarizes and provides some final comments.

# 2 Theoretical framework

We develop a model in which the time and effort it takes for an inventor to develop and exploit a new idea depends on the efficiency with which they search and use prior results, and the expected value of the recombination when discovered. Research projects do not typically start from scratch, but are based on earlier findings - what is termed recombinant innovation. Researchers devote time talking to other researchers, read academic journals, visit fairs and conferences, reverse-engineer a competitor's product, and search patent databases. The more effort a researcher puts into finding and accessing these activities, the more likely it is that they develop a useful new technology.

In our model a researcher maximizes expected profits by searching for a recombination of existing technology with new ideas. The researcher decides how much effort to spend on searching for recombination of his own knowledge with knowledge of other researchers and on subsequently developing that knowledge. A successful recombination of technologies leads to a new innovation.

The expected value of the new innovation, $V_{\text{new}}$, depends on the value of the technology it is built on, $V_{\text{old}}$, and information available at time zero, $\Omega_0$, for example, information on future technological and demand opportunities. This can be written as

$$v \equiv \mathrm{E}(V_{\text{new}}|\Omega_0) = V_{\text{old}} + \mathrm{E}(\varepsilon|\Omega_0), \tag{1}$$

where $\varepsilon$ is the difference between the values of the new and old technologies, since $V_{\text{old}}$ is known at time zero. What matters in a researcher's search decision is the expected value of the new technology, not the realized value of it. The expected value $v$ consists of $V_{\text{old}}$ and $\mathrm{E}(\varepsilon|\Omega_0)$. In the next section we show how we can control for $v$, which is unobserved by the econometrician, in our econometric framework.

For simplicity we start by assuming that the researcher only has one direction in which to search for technology. We then we introduce a second direction for which efficiency of the search process and the value of recombinant innovation may differ. We assume that effort takes the form of expenditure by the researcher. In particular, the researcher has to spend $e_t > 0$ for all $t$ to continue the project.

Let $T$ be the moment when a recombination of technologies is discovered by the researcher. $T$ is a stochastic variable with marginal density function $f(t)$ and survival function $S(t)$. The expected revenue from searching for a short time interval $[t,\, t + \mathrm{d}t)$ equals the value of the innovation times the probability of a recombination during that interval, given that the recombination has not occurred at an earlier time:

$$\Pr\left(t \leq T < t + \mathrm{d}t | T \geq t\right) v.$$

The search is stopped as soon as a suitable technology is found. The continuation cost during

$[t,\, t + \mathrm{d}t)$ equals $e_t\, \mathrm{d}t$ if the technology has not been found before $t + \mathrm{d}t$ and zero otherwise:

$$\Pr\left(T \geq t + \mathrm{d}t | T \geq t\right) e_t \mathrm{d}t.$$

The expected discounted profits $\pi$ at time zero can be expressed as the integral over $t$ of expected increments in profits:

$$\mathrm{E}\left(\pi\right) = \int_0^\infty \exp\left(-\rho t\right) \mathrm{E}\left(\mathrm{d}\pi_t\right).$$

The value of the outside option is captured by the discount rate $\rho$. An expected increment in profits equals the expected increment in revenue minus the expected increment in cost:

$$\mathrm{E}\left(\mathrm{d}\pi_t\right) = \Pr\left(t \leq T < t + \mathrm{d}t | T \geq t\right) v - \Pr\left(T \geq t + \mathrm{d}t | T \geq t\right) e_t\, \mathrm{d}t.$$

After some manipulation, the profit increments can be written as a function of the hazard $\lambda\left(t\right)$ that a recombination takes place at $t$. Specifically,

$$\begin{aligned}
\mathrm{E}\left(\mathrm{d}\pi_t\right) &= \frac{\Pr\left(t \leq T < t + \mathrm{d}t\right) v - \Pr\left(T \geq t + \mathrm{d}t\right) e_t\, \mathrm{d}t}{\Pr\left(T \geq t\right)} \\
&= \frac{f\left(t\right) v \mathrm{d}t - S\left(t + \mathrm{d}t\right) e_t\, \mathrm{d}t}{S\left(t\right)} \\
&= \lambda\left(t\right) v \mathrm{d}t - \left[1 - \lambda\left(t\right)\right] e_t\, \mathrm{d}t \\
&= \left[\lambda\left(t\right)\left(v + e_t\right) - e_t\right] \mathrm{d}t.
\end{aligned}$$

The researcher can influence the hazard rate by varying effort at any point in time. If the response of the hazard rate to effort is instantaneous, we can write the current hazard as a function of the current effort. In particular, assume that the hazard $\lambda\left(t | e_t\right)$ is concave and monotonically increasing in $e_t$. The profit maximization problem for the researcher is dynamic, but does not involve a state variable, as the hazard rate is not affected by previous decisions made by the researcher.[1] The researcher maximizes expected profits by choosing an expenditure path:

$$\max_{e_t} \int_0^\infty \exp(-\rho t) \left[\lambda(t|e_t)(v+e_t) - e_t\right] \mathrm{d}t.$$

We now introduce a second direction for which the efficiency of searching may differ, and we allow the value of an invention to be different across directions. Let the expected value of recombination of the researcher's knowledge and a technology found in direction $i$ ("technology $i$") be $v_i$ and let the expected value of recombination with a technology $j$ be $v_j$. Expenditure on search in one direction does not affect the hazard rate in the second location for given expenditure in the latter direction.[2] Once a suitable technology has been found in either direction, searching in both directions is stopped.

In the two-direction case the expected flow of profits depends on the expenditure on searching in both directions:

$$\frac{\mathrm{E}(\mathrm{d}\pi_t)}{\mathrm{d}t} = \lambda_i(t|e_{it})\, v_i + \lambda_j(t|e_{jt})\, v_j - \left[1 - \lambda_i(t|e_{it}) - \lambda_j(t|e_{jt})\right](e_{it} + e_{jt}). \tag{2}$$

The first-order conditions for maximizing profits yield the condition that the ratio of marginal hazards should equal the inverse ratio of the values. That is, optimal expenditure paths $e_{it}^*$ and $e_{jt}^*$ satisfy

$$\frac{\partial\lambda_i(t|e_{it}^*)/\partial e}{\partial\lambda_j\left(t|e_{jt}^*\right)/\partial e} = \frac{v_j + e_{it}^* + e_{jt}^*}{v_i + e_{it}^* + e_{jt}^*}. \tag{3}$$

The equation (3) is a key equation to characterize the optimal expenditures. The following propositions consider two polar cases.

