

Strategic Patenting and Software Innovation*

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May 23, 2006

Abstract

Strategic patenting is widely believed to raise the costs of innovating, especially in industries characterised by cumulative innovation. This paper studies the effects of strategic patenting on R&D, patenting and market value in the computer software industry. We focus on two key aspects: patent portfolio size which affects bargaining power in patent disputes, and the fragmentation of patent rights ('patent thickets') which increases the transaction costs of enforcement. We develop a model that incorporates both effects, together with R&D spillovers. Using panel data for the period 1980-99, we find evidence that both strategic patenting and R&D spillovers strongly affect innovation and market value of software firms.

JEL No. L43, L86, O31, O32, O33, O34, O38

Keywords: patents, anti-commons, patent thickets, R&D spillovers, market value

***Acknowledgement:** We would like to thank Anne Layne-Farrar for her help at many stages of this project, and the Microsoft Corporation for financial support for the research. We are grateful to Sharon Belenzon, Bronwyn Hall, Josh Lerner, Marc Rysman and Manuel Trajtenberg for constructive suggestions on an early version of the paper. We alone are responsible for any findings and conclusions in the paper.

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1 Introduction

There is an extensive empirical literature demonstrating that R&D creates positive technology spillovers that contribute to innovation and productivity. This consensus underpins the justification for government R&D-support policies. At the same time, however, there is a growing concern that the *patenting* of innovations is itself becoming an impediment to the innovation process. The argument is that strategic patenting activity creates patent thickets that constrain firms' freedom of action in R&D and thus raise the costs of innovation. The dangers of patent thickets are frequently raised in public debates on patent reform – for example, National Research Council (2004).

The concerns have been intensified by the acceleration in patenting over the past two decades, especially in high tech industries. During the period 1976-1996, the total number of patent applications in the U.S. grew at an average annual rate of 1.8 percent. The growth accelerated from the mid-1980s, when there was a pro-patent shift associated with the establishment of the specialized Court of Appeals for the Federal Circuit (CAFC) and other developments (Kortum and Lerner, 1999; Jaffe and Lerner, 2004). In the period 1986-1996, aggregate patenting grew at 3.5 percent annually. This growth was particularly rapid in high tech industries – for example, 4.0 percent in pharmaceuticals, 7.1 in medical instruments, 9.3 in biotechnology, 11.0 in semiconductors and 11.2 percent in software. The growth in software patenting was due in part to recent judicial decisions during this period that limited the scope of software copyright protection, and extended the patentability of software (in particular algorithms not embedded in hardware).

There is evidence that firms, especially in high-tech industries, try to resolve patent disputes by cross licensing agreements, patent pools and other cooperative mechanisms (Lanjouw and Schankerman, 2004). The importance of such mechanisms is greatest in complex technology industries where innovation is cumulative, building on component innovations from different firms (Hall and Ziedonis, 2001; Ziedonis, 2003a, 2003b). In such industries, it is a widely held view that patenting activity creates a 'thicket' of fragmented property rights that impedes R&D activity by constraining the ability of firms to operate without extensive licensing of complementary technologies. This position was first enunciated by Heller and Eisenberg (1998), who labelled it the 'problem of the

anti-commons.¹ By increasing the transaction costs of R&D, patent thickets provide an incentive for firms to patent defensively. In effect, this argument implies that patenting creates a negative externality on other firms: by increasing the firm's bargaining power in the form of more 'chits to trade' in patent disputes, patenting by one firm raises the cost to other firms of protecting or appropriating the rents from their innovations. Some authors have claimed that this creates a prisoner's dilemma which can lead to excessive patenting in complex technology industries, including semiconductors and software (Bessen and Maskin, 2000).

Strategic patenting encompasses two conceptually distinct issues, which have not always been sharply distinguished in the literature. The first involves the link between patent portfolio size and bargaining power. Having a larger patent portfolio puts a firm in a better position to bargain with other firms when patent disputes arise. More 'patent chits' mean greater bargaining power and thus more favourable outcomes in the resolution of patent disputes. The second aspect involves the link between transaction costs and the number of potential disputants. When a firm faces many firms with whom patent disputes may arise, transaction costs rise. Moreover, since disputes are normally resolved bilaterally (not collectively), having to deal with many disputants makes bargaining failures more likely and creates the 'complements problem' – value maximisation requires coordinated resolution which is ignored by independent claimants (Shapiro, 2001).

Despite widespread concern over the issue, the econometric evidence on the effects of patent thickets is limited. The two leading empirical studies are Hall and Ziedonis (2001) and Ziedonis (2003a), both of which focus on the semiconductor industry. The Hall and Ziedonis study shows that patenting rose sharply in the 1990's (after controlling for R&D and other factors), especially for capital intensive semiconductor firms. While indirect, this evidence is consistent with defensive patenting and patent thickets, since the danger of ex post holdup would be greater for such firms. Ziedonis (2003b) tests the hypothesis more directly by examining the relationship between firm-level patenting and a measure of the fragmentation of patent rights. She finds that patenting is higher (in the cross section of firms) when firms face greater fragmentation (lower concentration)

¹For opposing views on the dangers of patent thickets in software, see Lessig (2001) and Mann (2005). Merges (1996, 1999) has been a leading voice arguing that firms find ways to contract around patent thickets. Walsh, Arora and Cohen (2003) and Walsh, Cho and Cohen (2005) present supporting survey evidence in the context of biomedical research activity.

of patent rights among rival firms. Both of these papers focus exclusively on the impact of patent thickets on patenting behaviour. The impact of patent thickets on the R&D decision and the market valuation of firms remains unexplored. In addition, there is a need for a formal analytical model that generates testable predictions about the impact of strategic patenting – both patent portfolio size and the fragmentation of patent rights.²

This paper studies the impact of strategic patenting by technology rivals on the R&D spending, patenting and market value of firms in the computer software industry. Like semiconductors, software is a classic example of a complex technology in which cumulative innovation plays a central role. In this paper we incorporate both aspects of strategic patenting – portfolio size to capture the bargaining power, and fragmentation of patent rights to capture the transaction costs of enforcing patent rights. We develop a model that allows us identify the two negative externalities from patenting, as well as the positive technology spillovers from R&D. All three externalities are related to the firm’s proximity to other firms in technology space. We measure technology proximity using information on the distribution of the citations contained in a firm’s patents to different technology classes. In the empirical specification of the model, we follow the approach developed in Bloom, Schankerman and Van Reenen (2005), using multiple indicators of performance (market value, patents and R&D) in order to help identify the three types of externalities in which we are interested.

Using panel data on ‘software firms’ in the U.S. during 1980-99, we find evidence of both strategic patenting and R&D spillovers. There are three key findings. First, greater patenting activity by technology rivals significantly reduces the firm’s market value, patenting and R&D. We interpret this finding as indicating the importance of bargaining power in resolving patent disputes. Second, we find that higher concentration (less fragmentation) of patent rights – which corresponds to lower transaction costs – is associated with higher market value, but lower R&D and patenting activity. The third finding is that R&D spillovers significantly increase patenting and market value, controlling for the firm’s stock of R&D. These three findings are all consistent with the predictions of the model. Finally, we also find that there is a large ‘patent premium’ in the stock market for

²While not specifically testing the patent thickets hypothesis, in an unpublished empirical paper Bessen and Hunt (2003) argue that software patenting has actually reduced the level of R&D. This highly controversial paper has been sharply criticised by Hahn and Wallsten (2003).

these software firms, controlling for the stock of R&D and other factors. Calculations suggest that this patent premium accounts for about 20 percent of the private return to R&D for these software firms.