[1]The only possible effect of previous decisions is that the search was successful at an earlier moment. If a technology is found, a new search can be started and optimal expenditure will be the same as if no technology had been found.

[2]If the researcher faced a budget constraint, an increase in search efficiency for one direction could lead to reduction of effort in the other direction.

**Proposition 1** *Suppose that search efficiency is the same between two technologies:* $\lambda_i(t|e) = \lambda_j(t|e)$ *for all* $t$ *and* $e$*. If* $v_i \geq v_j$*, then* $e^*_{it} \geq e^*_{jt}$*.*

**Proof.** Let $\lambda(t|e)$ denote the common hazard function, that is $\lambda(t|e) = \lambda_i(t|e) = \lambda_j(t|e)$ for all $t$ and $e$. If $v_i \geq v_j$, it follows from (3) that

$$\frac{\partial\lambda(t|e^*_{it})}{\partial e} \leq \frac{\partial\lambda\left(t|e^*_{jt}\right)}{\partial e}.$$

As the hazard function is a concave function of effort, $e^*_{it} \geq e^*_{jt}$. ■

Proposition 1 says that when the expected value of technology $i$ rises relative to the expected value of technology $j$, then the hazard rate of finding technology $i$ increases relative to the hazard rate of $j$, provided search efficiencies are symmetric. In other words, it predicts that the *ex ante* more usefulness of recombination will lead to faster patent citations.

**Proposition 2** *Suppose that values of recombination are the same between two technologies:* $v_i = v_j$*. If*

$$\frac{\partial\lambda_i(t|e)}{\partial e} \geq \frac{\partial\lambda_j(t|e)}{\partial e} \quad \textit{for all } e, \tag{4}$$

*then* $e^*_{it} \geq e^*_{jt}$*.*

**Proof.** Since $v_i = v_j$, it follows from (3) that

$$\frac{\partial\lambda_i(t|e^*_{it})}{\partial e} = \frac{\partial\lambda_j\left(t|e^*_{jt}\right)}{\partial e}.$$

Hence, if (4) holds, then it must be that $e^*_{it} \geq e^*_{jt}$. ■

Proposition 2 says that when the expected value of recombination is the same for both directions, then higher search efficiency (expressed as a larger marginal increase in the hazard rate with respect to the expenditure) will result in faster patent citations.

The two propositions together imply that any difference in hazard rates between the two directions can be due to differences in search efficiency, differences in the expected value of technology, or both. In particular, Propositions 1 and 2 suggest that if we want to investigate the effect of barriers to knowledge diffusion we need to condition on expected values of recombination.

The expected values of recombination are intrinsically difficult to observe. Recall that $v_j = V_{\text{old, j}} + \mathrm{E}(\varepsilon_j|\Omega_0)$. In other words, $\mathrm{E}(\varepsilon_j|\Omega_0)$ represents the *ex ante* average difference between values of new and old technologies in direction $j$. Suppose that the second term $\mathrm{E}(\varepsilon_j|\Omega_0)$ can be well approximated by observed characteristics of the citing patent (that patent that makes the citation). This is a reasonable first-order approximation since the *ex ante* average difference is determined at time zero. Therefore, we will use an estimation method that is robust to *unobserved* quality differences in the cited patents $V_{\text{old, j}}$, while controlling for $\mathrm{E}(\varepsilon_j|\Omega_0)$ by including characteristics of the citing patent. Once we control for the expected value of recombination, then we can isolate differences in (marginal) search efficiency $(\partial\lambda_i(t|e)/\partial e)$. In this paper, our focus is whether and to what extent firm boundaries are a barrier to the diffusion of knowledge. Since other factors such as geographic proximity are likely to affect search costs, our estimation strategy controls for these other factors as additional explanatory variables.

# 3 Econometric approach

We are interested in investigating how firm boundaries affect the cost of searching for a new recombination. To isolate this effect we use a multiple-spell duration model similar to that of Griffith et al. (2011).

Cross-firm citations are likely to differ from within-firm citations for a number of reasons. Patents belonging to the same firm are more likely to have common inventors, draw from inventions originating in the same geographical area, and to have similar technological characteristics. All these factors can potentially explain why cross-firm citations are slower. We control for cross-inventor citations, cross-border citations, and cross-technology citations. If a substantial part of the cross-firm delay remains unexplained after controlling for these factors, we interpret this as suggesting that market frictions affect the citation duration.

A fourth reason why citations between firms might differ from citations within firms, is that patents cited between firms are more valuable than patents cited within the firm. Inventions are more likely to lead to follow-up research when they are valuable, such that valuable inventions have larger probability of being cited. If, in addition, follow-up research is more profitable if it is based on a patent owned by the same firm, then the expected value of cited patents will be smaller for within-firm citations then for cross-firm citation. Ignoring heterogeneity in the value of cited patents could lead to underestimation of the cross-firm citation delay. It is therefore crucial that we control for (unobserved) characteristics of cited patents.

We follow the literature that uses patent citation information as a direct measure of the recombination of knowledge. The citation of one patent by another strongly suggests that the first patent contained useful knowledge which helped the second innovation.[3] As in Griffith et al. (2011), we consider the intensity with which a patent is cited, and adopt a duration modelling framework that explicitly deals with the problem of unobserved patent characteristics that may be correlated with location or other characteristics.

Consider a patent application that will be cited by other patent applications. The time it takes for a patent to be cited is expected to be shorter if efficiency of searching is higher. This is especially relevant for the first few citations a patent receives as they are more likely to reflect newly acquired knowledge.

As emphasised in Section 2, firms will also search harder if the expected value of finding new recombination is larger. The *ex post* value of a recombination is not known prior to invention; we assume that the expectation that researchers have about the value of a recombination is a function of the value of the patent on which they intend to build. High-quality patents are more likely to lead to a new recombination than patents with a low quality. We treat the quality of cited patents as an unobserved (to us) characteristic. We estimate how the hazard of being

[3] A classic paper in this literature is Jaffe et al. (1993). Also, see the monograph by Jaffe and Trajtenberg (Jaffe and Trajtenberg, 2002) and other recent work (Thompson and Fox Kean, 2005; Thompson, 2006).

cited differs for citations within firms and citations between firms. We control for unobserved characteristics of the cited patent by using a method that is analogous to first-differencing a linear model - we compare citations that are adjacent in time for each cited patent (in particular, the first and second citations).

Let citing patents be indexed by $k$ and let cited patents be indexed by $\ell$. A citation of $\ell$ by $k$ has a duration $T_{\ell k}$, which is defined as the number of days between the application date of the cited patent and the application date of the citing patent. Let $X_{\ell k}$ be a vector of other observed attributes of citation $T_{\ell k}$ (including attributes of $k$ that do not vary with $\ell$) and let $V_\ell$ be the unobserved characteristics of the cited patent.

We model the hazard $\lambda$ that patent $\ell$ is cited by $k$ after $t_{\ell k}$ days, conditional on $X_{\ell k} = x_{\ell k}$ and $V_\ell = v_\ell$, as

$$\lambda\left(t_{\ell k}|x_{\ell k}, v_\ell\right) = \theta_\ell\left(t_{\ell k}|v_\ell\right)\exp\left(x'_{\ell k}\beta\right), \tag{5}$$

with $\theta_\ell\left(\cdot\right)$ being a cited-patent specific baseline hazard function and $\beta$ a vector of coefficients to be estimated. The empirical specification in (5) is motivated by the theoretical framework in Section 2, taking the particular shape of a mixed proportional hazard model. We aim to estimate effects of search costs using characteristics of citing patents ($X_{\ell k}$), while controlling for differences in values of cited patents with fixed effects $V_\ell$.

A patent can be cited by more than one other patent, so there can be multiple spells for a cited patent. We allow the attributes $X_{\ell k}$ and the unobserved characteristics $V_\ell$ to be correlated arbitrarily, but are assumed to be constant over time. We assume that $V_\ell$ is constant across citing firms, implying that a technology has the same *ex ante* value to everyone and is not more valuable to one firm than another. The baseline hazard function $\theta_\ell\left(\cdot\right)$ depends on the unobserved characteristics of the cited patent and is left unspecified. That is, the baseline hazard function is allowed to differ across cited patents in a general, unspecified way. The attributes $X_{\ell k}$ include 0-1 indicator variables for, amongst others, between-firm citations, cross-border citations, and cross-technology citations. The hazard rate will be smaller for citations that are more costly.

We can estimate the coefficients $\beta$ without knowing the cited-patent specific baseline hazard by exploiting observations on cited patents that receive multiple citations. Assuming that $X_{\ell k}$ and $X_{\ell k'}$ ($k \neq k'$) are independent of each other conditional on $X_{\ell k}$, $X_{\ell k'}$ , and $V_\ell$, we can follow the conditional likelihood approach of Griffith et al. (2011).[4] The intuition behind this approach is the following. Suppose a patent receives two citations. The probability that the observed first citation is first conditional on the duration of the first citation and conditional on the characteristics of both citations, is independent of the baseline hazard:

$$\begin{aligned}
&\Pr\left[T_{\ell 1} \leq T_{\ell 2} | T_{\ell 1} = t_{\ell 1}, X_{\ell 1} = x_{\ell 1}, X_{\ell 2} = x_{\ell 2}, V_\ell = v_\ell\right] \\
&= \frac{\theta_\ell\left(t_{\ell 1}|v_\ell\right) \exp\left(x'_{\ell 1}\beta\right)}{\theta_\ell\left(t_{\ell 1}|v_\ell\right) \exp\left(x'_{\ell 1}\beta\right) + \theta_\ell\left(t_{\ell 1}|v_\ell\right) \exp\left(x'_{\ell 2}\beta\right)} \\
&= \frac{\exp\left(x'_{\ell 1}\beta\right)}{\exp\left(x'_{\ell 1}\beta\right) + \exp\left(x'_{\ell 2}\beta\right)},
\end{aligned} \tag{6}$$

which does not depend on $v_\ell$ or $\theta_\ell(\cdot)$. For patents that are cited twice or more it is possible to estimate the coefficients $\beta$ without the incidental parameters problem.

There remains a problem of censoring. We need to observe at least two citations to implement this estimator, but for a large number of patents we do not (yet) observe two citations. The exclusion of these censored observations can lead to sample selection bias in the estimation results. For example, a patent granted in 1999 is more likely to have received two citations than a patent granted in 2004. Older patents are therefore more likely to be included in our sample than young patents. We correct for bias due to censoring in two stages. First, we exclude all patents that did not receive at least one citation within five years of the application date. We view these as a different type of patents - either low quality, or for other reasons not relevant for recombinant innovation. We restrict our analysis to the population of patents that receive at least one citation within five years. Second, to correct for those patents for which we do

[4]See, also, Chamberlain (1985), Ridder and Tunalı (1999), Horowitz and Lee (2004), and Lee (2008), among others.

not observe a second citation we weight all observations with the inverse censoring probability, as in Griffith et al. (2011). This is valid if the censoring is independent of citation durations and covariates. See the appendix of Griffith et al. (2011) for further details of the conditional maximum likelihood estimation method we have adopted.

# 4 Data

We use data on European patent applications made between 1985 and 2004 from the European Patent Office's (EPO's) Worldwide Statistical Patent Database (PATSTAT). The number of days between the date of application of a patent and the application dates of patents that are cited on that application provides information on the time it takes for one invention to lead to another.

Any legal person can apply for a patent, such that the applicant(s) listed on a patent application can be subsidiaries of a firm, parent companies or natural persons. The legal person(s) listed as applicants might not be the ultimate owners of the patent. For our purpose we are interested in the ultimate owner, as this relevant for considering the search costs and market frictions; therefore, we need information on the ownership structure of firms. Without this information, a subsidiary citing a patent from another subsidiary belonging to the same parent firm would be incorrectly identified as an inter-firm citation.