Before proceeding we want to emphasise that, in addition to technology (or knowledge) spillovers, R&D can also create a product market rivalry or business stealing effect.³ In a recent paper, Bloom, Schankerman and Van Reenen (BSV, 2005) develop a methodology for distinguishing between technology spillovers and product market rivalry and apply it to a large panel of U.S. firms. Their identification strategy relies on two features: first, using distinct measures for distance between firms in the technology and product market spaces, and second, using multiple outcome measures that are affected by spillovers and product market rivalry (namely, R&D, patents and market value). As pointed out above, the current paper follows BSV in exploiting these three outcome measures. However, the objective of the current paper is very different in that we want to identify the effects of strategic patenting in the context of technology spillovers. To keep the framework tractable, we do not incorporate product market rivalry into the model or the empirical analysis. In principle, it should be possible to construct an encompassing model that includes strategic product market rivalry as well as strategic patenting effects, but we do not do that here. On the empirical side, the current paper focuses on software firms (whereas the BSV paper studies a wide range of manufacturing and non-manufacturing industries). If demand complementarities are especially important in software, as many believe, then it may prove empirically difficult to isolate product market rivalry effects in this industry, but that question is beyond the scope of this paper.

The paper is organised as follows. Section 2 presents the theoretical model (details are in Appendix 1) and summarises the empirical predictions. In Sections 3 and 4 we describe the data set and the construction of the strategic patenting and technology spillover variables. Section 5 presents the econometric specification of the three equations in the model – market value, patenting and R&D. The empirical results and their implications are discussed in Section 6.

³The earliest attempt to distinguish technology spillovers and product market rivalry is Jaffe 1988. Branstetter and Sakikabara (2002) study the issue in the context of research consortia. For a theoretical and empirical analysis of these issues, see Bloom, Schankerman and Van Reenen (2005).

2 Analytical Framework

A firm (say, firm 0) produces knowledge by investing in R&D, but it also may benefit from technology spillovers from firms that are close in technology space (technology rivals, denoted by τ). The knowledge production function is $k_0 = \phi(r_0, r_\tau)$. Its technology rivals have a similar knowledge production function, $k_\tau = \phi(r_\tau, r_0)$. We assume that ϕ is non-decreasing and concave in both arguments. When a firm makes its R&D decision, it recognises that it generates as well as receives technology spillovers.

The firm chooses the fraction of its knowledge that it protects by patenting ('patent propensity'). We let $\rho \in (0, 1)$ denote the patent propensity and $\lambda \geq 1$ denote patent effectiveness, i.e., the appropriation of rents from a given innovation if it patented relative to the rents if it is not patented. Thus $\lambda - 1$ represents the patent premium.

The firm has a variable profit function defined over prices of variable inputs, w , and the stock of knowledge, k_0 , which we denote by $\pi(\theta_0 k_0, w)$ where $\theta_0 = \rho_0 \lambda + (1 - \rho_0)$. The profit function is increasing and concave in k_0 , and decreasing and convex in w . For notational simplicity we suppress the input prices in what follows.

Patenting is costly. The unit cost of a patent includes a fixed administrative fee denoted by f , and a patent enforcement cost denoted by H . Enforcement costs depend on two features of the patenting environment in which the firm operates. The first is the degree to which patent rights are held by a relatively small number of other firms rather than being widely dispersed. When patent rights are more concentrated, it is less costly for a patentee to contract with other relevant patentholders to conduct its R&D activity, which is referred to by Shapiro (2001) as 'navigating the patent thicket.' The second determinant of enforcement costs is the portfolio size of the firm relative to firms with whom it needs to negotiate in order to avoid, or resolve, disputes. Having a larger relative portfolio size puts the firm in a better bargaining position, and facilitates patent trading (cross licensing) arrangements to resolve disputes without resorting to expensive litigation.

To capture these ideas, we assume that the enforcement cost for firm 0 is a function of two factors: (1) the number of patents held by firm 0 relative to firm τ , denoted by $x = \frac{\rho_0 k_0}{\rho_\tau k_\tau}$ (the bargaining power effect), and (2) the degree of concentration of patents held by firms in similar

technology areas, denoted by c (the patent thicket effect).⁴ Formally, we let $H = H(x, c)$, where it is assumed that $H_x \leq 0$, $H_{xx} \geq 0$, $H_c \leq 0$, $H_{xc} \leq 0$, and $H(0, 0) > 0$. Relative portfolio size, x , is endogenous since the firm chooses its patent propensity ρ_0 . We treat the concentration of patents by firms in similar technology areas, c , as exogenous to the firm.

By assuming that bargaining power depends on the relative (rather than absolute) number of patents between a firm and its technology neighbors, we highlight the idea that it might be mutually beneficial for firms to reduce their propensities to patent, putting aside the lower level of innovation rents if there was a patent premium. In other words, there may be a prisoner’s dilemma aspect to strategic patenting. In the empirical section, we will use the parameter estimates to test whether this prisoner’s dilemma actually operates for the software firms in our sample.

The direct effect of higher concentration of patents among a firm’s technology rivals is to reduce its enforcement costs – that is, $H_c \leq 0$. However, there is also an indirect effect because higher concentration may change the marginal value of accumulating patents to reduce enforcement costs, which is $|H_x|$. This indirect effect can be either positive or negative – it depends on the sign of H_{xc} . We find it most plausible that higher concentration of patent rights reduces the marginal value of accumulating patent portfolios – $H_{xc} > 0$ – because in such cases firms are more likely to have other ways of ‘tacit cooperation’ apart from explicit patent trading arrangements. We will investigate the theoretical implications of this hypothesis below and test it in the empirical section.

Firm 0 sets (r_0, ρ_0) to maximise the value of the firm:

$$\max_{r_0, \rho_0} V = \pi(\theta_0 \phi(r_0, r_\tau)) - r_0 - \{f\rho_0 + H(x, c)\}\phi(r_0, r_\tau) \quad (1)$$

Recall that $k_0 = \phi(r_0, r_\tau)$ also enters the function $H(x, c)$ since $x = \frac{\rho_0 k_0}{\rho_\tau k_\tau}$. In this specification we assume that the enforcement cost applies both to patented and unpatented innovations. The idea is that if a firm has more trading chits in the form of patents, it can also more easily resolve disputes over unpatented innovations.⁵

⁴Patent concentration is the obverse of the fragmentation of patent rights discussed in the literature on patent thickets. In the next section we discuss the measurement of this variable.

⁵An alternative specification is to assume that the enforcement cost is higher for patented innovations. We can do this by expressing unit cost as $f\alpha_0 + \{(1 + \mu)\alpha_0 + (1 - \alpha_0)\}H$, where $\mu \geq 0$. The qualitative predictions in this specification are similar to those in the text.

The first order conditions are

$$V_{r_0} = \phi_1^0 \{ \theta_0 \pi' - f \rho_0 - H \} - \left(\frac{\rho_0 k_0}{\rho_\tau k_\tau} \right) (k_\tau \phi_1^0 - k_0 \phi_2^\tau) H_x - 1 = 0 \quad (2)$$

$$V_{\rho_0} = \phi_1^0 (\lambda - 1) \pi' + f k_0 + k_0 \left(\frac{k_0}{\rho_\tau k_\tau} \right) H_x = 0 \quad (3)$$

where the superscripts on ϕ refer to the firm and subscripts 1 and 2 denote partial derivatives with respect to the different arguments. The first term in equation (2) is the marginal benefit of R&D net of patent enforcement costs. The second term is the reduction in marginal enforcement cost from increasing the stock of knowledge, holding the patent propensity constant. The sum of these benefits must equal the marginal cost of R&D. In equation (3), the firm's choice of patent propensity trades off the administrative cost of patenting against the increased appropriation of innovation rent due to the patent premium and the reduction in patent enforcement costs due to having a larger patent portfolio.

We analyse the comparative statics of the best response functions of firm 0, treating the R&D and patenting decisions of rivals τ as given (Appendix for details). Table 1 summarises the model's predictions about the impact of the patent propensity of rivals (ρ_τ , capturing bargaining power), concentration of patent rights (c , capturing patent thickets), and technology spillovers (r_τ). All three effects have testable implications in the R&D, patents and market value equations. Thus using multiple outcomes provides a stronger test of the model than we would have from any single indicator.