We use commercially available data on ownership structure for European firms (Amadeus) and US firms with European subsidiaries (Icarus) from Bureau Van Dijk (BVD). Names of corporate applicants in PATSTAT have been matched to BVD company names in order to identify the parent firms of applicants. The matching procedure as well as the resulting database are described in Abramovsky et al. (2008). Applicant names have been matched to company names for 15 European countries, four of which have been dropped because the number of patent applications from these countries is small.[5] The remaining 11 European countries are: Belgium, Denmark, Finland, France, Germany, Italy, Netherlands, Norway, Spain, Sweden and

[5]The following countries are dropped: Czech Republic, Greece, Poland and Portugal.

Table 1: Number of patents by country and industry of parent firm

| | BE, NL | DE | FR | GB | IT, ES | SCA | US | Total |
|---|---|---|---|---|---|---|---|---|
| Chemical | 11220 | 42107 | 11883 | 8102 | 5755 | 4818 | 68713 | 152598 |
| Electric | 6708 | 30896 | 13200 | 6048 | 5721 | 4269 | 41703 | 108545 |
| Engineer | 7884 | 52163 | 18367 | 10152 | 12129 | 9968 | 47353 | 158016 |
| ICT | 10653 | 18747 | 11624 | 5628 | 3580 | 7166 | 65072 | 122470 |
| Pharma | 5459 | 11053 | 5459 | 6617 | 3236 | 3861 | 37646 | 73331 |
| Other | 1840 | 6894 | 2404 | 1917 | 1202 | 1335 | 12458 | 28050 |
| Total | 43764 | 161860 | 62937 | 38464 | 31623 | 31417 | 272945 | 643010 |

Notes: Number of applications for a European Patent between 1985 and 1999. Excludes applications by non-corporate applicants (individuals, universities, etc.). Includes patents that are not cited. The row "Other" refers to applications without a Derwent Code. The country or country group of an application refers to the location of the parent company of the applicant. "BE" is Belgium, "NL" is Netherlands, "DE" is Germany, "FR" is France, "GB" is Great Britain, "IT" is Italy, "ES" is Spain, and "SCA" comprises Denmark, Finland, Norway, and Sweden.

UK. We use information on parent firms in these European countries plus the US and EPO patent applications made by their subsidiaries that are located in these countries. The sample period of our data spans from 1985 through 2004 and we focus on applications for a European patent between 1985 and 1999 to have a five-year window of forward citations.

We identify the industries in which the technology developed in each patent is applied using the Derwent Innovation Index Manual Codes. Abramovsky et al. (2008) provide a comparison of Derwent Codes with NACE and International Patent Classification (IPC) codes. Table 1 shows the number of cited patents by industry and country of the parent firm.[6] Engineering, ICT, and chemical are the industries with the largest number of patent applications. The pharmaceutical industry has the smallest number of applications. The United States has by far the most patent applications, followed by Germany. The three largest cells in the table are ICT and chemical in the US and engineering in Germany.

Identification of the cited-patent fixed effects requires that we observe at least two citations per patent. Table 2 displays summary statistics for our data. The first three rows are proportions of all patent applications made by corporations. More than eighty percent of all patent

[6] The industries are aggregates of Derwent Sections: "Chemical" includes the sections A, C, E, F, G, H, J, K, L, M, N; "Electric" includes S, V, X; "Engineer" includes P, Q; "ICT" includes W, T, U; "Pharma" includes B, D.

Table 2: Descriptive statistics by industry

| | Chemical | Electric | Engineer | ICT | Pharma | Other | Total |
|---|---|---|---|---|---|---|---|
| *Proportion of all patents (1985-1999)* | | | | | | | |
| with $\geq 2$ citations | 0.108 | 0.085 | 0.073 | 0.102 | 0.085 | 0.104 | 0.091 |
| with 1 citation | 0.099 | 0.093 | 0.087 | 0.098 | 0.066 | 0.090 | 0.090 |
| without citations | 0.793 | 0.823 | 0.841 | 0.800 | 0.850 | 0.806 | 0.818 |
| *Proportion of second citations* | | | | | | | |
| Cross-firm | 0.690 | 0.790 | 0.782 | 0.801 | 0.678 | 0.742 | 0.748 |
| Cross-inventor | 0.939 | 0.971 | 0.966 | 0.975 | 0.937 | 0.958 | 0.958 |
| Cross-border | 0.394 | 0.476 | 0.457 | 0.468 | 0.377 | 0.429 | 0.435 |
| Cross-tech. (3 digit) | 0.084 | 0.155 | 0.830 | 0.093 | 0.058 | N.A. | 0.252 |
| Cross-tech. (4 digit) | 0.130 | 0.217 | 0.850 | 0.162 | 0.115 | N.A. | 0.301 |

Notes: Data consist of corporate applications for a European Patent between 1985 and 1999. The first three rows are proportions of all patents in the sample; the other rows are proportions of all second citations of patents that have received their first citation within five years. Citations may occur between 1985 and 2005. "Cross-firm" requires that the cited patent and the citing patent have different ultimate owners. "Cross-border" requires that none of the inventors on the cited patent is located in the same country as any of the inventors on the citing patent. "Cross tech." refers to a match between the Derwent Code of the cited and citing patent (match at three- and four-digit level; a patent can be assigned several Derwent Codes).

applications since 1985 were not cited within five years. In pharmaceuticals this proportion is even higher. Nine percent of all applications received exactly one citation, another nine percent of all applications received two citations or more. Patent citations are censored at December 31, 2004. The patents that did not receive a citation prior to that date may still receive a citation at a future date. As this applies *a fortiori* for patents with an application date approaching the end of 2004, citations to these young patents are likely to be underrepresented compared to citations of older patents. We take censoring into account when estimating (Section 3).

The remaining rows of Table 2 show the proportion of second citations for our main variables of interest for patents that have received their first citation within five years. A citation is classified as a cross-firm citation if none of the applicants on the cited patent belong to the same parent firm as any of the applicants on the citing patent. A citation is considered to be a cross-inventor citation if none of the inventors on the citing patent are also listed as inventors on the cited patent. A cross-border citation requires that none of the inventors on the cited patent are located in the same country as any of the inventors on the citing patent.

A cross-technology citation means that none of the Derwent codes assigned to the cited patent match any of the Derwent codes assigned to the citing patent. We consider both three- and four-digit aggregation levels. Derwent manual codes, which are published by Thomson, classify patents according to the industries in which they are used. We use Derwent codes rather than the standard International Patent Classification (IPC) codes, as the IPC identifies patents according to their technological similarity and not their economic relatedness. Using Derwent codes we can construct a measure of technological distance that better reflects the perspective of inventors than examiners. About 75 percent of citations are across firms, 96 percent are across inventors, 44 percent are across countries, and 25 (30) percent of citations are across technology at the three-digit (four-digit) level.

Stylized facts suggest that differences ownership associated with substantial delays in the recombination of knowledge. The top panel of Table 3 shows the time it takes for a patent to be cited for the first time. It shows the number of days between the application date of the cited patent and the application date of the citing patent. The first line has the average number of days for citations of belonging to different firms and citations of patents belonging to the same firm. The average duration of citations between firms is 932 days, while the average duration of citations within firms is 730 days. Cross-firm citations are on average 28 percent slower than within-firm citations. The remaining part of the top panel of Table 3 displays the time to first citation for five industries. Citations take the least time in the pharmaceutical industry and take the most time in engineering. This holds both for citations between firms and citations within firms. The relative lag of citations between firm is smallest in electrical engineering and longest in pharmaceuticals. The bottom panel of Table 3 shows the time it takes for a patent to be cited for the second time. Cross-firm citations are on average 47 percent slower than within-firm citations. Citation patterns across industries are similar between the first and second citation.

That citations between firms are slower than citations within firms is not just a property of the mean citation time, but applies to the distribution of citation times as well. Figures 3 show

Table 3: Time to first and second citation in days if cited within 5 years

| | Between firms | Within firms | Difference | |
|---|---|---|---|---|
| | (days) | (days) | (days) | (% of within firm) |
| All first citations | 932 | 730 | 202 | 28 |
| *Industry* | | | | |
| Chemical | 899 | 701 | 199 | 28 |
| Electric | 961 | 791 | 170 | 21 |
| Engineer | 978 | 800 | 178 | 22 |
| ICT | 944 | 737 | 207 | 28 |
| Pharma | 804 | 618 | 186 | 30 |
| Other | 935 | 721 | 213 | 30 |
| All second citations | 1725 | 1174 | 550 | 47 |
| *Industry* | | | | |
| Chemical | 1693 | 1135 | 558 | 49 |
| Electric | 1813 | 1279 | 534 | 42 |
| Engineer | 1899 | 1370 | 529 | 39 |
| ICT | 1620 | 1151 | 469 | 41 |
| Pharma | 1504 | 952 | 552 | 58 |
| Other | 1777 | 1189 | 588 | 49 |

Notes: The data in the table are the average number of days between the application date of the cited patent and the application date of the patent that contains the first (second) citation if the first citation occurs within 5 years. Industry “Other” refers to patents that were not assigned a Derwent code. Section 4 describes the data in detail.

the cumulative density of citation time for between-firm citations and within-firm citations.

The number of observations available for our analysis might appear to be small in comparison with studies on patent application at the United States Patent and Trademark Office (USPTO). This is because of a number of differences in the patent application and examination process in the EPO and the USPTO.

One main reason is that there is that more innovation in the US than in Europe, and the EPO is a younger organization than the USPTO. In addition, there are some institutional reasons. The novelty requirements of the EPO are more strict than those of the USPTO. The EPO does not grant a patent when it is based on an idea that has been described before, or used for the same purpose before *anywhere in the world*. The USPTO requires that the invention was not known by others *in the United States*, and that the invention was not patented or

Table 4: Description of variables

| | |
|---|---|
| Citation duration | Number of days between the application date of the cited patent and the application date of the citing patent |
| Cross-firm | Equals one if none of the applicants on the citing patent have the same ultimate owner as any of the applicants on the cited patent |
| Cross-inventor | Equals one if none of the inventors on the citing patent are listed as an inventor on the cited patent |
| Cross-border | Equals one if none of the countries of the inventors on the citing patent match any of the inventor countries of the cited patent |
| Cross-technology | Equals one if none of the Derwent Codes at 4 (3) digit level on the citing patent match any of the 4 (3) digit Derwent Codes of the cited patent |
| Citing firm has >100 patents | Equals one if the number of patents applied for by the citing firm (ultimate owner) during the sample period is larger than 100 |
| Citations per patent of citing firm | Equals one if the average number of citations received by patents applied for by the citing firm (ultimate owner) during the sample period exceeds one |
| Log patents per industry/country/year | The natural logarithm of yearly number of applications per Derwent Section (2 digit) and country of citing firm (ultimate owner) |
| Cross-Atlantic | Indicator variable for citations on applications by US ultimate owners to applications by European ultimate owners, and vice versa |
| Citing patent is triadic | Equals one if a citing application is for an invention that also has patent applications with the USPTO and the JPO |
| Industry dummies | Indicator variables for Derwent Sections (2 digit) of the citing patent |

Table 5: Descriptive statistics

| | First citation | | | | Second citation | | | |
|---|---|---|---|---|---|---|---|---|
| Variable | Mean | Std. Dev. | Min | Max | Mean | Std. Dev. | Min | Max |
| Citation Duration | 802.37 | 429.50 | 0.00 | 1825 | 1592.29 | 1025.68 | 0.00 | 7128 |
| Cross-firm | 0.68 | 0.47 | 0.00 | 1.00 | 0.75 | 0.43 | 0.00 | 1.00 |
| Cross-inventor | 0.92 | 0.27 | 0.00 | 1.00 | 0.96 | 0.20 | 0.00 | 1.00 |
| Cross-border | 0.39 | 0.49 | 0.00 | 1.00 | 0.44 | 0.50 | 0.00 | 1.00 |
| Cross-tech. (3 digit) | 0.24 | 0.43 | 0.00 | 1.00 | 0.25 | 0.43 | 0.00 | 1.00 |
| Cross-tech. (4 digit) | 0.28 | 0.45 | 0.00 | 1.00 | 0.30 | 0.46 | 0.00 | 1.00 |
| Citing firm has > 100 patents | 0.65 | 0.48 | 0.00 | 1.00 | 0.65 | 0.48 | 0.00 | 1.00 |
| Citations per patent of citing firm | 0.37 | 0.48 | 0.00 | 1.00 | 0.28 | 0.45 | 0.00 | 1.00 |
| Log patents per industry/country/year | 6.43 | 1.13 | 0.00 | 8.48 | 6.54 | 1.15 | 0.00 | 8.53 |
| Cross-Atlantic | 0.24 | 0.42 | 0.00 | 1.00 | 0.27 | 0.44 | 0.00 | 1.00 |
| Citing patent is triadic | 0.41 | 0.49 | 0.00 | 1.00 | 0.39 | 0.49 | 0.00 | 1.00 |

described in a printed publication anywhere in the world.[7] As a consequence the number of patents granted by the USPTO is larger than the number of patents granted by the EPO.[8]