[Table 1 about here]

We can summarize the model's predictions as follows. First, a higher patent propensity by technology rivals (given their R&D spending) means less bargaining power in patent disputes for a firm. This lowers optimal R&D, patents and market value.⁶ Second, greater concentration of patent

⁶The result that more patenting by rivals reduces a firm's own patenting (conditional on its R&D) may be surprising. If other firms have more patents, then it may seem that the incentive to accumulate countervailing bargaining chips would be higher. In the model, what matters is how patenting by rivals affects the firm's *marginal*

rights among technology rivals means lower transaction costs for a firm in licensing complementary patents and resolving patent disputes. This increases market value unambiguously. The direct effect of higher concentration on R&D and patenting is also to raise R&D and patenting. However, the indirect effect can go either way, depending on the sign of H_{xc} . If concentration reduces the marginal value of accumulating patents in enforcing patent rights ($H_{xc} > 0$), then the direct and indirect effects work in opposite directions and the impact on R&D and patents is ambiguous. Conversely, if $H_{xc} < 0$ then concentration must raise R&D and patenting. Therefore, if we find that concentration has a negative impact on R&D and patenting, we can infer that $H_{xc} > 0$. Third, technology spillovers increase patents and market value, but the effect on R&D depends on how spillovers affect the marginal product of own-R&D.

3 Data

Our data set covers the period 1976-1999 and is constructed from three sources. We use Compustat data on public firms for information on R&D and components of Tobin's Q: value of equities, debt and physical assets. We use a variety of patent data from the U.S. Patent and Technology Office, including the number of patents granted (dated by year of application), the number of backward and forward citations, U.S. patent classifications and the identity of the assignee.⁷ In addition to using patent counts in the patent equation, we use these data to construct technological proximity and technological opportunity variables.

We focus on firms whose patents are predominantly in software. Unfortunately, there is no patent class simply called 'software' so we need a procedure that can sensibly identify software patents.⁸ One approach is to do a keyword search on the USPTO database (this is the approach

return to patent accumulation in terms of reducing patent enforcement costs. This depends on the sign of the cross-derivative $H_{\rho_0\rho_\tau}$. Recall the enforcement cost $H(x,c)$ where $x = \frac{\rho_0 k_0}{\rho_\tau k_\tau}$. It follows that $\text{sign } H_{\rho_0\rho_\tau} = \text{sign } (-\rho_0 k_0 H_{xx} - H_x)$. Since $H_x < 0$, we obtain $H_{\rho_0\rho_\tau} > 0$ provided that H_{xx} is 'small' (diminishing returns to patent accumulation for enforcement are not too strong). Thus greater patenting by rivals reduces the incentive for a firm to accumulate patents (recall that $H_x < 0$). In the appendix on comparative statics, we assume this holds (the resulting predictions are verified in the empirical section).

⁷Following the literature, we date patents by their application year because that is more closely tied to measures of R&D and firm value.

⁸For good discussions of different approaches to defining software patents, see Layne-Farrar (2005) and Hall and MacGarvie (2006).

adopted by Bessen and Hunt, 2003). This can be difficult because many patent applications may contain the word software or other related words but not be primarily about software itself. An arduous alternative is to read each of the (thousands of) potential candidate patents and make a subjective determination on each one (Allison and Tiller, 2003). A third approach is to base the definition on a specific set of patent classes – e.g., Graham and Mowery (2003) use the classes most common to well-known software firms such as Microsoft or Adobe. We adopt a related approach: we define a software patent as any patent classified by the Patent Office in International Patent Classification G06F (‘Electric Digital Data Processing’). This single class accounts for about half of all patents issued to the largest 100 packaged software companies, as tabulated by the trade publication Softletter (1998).

Software (G06F) patents are taken out by firms in many diverse industries (Schankerman and Trajtenberg, 2006). Moreover, even ‘pure’ software firms are likely to patent outside G06F, and may have genuinely non-software patents. The firm with the highest specialisation in G06F patents for large firms in our dataset is Microsoft – yet even it has only 71 percent of its patents classified in this category. Therefore, we define a software firm as one which has at least 45 percent of its patents classified as software (G06F) patents, after normalization by Microsoft’s G06F percentage. There are 149 publicly traded software firms that satisfy this criterion and have R&D and market value data. Of these, 121 firms have complete data for at least two consecutive years, and these constitute the final sample. We use all the patents held by a firm, both software and non-software, because R&D and market value refer to the entire firm. The 121 publicly traded firms in the final sample cover the period 1980-99 and include 29,363 patents of which 12,507 are software patents. This sample accounts for about 39 percent of all G06F patents issued to public firms during this period.⁹ About two-thirds of the firms (82 of 121) are classified in SIC 7372 (‘prepackaged software’), the remainder falling into various computer, communications and semi-conductor classes. Appendix 2 provides a list of the firms in our sample, together with their primary industry (SIC) classification.

⁹In the full Compustat data set of public firms, there are 3441 firms holding 31,950 G06F patents. More than a third of these patents (12,612) are held by five large firms: IBM, Hitachi, Hewlett Packard, Motorola, and Texas Instruments. Of these five firms, only IBM satisfies the software patent threshold we use (46 percent of its patents are in the G06F class); the others are well below a 30 percent cutoff. Excluding IBM dramatically reduces the percentage of G06F patents captured by the sample, from 39 percent to only 18 percent. We check robustness of our empirical results by rerunning all of the econometric experiments and computations using a 50 percent threshold to define the sample, which excludes IBM. The results were very similar to those reported in Section 6.

Finally, we must be careful to identify all patents held by each parent firm for whom we have R&D and value information. A parent firm may register a patent in its own name or in the name of one of its subsidiaries. The fact that subsidiaries can be bought and sold makes matching the patent to data from the parent firm more difficult. Hall, Jaffe, Trajtenberg (2005) matched patent assignees to the parent firm for patents for the period 1963-99 using 1989 ownership patterns. The resulting database is known as the ‘NBER patent database’ since it resides at NBER. However, for the group of software firms in which we are interested (some of which were established in the 1990’s), the 1989 match is antiquated. Therefore, for all firms that recorded at least one software patent between 1980 and 1999, we performed a new match of that firm to its parent and all its subsidiaries, based on 1999 ownership patterns. We then linked all patents of the subsidiaries to the parent company to produce a consolidated account of patent activity of our sample firms. For every assignee in the NBER patent database that had at least one G06F patent assigned to it, we checked whether the assignee was a parent firm or a subsidiary to some parent firm in 1999. If the firm was a subsidiary, we treated all patents of that subsidiary to be the patents of the parent firm. If the assignee was a parent firm, then we included it in our dataset if three conditions are met: the firm is publicly traded, we have Compustat data for it, and the firm meets the 45% G06F-to-total-patents cutoff, which is our lower limit for calling it a ‘software firm’. Appendix 2 provides details on the how the matching was done.

Table 2 presents descriptive statistics for the sample.

[Table 2 about here]

A few points are worth noting. First, the sample firms are large and R&D intensive. The mean market value is \$2.46 billion but the distribution is sharply skewed (median = \$97 million). The mean R&D stock is nearly six times as large as the physical capital stock. Second, Tobin’s Q is very high, as compared with other industries. This mainly reflects the fact that software firms use relatively little physical capital as compared to R&D, but also the over-valuation in the high tech bubble of the 1990s. Third, there is substantial variation in the patent propensity of technology rivals (*Patprop*). It is also worth noting (not reported in the table) that *Patprop* rose sharply after 1994, after several court decisions significantly weakened the copyright protection previously

available to software inventions.¹⁰ The mean *Patprop* rose from 0.028 in the period 1980-94 to 0.133 for 1995-99. Finally, the 4-firm citation concentration measure (*Citecon*) indicates that patent citations are not dramatically fragmented – the sample mean is 0.47, which indicates that firms cite about eight other firms, on average. This concentration index does not differ between the pre- and post-1994 periods.