In addition, EPO applicants are not subject to a 'duty of candor' (Alcácer et al. (2008)). The incentive for applicants to cite other patents is therefore much smaller for EPO patents than it is for USPTO patents. Not only does this imply that European Patents on average receive fewer citations than their US counterparts, it also means that the proportion of EPO citations added by examiners is larger (Criscuolo and Verspagen (2008)). For this reason our main results are based on both inventor-added and examiner-added citations. Thompson (2006) shows that citations added by inventors are 20 percent more likely to match the country of the cited patent than examiner-added citations. This could lead us to underestimated border effects.

Tables 4 and 5 give a description of variables used in the next section and presents descriptive statistics for those variables. There are more cross-firm, more cross-inventor, more cross-border, more cross-tech, more cross-Atlantic citations in the second citations than in the first citations. 65 percent of citations are by firms with more than 100 patents and about 40 percent of citations are by triadic applications.

# 5 Empirical Results

We start by estimating the hazard function (5). Column (1) of Table 6 presents the estimates using the Cox estimator with an indicator for whether the citation is made across firms, including controls for the industry and country of the citing patents. This estimator does not control for unobserved cited patent characteristics or censoring. The negative and significant coefficient suggests that inventors are quicker to cite patent applications within the firm than from a different firm. Column (2) adds controls for whether the citation is cross-inventor, cross-border and cross-technology. If citations within a firm tend to be quicker, this could simply be a reflection of the fact that inventor self-citations are more prevalent among citations within firms

[7] 35 U.S.C. 102 Conditions for patentability; novelty and loss of right to patent.

[8] The difference in novelty requirements makes it more attractive for firms to apply for a patent in the US, as this already excludes the possibility of somebody else being granted a patent for the same invention.

Table 6: Estimation results

| Coefficient | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| Cross-firm | -0.373 | -0.244 | -0.444 | -0.441 | -0.391 |
| | (0.010) | (0.012) | (0.022) | (0.023) | (0.024) |
| Cross-inventor | | -0.671 | -0.765 | -0.737 | -0.706 |
| | | (0.018) | (0.038) | (0.038) | (0.039) |
| Cross-border | | -0.069 | -0.048 | -0.046 | -0.052 |
| | | (0.011) | (0.019) | (0.019) | (0.023) |
| Cross-technology | | -0.008 | 0.106 | 0.108 | 0.103 |
| (3-digit) | | (0.026) | (0.045) | (0.045) | (0.046) |
| Cross-technology | | -0.124 | -0.249 | -0.234 | -0.229 |
| (4-digit) | | (0.023) | (0.037) | (0.037) | (0.038) |
| Citing firm has | | | | -0.064 | -0.059 |
| >100 patents | | | | (0.019) | (0.019) |
| Citations per patent of | | | | 0.437 | 0.425 |
| citing firm | | | | (0.015) | (0.016) |
| Patents per industry/country/year | | | | | -1.144 |
| of citing patent | | | | | (0.046) |
| Cross-Atlantic citation | | | | | -0.097 |
| | | | | | (0.024) |
| Citing patent is triadic | | | | | 0.112 |
| | | | | | (0.016) |
| Estimator | Cox | Cox | Fixed effects (censoring) | Fixed effects (censoring) | Fixed effects (censoring) |

Notes: Standard errors are reported in parentheses. The duration is the time between the application dates of the cited and citing patent. All patents are included that have been cited at least twice and with the first citation occurring within five years since the application date. The number of observations is 48,816. In each specification, dummies are included for the countries and Derwent Sections of citing patents.

than among citations across firms. Unsurprisingly, cross-inventor citations are notably slower than citations to patents that share at least one inventor. The magnitude of the coefficient for across-firm citations declines from -0.37 to -0.24.

Searching for a patent that was applied for in another country can be more costly than searching domestically, because of differences in language and terminology, and because the probability of learning about a patent through other channels than searching a patent database will be smaller for foreign patents. Likewise, searching for a patent in an unfamiliar technological field is more costly than searching for patents in a related technological field. The estimated coefficients for cross-border citations and cross-technology citations are less than half of the size of the coefficient for cross-firm citations. This suggests that the effect of firm boundaries is more than two times as strong as the effects of national borders or technology, though it is half the size of the cross-inventor effect.

If an existing patent is particularly valuable, then this will induce researchers to seek to build on this patent, rather than on a patent that is less valuable. If within-firm recombinations are less costly or more rewarding than cross-firm inventions, this can make modest inventions more likely to be the result of within-firm recombinations. The average quality of patents cited across firms could be larger than the average quality of patents receiving citations from the same firm. This could lead to underestimation of the delay in citations to the patents of other firms.

In column (3) we correct for biases due to heterogeneity in patent quality by using the fixed effects estimator (6), also controlling for right censoring. The cross-firm coefficient increases in absolute terms from -0.24 to -0.45, suggesting that the average expected value of recombinations based on a patent from within your own firm is smaller than for recombinations based on patents of another firm. This is consistent with Arrow's replacement effect (Arrow (1962)).

Controlling for the quality of inventions also changes the other coefficients. The estimated effects of cross-inventor and cross-technology increase, which is consistent with the hypotheses that it is more difficult to follow-up on other people's inventions and that it is more difficult to combine distinct technologies. The decrease in the effect of national borders is statistically insignificant.