4 Measuring strategic patenting and technology spillovers

While our sample cover only software firms, these firms have patenting activity in other technology fields as well. Thus we need to take into account the potential technology spillovers from R&D done by these firms in all of their areas of activity. The standard approach (Jaffe, 1986) is to measure technological proximity between firms as the uncentered correlation coefficient between their patent distributions across patent classes, and then to measure spillovers as a weighted sum of R&D by other firms using this proximity measure. We follow a similar approach except that, instead of using the distribution of patenting by each firm, we use the distribution of a firm’s *backward patent citations* across different patent classes to measure technological proximity. The backward patent citations of a firm i as of period t include all citations to previous patents (except a firm’s own patents) listed in firm i ’s patents up to year t . Since the citations in a patent reflect the preceding patents that an inventor is directly drawing on, this approach has strong appeal. To our knowledge this is the first time the citations-based proximity measure has been implemented.

Formally, let $W_i = \{w_{ik}\}_{k=1}^K$ be the distribution of firm i ’s backward citations across patent classes – i.e., w_{ik} is the share of firm i ’s total citations to preceding patents that fall into patent class k . Then technological proximity between firm i and j is

$$\tau_{ij} = \frac{W_i'W_j}{(W_i'W_i)^{\frac{1}{2}}(W_j'W_j)^{\frac{1}{2}}}$$

Self-cites are excluded. As a robustness check, we also constructed the standard Jaffe measure based on the distribution of patents. The cross-firm correlation between the two technology proximity

¹⁰See *Computer Associates Int’l Inc. v. Altai Inc.* 23 USPQ.2d 1241 (2nd Cir. 1992), *Apple Computer Inc. v. Microsoft Corp.* 35 F. 3d 1435 (9th Cir. 1994), and *Lotus Development Corp v. Borland Int’l Inc.*, 49 F. 3d 807 (1st Cir. 1995.) For details on the latter, see Lerner and Zhu (2005).

measures is 0.69 (the econometric results are similar to those we report in Section 6 when we use the patent-based measure).

We measure technology spillovers as the weighted sum of other firms' R&D stock, G_{jt} , using these technology proximity weights:

$$Spillover_{it} = \sum_{j \neq i} \tau_{ij} G_{jt} \quad (4)$$

The R&D stock is constructed by initialising the stock at the beginning of the sample period and using a 15 percent depreciation rate.¹¹

To capture the patent portfolio effect of strategic patenting, we compute the weighted average of the 'patent propensity' (the patent-R&D ratio) of other firms that are rivals in technology space. The idea is that, given the stock of own R&D and technology spillovers, firms facing technology rivals with higher patent propensities will find themselves at a disadvantage in bargaining over patent disputes. Let $Z_{jt} = \frac{PS_{jt}}{G_{jt}}$ denote the patent propensity of firm j , where PS is the stock of patents defined in the same way as the R&D stock, G . The patent propensity measure we use is¹²

$$Patprop_{it} = \sum_{j \neq i} \frac{\tau_{ij}}{\sum_{j \neq i} \tau_{ij}} Z_{jt} \quad (5)$$

To capture the patent thicket effect of strategic patenting, we want a measure of how many rivals a firm must negotiate with in order to preserve freedom of operation in its R&D activity. For this purpose, we use a concentration index of a firm's patent citations – that is, the degree to which patents cited by firm i (called 'backward citations') are held by relatively few firms. The idea is that when a firm's patent citations are more concentrated among a few technology rivals, that firm will have lower transaction costs in dealing with any patent disputes that may arise. To construct this concentration index of patent citations, we first identify the firm which owns (patent assignee)

¹¹This is conventional procedure (see Hall, Jaffe, and Trajtenberg, 2005). Initial stock is defined as the initial sample value of R&D divided by the sum of the depreciation rate and the average growth in R&D in the first three years of the sample. We experimented with variations of this method and other depreciation rates with similar results.

¹²We also experimented with an alternative measure that does not normalise the weights. Empirical results are similar to those reported in the text. However, the non-normalised measure results in a higher *Patprop* when there are more technological competitors, in addition to when the average competitor patent propensity is higher. As such, this measure blurs the distinction between the effects of patent propensity and concentration.

each patent that firm i cites in any of the patents it holds as of year t . From this information, we compute the share of firm i 's backward citations that is accounted for by each of its cited firms. Self-cites are excluded. We then compute the 4-firm concentration measure for each firm in each year (this varies over time as patents are accumulated).

Formally, let s_{ijt} ($i \neq j$) denote the share of the total number of citations by firm i that refer to patents held by firm j , cumulated up to year t and arranged in descending order. The 4-firm concentration measure is

$$Citecon_{it} = \sum_{j=1}^4 s_{ijt} \quad (6)$$

We also experimented with two alternative measures – an 8-firm and a Herfindahl index of concentration. The econometric results are similar to those reported in Section 6.

5 Econometric Specification

5.1 Market Value (Tobin's-Q) Equation

In the empirical specification, we follow the approach of Bloom, Schankerman and Van Reenen (2005) in using three outcome measures – market value, patents and R&D. In this section of the paper we discuss the econometric specification of these equations.

We adopt the representation of the market value function originally proposed by Griliches (1981):

$$\ln \left(\frac{V}{A} \right)_{it} = \ln \kappa_{it} + \ln \left(1 + \gamma^v \left(\frac{G}{A} \right)_{it} \right) \quad (7)$$

where V is the market value of the firm, A is the stock of tangible assets, G is the stock of R&D, and the superscript v indicates that the parameter is for the market value equation.¹³ The parameter κ_{it} is the shadow price of physical capital, and γ^v is the ratio of the shadow price of R&D capital to the shadow price of physical capital. The deviation of V/A ('Tobin's average Q') from unity depends on the ratio of the R&D stock to the tangible capital stock (G/A) and the determinants

¹³For a good discussion of issues arising in such specifications, see Hall, Jaffe and Trajtenberg (2005).

of κ_{it} . We parameterize the latter as¹⁴

$$\begin{aligned} \ln \kappa_{it} &= \beta_1^v \ln Patprop_{it-1} + \beta_2^v \ln Citecon_{it-1} + \beta_3^v \ln Spillover_{it-1} \\ &\quad + X_{it-1}^{V'} \beta_4^v + \xi_I^v + \eta_t^v + v_{it}^v \end{aligned} \quad (8)$$

where ξ_I^v is a full set of four-digit industry dummies, η_t^v a full set of time dummies, X_{it}^v denotes other control variables such as industry demand and technological opportunity (explained below), and v_{it}^v is an idiosyncratic error term.

The specification of the value function is nonlinear in the parameter γ^v . If (G/A) were ‘small,’ we could approximate $\ln(1 + \gamma^v (\frac{G}{A})_{it})$ by $(\frac{G}{A})_{it}$, but this will not be adequate for many high tech firms (Hall and Oriani, 2004). Therefore, we approximate $\ln(1 + \gamma^v (\frac{G}{A})_{it})$ by a higher-order series expansion, which we denote by $\Phi(G/A)$. We found that a fifth order polynomial is satisfactory.

Taking these elements together, our basic empirical market value equation is:

$$\begin{aligned} \ln \left(\frac{V}{A} \right)_{it} &= \Phi((G/A)_{it-1}) + \beta_1^v \ln Patprop_{it-1} + \beta_2^v \ln Citecon_{it-1} + \beta_3^v \ln Spillover_{it-1} \\ &\quad + X_{it-1}^{v'} \beta_4^v + \xi_I^v + \eta_t^v + v_{it}^v \end{aligned} \quad (9)$$

We want to emphasise two points about this specification. The first point is that the interpretation of the *Spillover* variable can be difficult because of the reflection problem (Manski, 1991). Any variable that shifts the incentive for a firm to perform R&D and thus its market value will also be likely to affect other firms that operate in similar technology fields. Thus a positive correlation between R&D by technology rivals and the market value (or R&D decisions) of a firm can arise either from genuine technology spillovers or from common, unobserved demand or technology opportunity shocks. Our defences against this problem are: (1) we include controls for demand and technological opportunity (discussed below); (2) the spillover variable is based on stocks of R&D, which should mitigate correlation with contemporaneous shocks; (3) we lag the independent

¹⁴We introduce the spillover and strategic patenting variables in the simplest, additive specification. An alternative is to allow these variables to affect market value only through their impact on the R&D stock. While appealing, this interactive specification is more demanding on the data. Our approach can be thought of as an approximation to a more complicated specification.

variables, which should also reduce the problem; and (4) we are particularly interested in testing the strategic patenting coefficients β_1^v and β_2^v , which should be less directly affected by the reflection problem. These remarks also apply to the patent and R&D equations below.