Although we control for unobserved characteristics of the cited patents, it might be that our results are partly driven by characteristics particular to citing patents or citations. We add observable characteristics of citing patents in columns (4) and (5). In column (4) two controls are added. First, firms that have many patents (>100) could be more likely to cite one of their own patents, even if cross-firm citations would not be slower than within-firm citations. Second, firms that own patents that receive many citations are likely to produce better patents and would therefore be more likely to cite one of their own patents.[9] We find that citations by large firms tend to be somewhat slower and that citations by highly cited firms are considerably

[9] Recall that the variable labelled as "Citations per patent of citing firm" equals one if the average number of citations received by patents applied for by the citing firm (ultimate owner) during the sample period exceeds one.

faster. The estimated cross-firm effect, as well as the other estimates are not affected.

In column (5) we add three more regressors. The natural logarithm of the number of patents per industry-country-year of the citing patent is included to take into account that patents are more prevalent in some industries, countries and years. For a 10% increase in the number of patents per industry-country-year of the citing patent, the coefficient decreases by about 0.1 ($\approx -1.144 \times \ln(1.1)$). The negative sign of this coefficient is consistent with the estimated effect of the "base" variable in Griffith et al. (2011). Second, an indicator for cross-Atlantic citations is included as citations of or by patents owned by American firms might take longer than citations between European firms. As expected from the coefficient of the cross-border effect, cross-Atlantic citations have a negative effect (are slower). Third, an indicator for citing patents that are also applied for at USPTO and JPO (triadic patents) is included. Triadic patents are more valuable, the expected value of research leading to these patents will also have been larger. This increases the hazard rate of citations from a triadic patent. Adding these three controls reduces the absolute size of the other coefficients somewhat.

Our final result suggests that the mean hazard rate of a citation across firms is 32% smaller ($1-\exp(-0.39)$) than the hazard rate for a citation within the firm. The effect of ownership on the speed of recombination is substantial, much larger than the delay of recombination across geographic space 5% or technological fields (15%, 3-digit and 4-digit combined).

We also consider whether the effects of ownership on the speed of recombination vary across industries.[10] Table 7 shows the results for our final specification for subsamples of patent applications by industry of use (based on Derwent classification). The differences across industries are generally modest. Cross-firm citations are fastest in pharmaceuticals (a delay of 27%) and slowest in chemical engineering 37%. These results only slightly different from the delay of 32% found for the full sample. In the industry-by-industry estimates cross-border citations are not significantly slower than citations within countries (point estimates range from 1% to 5%). This is consistent with findings in Griffith et al. (2011), Keller (2002) and Thompson (2006). At

[10]We repeat this exercise excluding all observations that are cross-inventor and obtain equivalent results; these are available from the authors on request.

Table 7: Estimation results by industry of ultimate owner of cited patent

| | Chemical | Electric | Engineering | ICT | Pharma |
|---|---|---|---|---|---|
| Cross-firm | -0.461 | -0.409 | -0.409 | -0.333 | -0.312 |
| | (0.041) | (0.058) | (0.051) | (0.051) | (0.068) |
| Cross-inventor | -0.800 | -0.962 | -0.621 | -0.584 | -0.717 |
| | (0.060) | (0.113) | (0.089) | (0.104) | (0.093) |
| Cross-border | -0.047 | 0.005 | -0.015 | -0.041 | -0.049 |
| | (0.042) | (0.049) | (0.045) | (0.049) | (0.067) |
| Cross-technology | 0.085 | 0.130 | 0.056 | 0.042 | 0.099 |
| (3-digit) | (0.086) | (0.100) | (0.156) | (0.086) | (0.152) |
| Cross-technology | -0.234 | -0.247 | -0.269 | -0.112 | -0.387 |
| (4-digit) | (0.069) | (0.082) | (0.152) | (0.065) | (0.108) |
| Citing firm has | -0.110 | -0.017 | -0.126 | -0.037 | 0.079 |
| >100 patents | (0.036) | (0.042) | (0.041) | (0.041) | (0.060) |
| Citations per patent of | 0.457 | 0.422 | 0.458 | 0.370 | 0.378 |
| citing firm | (0.027) | (0.038) | (0.035) | (0.033) | (0.044) |
| Patents per industry/country/year | -0.637 | -0.815 | -0.887 | -1.367 | -0.609 |
| of citing patent | (0.066) | (0.054) | (0.061) | (0.059) | (0.070) |
| Cross-Atlantic citation | 0.006 | -0.003 | -0.122 | -0.116 | -0.049 |
| | (0.042) | (0.052) | (0.054) | (0.047) | (0.066) |
| Citing patent is triadic | 0.074 | 0.195 | 0.128 | 0.086 | 0.089 |
| | (0.027) | (0.040) | (0.038) | (0.032) | (0.046) |
| Number of obs. | 14,268 | 8,145 | 10,330 | 10,897 | 5,191 |

Notes: Results for fixed effects estimation with censoring correction. Standard errors are reported in parentheses. For each industry of the parent firm all patents are included that have been cited at least twice and with the first citation occurring within five years since the application date. Dummies are included for the countries and Derwent Sections of citing patents. Country-industry combinations with a small number of observations were clustered.

the 4 digit level, cross-technology citations are between 10% (ICT) and 30% (pharmaceuticals) slower. This is consistent with the delay of 20% found for the full sample.

# 6 Summary and discussion

We find robust empirical evidence that market frictions are substantial in the market for technology. Firm boundaries lead to slower citation times. Our baseline regression results imply that the delay caused by firm boundaries is about 230 days on average $0.32 * 780$, much larger than the delay due to national borders or technological distance. These results speak to the debate on how well technology markets work. The theoretical literature emphasizes the importance of these frictions, but there has been relatively less empirical work. Our results suggest that the empirical magnitude of market frictions are substantial, and we interpret our evidence as pointing towards substantial imperfections in the market for technology.

# References


Abramovsky, L., R. Griffith, G. Macartney, and H. Miller (2008). The location of innovative activity in Europe. IFS Working Paper WP08/10.

Acemoglu, D., K. Bimpikis, and A. Ozdaglar (2008). Experimentation, patents, and innovation. NBER Working Paper 14408.

Alcácer, J., M. Gittelman, and B. Samplat (2008). Applicant and examiner citations in US patents: An overview and analysis. Harvard Business School Working Paper 09-016.

Arrow, K. (1962). Economic welfare and the allocation of resources for invention. In *The Rate and Direction of Inventive Activity: Economic and Social Factors*, pp. 609–626. Princeton: NBER, Princeton University Press.