We control for the effects of demand and technological opportunity in three different ways. First, we include a full set of year dummies in all specifications. Second, we include two lag values of firm sales to pick up remaining demand shocks.¹⁵ Finally, we construct a measure of technological opportunity as the total patenting in a technology class weighted by firm i 's closeness to that class, as measured by its backward citations. The idea is that firms cite patents similar in nature to its own, and if there is a large amount of patenting in areas it cites, it is an active technological field. Let $W_i = \{w_{ik}\}_{k=1}^K$ be the distribution of firm i 's backward citations across patent classes (w_{ik} is the share of firm i 's total patent citations to preceding patents that fall in class k), and PS_{jkt} be the patent stock of firm j in class k at time t . We define technological opportunity for firm i as $Techopp_{it} = \sum_k \sum_{j \neq i} w_{ik} PS_{jkt}$. Two lagged values of $Techopp$ are included in the regression equations.¹⁶

The second point about the specification involves firm fixed effects. Since the software firms in our sample are classified into different SIC industries, we include four-digit industry dummies to pick up unobserved heterogeneity. Ideally we would want to include fixed firm effects in the specification, but when did so we found that it very hard to pin down any of the coefficients of interest. In a recent paper, Hall, Jaffe and Trajtenberg (2005) reach a similar conclusion. The reason is that going to the 'within-firm' dimension means that we are trying to explain variation over time in market value (around the firm mean), which can be very noisy. In a first-differenced specification, the variation over time would be very close to unpredictable, under the efficient markets hypothesis.¹⁷ The 'within-firm' estimator is not equivalent to first-differences, so it is possible in some samples to exploit fixed firm effects successfully (this depends on the time series properties of the data). Using a much broader sample of firms, Bloom, Schankerman and Van Reenen (2005) are able to

¹⁵We also constructed an industry sales measure for each firm, equal to a weighted average of the sales in each of the four-digit SIC classes in which the firm operates. The weights are constructed from Compustat information on the distribution of firm sales across SIC classes during the period 1993-2001. Results using this control are similar.

¹⁶We also experimented with measures using citations rather than patents, and flows rather than stock measures. Empirical results were similar to those reported in the text.

¹⁷Strictly speaking, under the (weak form) efficient market hypothesis, the market value in period t should not be predictable with information publicly available at $t - 1$.

estimate a market value equation with fixed firm effects, but in the current study we are not able to do so.

Following Hall, Jaffe and Trajtenberg (2005), we also estimate an extended version of the model that allows for the stock market to value the patents held by a firm, above and beyond its valuation of the firm's R&D. There are basically two reasons such a patent premium may be present. First, patenting may enhance the ability of the firm to appropriate rents from any given innovation outputs, relative to alternative methods of protection. Second, patents contain (noisy) information about innovation output and as such may contain additional information about the expected profit stream of the firm, above and beyond measures of R&D input.¹⁸ It is important to include the stock of R&D in the estimating equation, however, since some innovations may not be patented.

The extended specification of the model treats the stock of patents, denoted by PS , in the same way as the stock of R&D:

$$\ln \left(\frac{V}{A} \right)_{it} = \ln \kappa_{it} + \ln \left(1 + \gamma^v \left(\frac{G}{A} \right)_{it} + \delta^v \left(\frac{PS}{A} \right)_{it} \right)$$

where we expect $\delta^v > 0$ if there is a patent premium in the stock market. For estimation we approximate this term by adding a (fifth order) polynomial $\Psi(PS/A)$ to equation (10).¹⁹

5.2 Patent Equation

Because patents are counts, we use a version of the negative binomial count data model that allows for fixed effects.²⁰ The first moment of the estimator is

$$\begin{aligned} E(P_{it}|X_{it}) &= \exp\{\beta_1^p \ln Patprop_{it-1} + \beta_2^p \ln Citecon_{it-1} + \beta_3^p \ln Spillover_{it-1} \\ &\quad + X_{it}^{p'} \beta_3^p + \xi_I^p + \eta_t^p\} \end{aligned} \quad (10)$$

¹⁸A related interpretation is worth noting. Given the costs involved, we expect patents to be taken out on the more valuable innovations, other things equal. Thus the patent premium may reflect the additional market value associated with above-average quality R&D.

¹⁹We do not include an additional polynomial in the interaction term $\frac{G}{A} \frac{PS}{A}$ because it is too demanding on the available data.

²⁰See Blundell, Griffith and Van Reenen (1999) and Hausman, Hall and Griliches (1984) for discussions of count data models of innovation.

Writing this first moment as $E(P_{it}|X_{it}) = \exp(x'_{it}\beta^p)$, for shorthand, the variance is $V(P_{it}) = \exp(x'_{it}\beta^p) + \alpha \exp(2x'_{it}\beta^p)$ where the parameter α is a measure of over-dispersion. The Poisson model restricts the mean to equal the variance, which corresponds to the special case $\alpha = 0$. The Negative Binomial estimator relaxes this assumption (empirically, overdispersion is important in our data). We estimate the model by maximum likelihood. We allow for unobserved firm heterogeneity using the approach developed by Blundell, Griffith and Windmeijer (2002) and Blundell, Griffith and Van Reenen (2003). This uses pre-sample information on patents to control for heterogeneity. The alternative approach of Hausman, Hall and Griliches (1984), using conditional maximum likelihood, is only consistent for strictly exogenous regressors, which does not hold for our specification.

5.3 R&D Equation

We write the R&D equation as:

$$\begin{aligned} \ln R_{it} = & \varphi^r \ln R_{it-1} + \beta_1^r \ln Patprop_{it-1} + \beta_2^r \ln Citecon_{it-1} \\ & + \beta_3^r \ln Spillover_{it-1} + X_{it-1}^r \beta_3^r + \xi_i^r + \eta_t^r + v_{it}^r \end{aligned} \quad (11)$$

where ξ_i^r is a full set of firm dummies, η_t^r a full set of time dummies, X_{it}^r denotes other control variables such as industry demand, and v_{it}^r is an idiosyncratic error term. In the R&D equation we include fixed firm effects to capture unobserved heterogeneity.²¹ This specification allows for dynamics in R&D investment by including a lagged dependent variable. As in the market value equation, unobserved, transitory shocks to demand are captured by the time dummies and a distributed lag of firm sales, and firm level variables on the right hand side of the R&D equation are lagged by one period to mitigate endogeneity problems.

²¹The time dimension of the company panel is relatively long, so the ‘within groups bias’ on weakly endogenous variables (Nickell, 1981) is likely to be small. The average number of continuous time series observations is 9.1 (median is 7.0).

6 Empirical Results

6.1 Market Value Equation

[Table 3 about here]

Table 3 presents the parameter estimates for the market value equation. The basic specification in column 1 strongly supports the predictions of the model. First, not surprisingly we find that a firm's (lagged) R&D stock is strongly related to its market value. Using the coefficients on the polynomial in G/A , we find that a 10 percent increase in the stock of R&D is associated with a 8.4 percent increase in value. Evaluated at the sample means, this implies that an extra \$1 of R&D generates an increase of 96 cents in market value.²² This estimate for software firms is very similar to previous studies that do not focus on software – e.g., Hall, Jaffe & Trajtenberg (2005) estimate a marginal return to R&D of 86 cents. However, as we show below, this figure underestimates the full marginal return to R&D for software firms because there is a large indirect return in the form of a patent premium on innovation output.

The second finding is that R&D by technology-related rivals generates positive spillovers that are valued by the stock market. The coefficient on *Spillover* is positive and statistically significant, implying that a 10 percent increase in the pool of technology spillovers is associated with a 1.7 percent increase in a firm's market value. In absolute terms, the coefficient implies that \$1 of additional *Spillover* is associated with an increase in market value of 13 cents. In other words, an extra dollar of technology spillover is worth (in terms of market value) about 13 percent as much as a dollar of own R&D for these software firms. This estimate of the impact of technology spillovers (relative to own R&D) is larger than previous estimates that are based on samples covering a range of different industries (e.g., Hall, Jaffe and Trajtenberg, 2005; Bloom, Schankerman and Van Reenen, 2005), which is consistent with the widely-held view that cumulative innovation is particularly important in software.

We now turn to the effect of the strategic patenting variables. The third finding is that firms which face technological rivals with higher patent propensities have lower market value. The coef-

²²We compute the elasticity of market value with respect to R&D stock as $e_{VG} = \frac{G}{A}\Phi'(\frac{G}{A})$ where Φ' is the derivative of the polynomial Φ . The marginal value of R&D is $\frac{\partial V}{\partial G} = \frac{V}{A}\Phi'(\frac{G}{A})$.

ficient on *Patprop* is negative and statistically significant, implying that a 10 percent increase in rivals' patent propensity reduces a firm's value by 1.3 percent.

The fourth finding is that firms whose patent citations are more concentrated in fewer technology rivals have systematically higher market value. This finding is consistent with the hypothesis that higher concentration of patent rights should reduce the transactions costs of settling patent disputes. The coefficient on *Citecon* is statistically significant and implies that a five percentage point increase in the four-firm citation concentration ratio (this is a 10 percent increase at the sample mean) would raise market value by 1.7 percent. These two findings strongly support the model's predictions about strategic patenting – there is evidence both that patent portfolio size (bargaining power) and transaction costs associated with the fragmentation of property rights affect the market value of firm.

Finally, the coefficients on the firm sales and technological opportunity variables show that market value is positively related to the *growth* in demand and the *growth* in technological opportunity, as measured by aggregate patenting activity in the patent classes in which the firm operates. This is confirmed by noting that the estimated coefficients on the first and second lags of firm sales are nearly equal in magnitude but opposite in sign. The same holds for the coefficients on the first and second lags of the *Techopp* variable.

The basic specification relates market value to the firm's stock of R&D, as a proxy for knowledge. Since firms typically do not patent all of their innovation output, R&D input is more a more encompassing measure of knowledge than simply using patents. However, as Hall, Jaffe and Trajtenberg (2005) point out, there may also be a patent premium in the stock market for those innovations that the firm chooses to patent – i.e., their private value would be less if not patented. To test this for software firms, we add to the empirical specification a (fifth-order) polynomial in the ratio of the patent stock to stock of fixed assets (denoted by PS/A), analogously to our treatment of R&D (column 2). We find clear evidence of a patent premium. Using the estimated coefficients on the polynomial in PS/A (evaluating at the sample means), we compute an elasticity of market value with respect to the stock of patents, denoted by $e_{V,PS}$, at 0.31 – a 10 percent increase in the patent stock is associated with a 3.1 percent rise in market value, holding the stock

of R&D constant.²³ In this extended specification, we also estimate an elasticity of market value with respect to the R&D stock, denoted by e_{VG} , at 0.71. Taken together, these findings imply constant returns to scale in the value equation – a 10 percent increase in *both* the stocks of R&D *and* patents is associated with about a 10.2 percent increase in market value. Nonetheless, allowing for a patent premium in the specification of the market value equation has almost no effect on the other coefficients in the model – in particular, the coefficients on the technology spillovers and strategic patenting variables remain virtually unchanged.

As we indicated earlier, the full return to an increase in R&D includes both the direct market valuation of R&D plus the indirect return through the patent premium. Formally, we can express the total elasticity of market value with respect to R&D stock as $E_{VG} = e_{VG} + e_{V,PS} e_{PS,G}$. We use the parameter estimates on the polynomial terms in G/A and PS/A (column 2 in Table 3) to compute the elasticities e_{VG} and $e_{V,PS}$. To get the elasticity of patents with respect to R&D, $e_{PS,G}$, we use the coefficients estimated in the patent equation which are presented later (column 2 in Table 4). This computation yields the following decomposition: $E_{VG} = 0.71 + 0.31 \times 0.60 = 0.90$. That is, once we account for both the direct impact of R&D and the effect through the patent premium, a 10 percent increase in the stock of R&D raises market value by 9.0 percent. From this we conclude that the patent premium accounts for 21 percent of the total elasticity effect of R&D ($= 0.31 \times 0.60/0.90$).²⁴ This finding shows that patents are important as a means of appropriating innovation rents in software.

One other interesting implication of the empirical results is worth noting. We found patenting by its technology rivals reduces a firm’s market value (the coefficient on *Patprop* is negative). As we pointed out in the introduction, however, some researchers (e.g., Bessen and Maskin, 2000) have suggested that patent regimes in complex technology industries may create a prisoner’s dilemma in which firms could be better off by collectively reducing their levels of patenting. In our context,

²³We compute the elasticity of market value with respect to patent stock as $e_{V,PS} = \frac{PS}{A} \Psi'(\frac{PS}{A})$ where Ψ' is the derivative of the polynomial Ψ . It is interesting to note that Hall and MacGarvie (2006), using a very different sample (covering firms doing any software patenting, rather than ‘software’ firms as we define them) estimate an elasticity of market value with respect to patents per R&D dollar of 0.3, which is very similar to our finding.

²⁴We can also do the decomposition in terms of the marginal return to R&D (instead of elasticities). Note that $\frac{dV}{dG} = \frac{\partial V}{\partial G} + \frac{\partial V}{\partial PS} \frac{\partial P}{\partial G} \frac{\partial PS}{\partial P}$, where the last three terms constitute the patent premium. We compute the first three derivatives from the estimated coefficients of the polynomial Φ and Ψ . Using the relationship between the stock and flow of patents, we get $\frac{\partial PS}{\partial P} = \frac{1}{r+\delta}$ where r and δ are the real interest rate and depreciation rate (we set $r = .05$, $\delta = .15$). We find that the patent premium accounts for 25 percent of the full marginal return to R&D.

this hypothesis implies that a proportional increase in patenting by all firms would reduce the market value of the individual firm, holding R&D for all firms constant. In Table 3, this requires that the sum of the coefficient on *Patprop* and the elasticity on own patent stock (computed from the polynomial in PS/A) should be negative. The parameter estimates do not support this claim – using the estimates from column 2, we find that the sum of these elasticities is positive ($-0.12 + 0.31 = 0.19$).

The scope of software patent protection was gradually increased, and that of software copyright protection reduced, in a series of court decisions during the 1980s, culminating in two key decisions in 1994 and 1995 (for case references, see note 10). These decisions made it increasingly desirable for firms to protect software algorithms using patents rather than by copyright as they had done previously. As noted in the introduction, this led to a sharp increase in software patenting. We want to investigate whether the changes in patent policy toward software raised the shadow price on patents and R&D, or increased the importance of the strategic patenting variables. To examine this, we re-estimated the market value equation separately for the pre-1994 and post-1994 periods (columns 3 and 4 in Table 3).²⁵

There is no evidence that the shadow price of R&D changed as a result of the change in patent regime. We cannot reject the null hypothesis that the coefficients on R&D are the same in both periods (p-value = 0.20). However, we strongly reject the hypothesis that the coefficients on patents remained constant over the two periods (p-value < .01). Nonetheless, the elasticity of market value with respect to the stock of patents, implied by the coefficients, does not change very much between periods – it is estimated at 0.50 in the 1980-94 period and 0.39 for 1995-99. Similarly, the estimated marginal value of a patent is not sharply different between the periods – \$5.3 million versus \$3.9 million. However, we find that the coefficients on both strategic patenting variables increased substantially in the post-1994 period. The point estimates of the *Patprop* and *Citecon* coefficients are not statistically different from zero in the earlier period, but in the later period they are both larger (in absolute value) and statistically significant.