Arundel, A. (2001). The relative effectiveness of patents and secrecy for appropriation. *Research Policy 30*, 611–624.

Bessen, J. (2004). Holdup and licensing of cumulative innovations with private information. *Economic Letters 82*(3), 321–326.

Bessen, J. and E. Maskin (2009). Sequential innovation, patents and imitation. *RNAD Journal of Economic 40*(4), 611–635.

Boldrin, M. and D. Levine (2008). Perfectly competitive innovation. *Journal of Monetary Economics 55*, 435–453.

Boldrin, M. and D. Levine (2013). The case against patents. *Journal of Economic Perspectives 27*(1), 3–22.

Chamberlain, G. (1985). Heterogeneity, omitted variable bias, and duration dependence. In J. J. Heckman and B. Singer (Eds.), *Longitudinal Analysis of Labor Market Data*. Cambridge: Cambridge University Press.

Chang, H. (1995). Patent scope, antitrust policy, and cumulative innovation. *RAND Journal of Economics 26*(1), 34–57.

Coase, R. H. (1937). The nature of the firm. *Economica 16*(4), 386–405.

Costinot, A., L. Oldenski, and J. Rauch (2011). Adatation and the boundary of multinational firms. *Review of Economics and Statistics 93*, 298–308.

Criscuolo, P. and B. Verspagen (2008). Does it matter where patent citations come from? inventor vs. examiner citations in European patents. *Research Policy 37*, 1892–1908.

Davidson, W. and D. McFetridge (1984). International technology transactions and the theory of the firm. *Journal of Industrial Economics 32*, 253–264.

Gallini, N. and S. Scotchmer (2002). Intellectual property: When is it the best incentive system? *Innovation Policy and the Economy 2*, 51–77.

Green, J. and S. Scotchmer (1995). On the division of profit in sequential innovation. *RAND Journal of Economics 21*(1), 147–160.

Griffith, R., S. Lee, and J. Van Reenen (2011). Is distance dying at last? Falling home bias in fixed effects models of patent citations. *Quantitative Economics 2*, 211–249.

Grossman, G. and O. Hart (1986). The costs and benefits of ownership: A theory of vertical and lateral integration. *Journal of Political Economy 94*(4), 691–719.

Henderson, R. and K. Clark (1990). Architectural innovation: The reconfiguration of existing product technologies and the failure of established firms. *Administrative Science Quarterly 35*, 9–30.

Henderson, R. and I. Cockburn (1990). Measuring competence? Exploring firm effects in pharmaceutical research. *Strategic Management Journal 15*, 63–84.

Horowitz, J. L. and S. Lee (2004). Semiparametric estimation of a panel data proportional hazards model with fixed effects. *Journal of Econometrics 119*(1), 155–198.

Horstmann, I., G. MacDonald, and A. Slivinski (2004). Patents as information transfer mechanisms: To patent or (maybe) not to patent. *Journal of Political Economy 93*, 837–858.

Irarrazabal, A., A. Moxnes, and L. Opromolla (2013). The margins of multinational production and the role of intrafirm trade. *Journal of Political Economy 121*(1), 74–126.

Jaffe, A. B. and M. Trajtenberg (2002). *Patents, citations and innovation: A window on the knowledge economy*. Cambridge: MIT Press.

Jaffe, A. B., M. Trajtenberg, and R. Henderson (1993). Geographic localization of knowledge spillovers as evidenced by patent citations. *Quarterly Journal of Economics 108*(3), 577–598.

Jones, B. (2009). The burden of knowledge and the death of the renaissance man: Is innovation getting harder? *Review of Economic Studies 76*, 283–317.

Keller, W. (2002). Geographic localization of international technology diffusion. *American Economic Review 92*(1), 120–142.

Lee, S. (2008). Estimating panel data duration models with censored data. *Econometric Theory 24*, 1254–1276.

Mansfield, E. and A. Romeo (1980). Technology transfer to overseas subsidiaries by U.S.-based firms. *Quarterly Journal of Economic 95*, 737–750.

Nelson, R. (1959). The simple economics of basic scientific research. *Journal of Political Economy 67*(3), 297–306.

Nordhaus, W. (1969). *Invention, Growth and Welfare: A Theoretical Treatment of Technological Change*. Cambridge USA: MIT Press.

Ponzetto, G. (2012). Intellectual property rights and efficient firm organization. *CEPR Discussion Paper 9212*.

Ridder, G. and I. Tunalı(1999). Stratified partial likelihood estimation. *Journal of Econometrics 92*(2), 193–232.

Schumpeter, J. A. (1943). *Capitalism, Socialism and Democracy.* London: George Allen & Unwin.

Scotchmer, S. (1991). Standing on the shoulders of giants: Cumulative research and the patent law. *Journal of Economic Perspectives 5*(1), 29–41.

Shapiro, C. (2007). Patent reform: aligning reward and contribution. *NBER Working Paper 13141.*

Thompson, P. (2006). Patent citations and the geography of knowledge spillovers: Evidence from inventor- and examiner-added citations. *Review of Economics and Statistics 88*(2), 383–388.

Thompson, P. and M. Fox Kean (2005). Patent citations and the geography of knowledge spillovers: A reassessment. *American Economic Review 95*(1), 450–460.

Tirole, J. (1988). *The theory of industrial organization.* Cambridge, Mass. and London: MIT Press.

Weitzman, M. L. (1998). Recombinant growth. *Quarterly Journal of Economics 113*(2), 331–360.

Williams, H. (2013). Intellectual property rights and innovation: Evidence from the human genome. *Journal of Political Economy 121*(1), 1–27.

Williamson, O. (1971). Vertical integration of production: market failure considerations. *American Economic Review 61*(2), 112–123.

Williamson, O. (1975). *Markets and Hierarchies: Analysis and Antitrust Implications*. New York: The Free Press.

Williamson, O. (1979). Transaction-cost economics: the government of contractual relations. *The Journal of Law and Economics 22*(2), 233–261.

Wuchty, S., B. Jones, and B. Uzzi (2007). The increasing dominance of teams in production of knowledge. *Science 316*(18 May 2007), 1036–1039.