²⁵The are more observations in the second (shorter) sub-period because data are available for more firms. However, when we restrict the analysis to those firms that also appear in the first sub-period, we get very similar results. This point also applies the analysis of the patent equation in Section 6.2.

In summary, we conclude that the change in patent regime was associated with a sharp increase in the importance (as measured by the coefficients) of the strategic patenting variables. At the same time, despite a large increase in the level of patenting during this later period, we do not find a sharp reduction in the impact of patents on market value. Evidently, whatever diminishing returns that was associated with the intensification of software patenting appears to have been largely countervailed by the increased value from the strengthening of software patent protection.

6.2 Patent Equation

[Table 4 about here]

Table 4 presents the results for the patent equation.²⁶ In the regressions we allow for unobserved firm heterogeneity using the approach developed by Blundell, Griffith and Windmeijer (2002) which conditions on pre-sample patent counts.²⁷ The alternative approach of Hausman, Hall and Griliches (1984) for including firm fixed effects is only consistent for strictly exogenous regressors, which does not hold for our specification.

Not surprisingly, we find that patenting is significantly related to the firm's stock of R&D, but there are sharp decreasing returns both in the model without and with the control for unobserved firm heterogeneity (columns 1 and 2). Note that the coefficient on the pre-sample patents variable is positive and statistically significant (this holds in all specifications), which confirms that unobserved firm heterogeneity in patenting behaviour is important. Using the specification with the pre-sample control, the elasticity of patents with respect to the R&D stock is 0.60 and statistically significant. This finding is broadly in line with the extensive empirical literature on patent production functions.²⁸ Also note that the coefficients on our measures of technological opportunity

²⁶In all the empirical specifications in the table, the estimate of the over-dispersion coefficient, α , is significantly different from zero. This result rejects the Poisson model for patents ($\alpha = 0$) in favor of the Negative Binomial specification.

²⁷We also estimated the model using citation rather than patent counts (to capture variation in patent quality), and conditioning on pre-sample patent citations. The empirical results were very similar to those reported in the table.

²⁸The R&D elasticity drops sharply if we include firm size in the regression, which is not surprising since R&D stock is highly correlated with firm size. The case for including firm size here is not compelling. Conditional on R&D (i.e., the number of innovations generated), the decision to patent will depend on the incremental profits from patenting relative to protecting those innovations by alternative means. This will depend in part on the *incremental* sales associated with patenting, not the level of total sales which is what we observe.

(*Techopp*) are surprising – they suggest that the growth in ‘technological opportunity’ reduces current patenting (the coefficients are about equal in magnitude and opposite in sign). But recall that *Techopp* measures the aggregate patent activity in the patent classes in which the firm operates. Thus the estimated coefficients point to a ‘fishing out’ interpretation – when aggregate patenting growth is higher, the firm is less likely to generate patented innovations from its stock of R&D.²⁹

We now turn to the key variables of interest. Overall, the empirical results support the hypothesis that both technology spillovers and strategic patenting variables affect the decision to patent. First, we find strong R&D spillovers in patenting once we control for unobserved firm heterogeneity (column 2). The coefficient on *Spillover* is positive and highly significant. The spillover effect is substantial: a ten percent increase in technology spillovers is associated with a 6.4 percent increase in patenting, holding the firm’s own R&D stock constant.

Second, we find evidence that firms do less patenting, conditional on their R&D, when they face technology rivals with higher patent propensities. The point estimate on *Patprop* is negative and strongly significant in the specification with the pre-sample patents control. This finding is consistent with the view that firms are in a worse bargaining position in resolving patent disputes with rivals that have large patent portfolios, which thereby reduces the profitability of patenting. The effect is substantial – the point estimate implies that a 10 percent increase in the average patent propensity of technology rivals is associated with a reduction in patenting by the firm of 4.5 percent.

Third, there is strong evidence that greater concentration of citations (lower patent transaction costs) affects the level of patenting. Greater citations concentration is associated with a statistically significant reduction in patenting by the firm. This finding is consistent with the evidence for semiconductors from Ziedonis (2003a), who finds that greater fragmentation (lower concentration) of patent rights increases patenting, conditional on R&D. In the context of our model, this finding implies that greater concentration reduces the marginal value of accumulating a patent portfolio in

²⁹We experimented with alternative lags on *Techopp* and found that the ‘fishing out’ result is robust – higher past growth in aggregate patenting reduces the firm’s patenting, conditional on its R&D. One possible alternative explanation is that this result reflects resource constraints in a given field of expertise within the patent office. If a backlog of patent applications in a field builds up, the probability that any given new patent application is granted within a given time declines. Since our patent measure refers to patent grants, dated by their year of application, this explanation would work only if firms delay their applications to the patent office as a consequence of the backlog, which seems unlikely.

order to enforce patent rights (in the model, $H_{xc} > 0$). The point estimates are nearly identical, and statistically significant, in the specifications without and with the the pre-sample patent control. The effect is large – for example, the point estimate in column (2) implies that a 5 percentage point increase in citations concentration (equivalent to a 10 percent increase at the sample mean) reduces patenting by 12.8 percent.

As with the market value equation, we want to test whether the change in judicial treatment of software patentability increased the impact of patent portfolios or patent thickets on patenting behaviour. To examine this hypothesis, we estimate the patent equation separately for the pre-1994 and post-1994 periods (columns 3 and 4). The key results on R&D spillovers and the strategic patenting variables hold for both sub-periods, but we do not find any significant change between the two periods. While the point estimates on *Spillover* and *Citecon* are larger in the later sub-period, and the coefficient on *Patprop* is lower, the differences are not statistically significant.

6.3 R&D Equation

[Table 5 about here]

Finally, we turn to the parameter estimates for alternative specifications of the R&D equation. Overall, the results (Table 5) provide support for the hypothesis that the strategic patenting variables – especially the concentration of patent rights, *Citecon* – affect the R&D decision. We discuss each of the key findings in turn, looking across the specifications to check robustness.

First, we do not find strong evidence that technology spillovers affect the R&D decision, once we control for firm fixed effects. In the static specification with industry fixed effects, but not firm effects (column 1), we get a positive and significant coefficient on the *Spillover* variable (elasticity of 0.21). This also holds when we add dynamics to the specification without fixed effects (column 2), the implied long run elasticity of technology spillovers rising to 0.40. However, when we add fixed firm effects either to the static or dynamic specification (columns 3 and 4, respectively), the point estimate of the spillovers coefficient becomes negative but statistically insignificant.³⁰ Moreover, the firm fixed effects are jointly significant (p-value <.001). As an empirical matter, R&D at the

³⁰It is worth noting that these negative point estimates for the fixed effect specifications do not appear when we use the smaller sample based on a 50% software (G06F) patent threshold, which excludes IBM. In the latter case, the point estimates are 0.19 for column 3 and 0.21 for column 4, but neither is statistically significant.

firm level is highly persistent and one needs either firm effects or dynamics in the specification to capture it. Picking up this persistence with dynamics allows us to pin down a positive effect of technology spillovers, but not if we use fixed effects. However, we emphasize that this finding that technology spillovers do not affect the R&D decision is consistent with the model – it indicates that such spillovers do not materially affect the *marginal* product of own R&D. Nonetheless, recall from Sections 6.1 and 6.2 that spillovers strongly increase the number of patents and market value, indicating that such spillovers do raise the *average* product of the recipient firm’s R&D.

Second, there is only mixed evidence that R&D investment is affected by the patent propensities of technology rivals. While the point estimates of coefficient on *Patprop* are negative, as predicted by the model, and robust to introducing dynamics and fixed firm effects in the model (columns 2 and 3, respectively), they are not generally statistically significant. Thus it does not appear that patent portfolio accumulation by technology rivals is an important deterrent to doing R&D.

However, the R&D decision is significantly affected by the degree of concentration of patent rights, i.e., by the level of patent transaction costs. In the static model without fixed effects (column 1), we find that greater citations concentration (*Citecon*) is associated with a statistically significant reduction in R&D. This result holds up when we introduce dynamics or fixed firm effects in the regression (columns 2 and 3, respectively), and the size of the effect is substantial. In the static specification with fixed effects, the estimate implies that a 5 percentage point increase in citations concentration (this is a 10 percent increase at the sample mean) reduces R&D by 1.4 percent (the implied long run impact of this change in the dynamic specification is much larger, at 4.2 percent). As before, however, when we introduce both fixed effects and dynamics the point estimate is broadly similar but no longer statistically significant.

In the model, the effects of higher concentration of patent rights on the level of R&D and patents are ambiguous. The direction of the effect depends on how citations concentration affects the marginal value of having a larger patent portfolio in order to enforce patent rights (i.e., on the cross derivative of the patent enforcement cost function, H_{xc}). As explained in Section 2, our finding that higher concentration of patent rights reduces R&D implies that $H_{xc} > 0$. This means that there is a smaller gain from having a larger patent portfolio when patent rights are more concentrated among rival firms. This finding is consistent with our expectations, since tacit forms

of cooperation are more likely to develop in such cases and these make large patent portfolios less important as threats to resolve disputes.

Finally, it is interesting to note that the coefficients of the time dummies show no evidence that R&D changed systematically over the sample period. We cannot reject the null hypothesis that the coefficients on the year dummies are jointly zero in any of the specifications of the model. This finding suggests that the expansion of patentability over software during the 1980s and early 1990s was not associated with any major changes in R&D investment by these software firms as of the end of our sample period. Whether the expansion of software patentability will eventually intensify innovation incentives remains an important, but open, question. Nonetheless, we emphasise that our findings contradict the controversial claim by Bessen and Hunt (2003) that the expansion of software patenting led firms to *reduce* R&D over this period.

Table 6 concisely summarizes our main findings on market value, patents and R&D by comparing the predictions from the model with the empirical results from Tables 3-5. There is a close match between the theoretical predictions and the empirical findings for the key technology spillover variable (*Spillover*) and the strategic patenting variables (*Patprop* and *Citecon*).

[Table 6 about here]

7 Conclusion

This paper studies the impact of strategic patenting and technology spillovers on R&D investment, patenting activity and market value of firms in the computer software industry. Software is a classic example of a complex technology in which cumulative innovation plays a central role, and where there is growing concern that patent thickets may impede innovation. We develop a model to analyse and estimate the impact of strategic patenting and technology spillovers. The model incorporates two distinct aspects of strategic patenting – patent portfolio size (patent propensity) to capture the firm’s bargaining power in patent disputes and licensing, and concentration of patent rights among rivals to capture the transaction costs of enforcing patent rights. Using panel data for the period 1980-99, we find clear evidence that strategic patenting and technology spillovers are present.

There are four key empirical findings in the paper. First, there are large, positive technology spillovers from R&D for software firms. Second, we find that patenting by technology rivals reduces the firm's R&D investment, patenting and market value. Third, greater concentration (less fragmentation) of patent rights among rivals reduces both R&D and patenting by the firm – reflecting less need to have an arsenal of patents to resolve disputes when there are fewer players – but it increases market value because transaction costs are lower. Finally, we find that there is a large patent premium in the stock market valuation of these software firms, which accounts for about twenty percent of the overall private returns to R&D investments.

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Appendix 1. Comparative Statics

The first order conditions are

$$\begin{aligned} V_{r_0} &= \phi_1^0 \{ \theta_0 \Pi_1^0 - f \rho_0 - H \} - \left(\frac{\rho_0 k_0}{\rho_\tau k_\tau} \right) (k_\tau \phi_1^0 - k_0 \phi_2^\tau) H_x - 1 = 0 \\ V_{\rho_0} &= (\lambda - 1) k_0 \Pi_1^0 - f k_0 - k_0 \left(\frac{k_0}{\rho_\tau k_\tau} \right) H_x = 0 \end{aligned}$$

where superscripts on functions Π and ϕ refer to the firm and subscripts 1 and 2 denote partial derivatives with respect to the different arguments. To simplify notation, we suppress the arguments in functions, but it should be borne in mind that $H = H(\frac{\rho_0 k_0}{\rho_\tau k_\tau}, c)$. Differentiating totally we obtain

$$\begin{bmatrix} V_{r_0 r_0} \dots V_{r_0 \rho_0} \\ V_{\rho_0 r_0} \dots V_{\rho_0 \rho_0} \end{bmatrix} \begin{bmatrix} dr_0 \\ d\rho_0 \end{bmatrix} = - \begin{bmatrix} V_{r_0 \rho_\tau} \dots V_{r_0 c} \dots V_{r_0 r_\tau} \\ V_{\rho_0 \rho_\tau} \dots V_{\rho_0 c} \dots V_{\rho_0 r_\tau} \end{bmatrix} \begin{bmatrix} d\rho_\tau \\ dc \\ dr_\tau \end{bmatrix}$$

where, using the first order conditions and after considerable algebra, we obtain the following expressions:

$$V_{r_0 \rho_\tau} = \frac{\rho_0 k_0}{(\rho_\tau^2 k_\tau)} \phi_1^0 H_x + \frac{\rho_0 k_0}{(\rho_\tau k_\tau)^2} (k_\tau \phi_1^0 - k_0 \phi_2^\tau) \{ H_x + \left(\frac{\rho_0 k_0}{\rho_\tau k_\tau} \right) H_{xx} \} \leq 0$$

$$\begin{aligned} V_{r_0 r_\tau} &= \frac{\phi_{12}^0}{\phi_1^0} + \phi_1^0 \phi_2^0 \Pi_{11} - A H_x - \frac{\rho_0^2 k_0}{\rho_\tau^2 k_\tau^4} (k_\tau \phi_2^0 - k_0 \phi_1^\tau) H_{xx} \\ \text{where } A &= -\frac{\rho_0}{\rho_\tau k_\tau^2} \left\{ k_0^2 \left(\frac{\phi_{12}^0 \phi_2^\tau - \phi_{21}^\tau \phi_1^0}{\phi_1^0} \right) - 2k_0 (\phi_2^0 \phi_2^\tau + \phi_1^\tau \phi_1^0) \right. \\ &\quad \left. + 2(k_0 \phi_1^0 \phi_2^0 + \frac{k_0}{k_\tau} \phi_2^\tau \phi_1^\tau) \right\} \end{aligned}$$

$$V_{r_0 c} = -\phi_1^0 H_c - (k_\tau \phi_1^0 - k_0 \phi_2^\tau) H_{xc} \leq 0$$

$$V_{\rho_0\rho_\tau} = \frac{k_0^2 k_\tau}{(\rho_\tau k_\tau)^2} \{H_x + \frac{\rho_0 k_0}{\rho_\tau k_\tau} H_{xx}\} \leq 0$$

$$V_{\rho_0 r_\tau} = (\lambda - 1)\theta_0 k_0 \phi_2^0 \pi'' - \frac{k_0}{\rho_\tau k_\tau^2} (k_\tau \phi_2^0 - k_0 \phi_1^\tau) \{H_x + \frac{\rho_0 k_0}{\rho_\tau k_\tau} H_{xx}\} \leq 0$$

$$V_{\rho_0 c} = -\frac{k_0^2}{\rho_\tau k_\tau} H_{xc} \leq 0$$

Second order conditions imply $V_{r_0 r_0} < 0$, $V_{\rho_0 \rho_0} < 0$, and $V_{r_0 r_0} V_{\rho_0 \rho_0} - V_{r_0 \rho_0}^2 > 0$. We can also show that $V_{r_0 \rho_0} > 0$ provided that $\phi_1^0 \gg \phi_2^\tau$ (spillovers are not too large) and H_{xx} is sufficiently small.³¹ Under these same two conditions, we can unambiguously sign $V_{r_0 \rho_\tau} \leq 0$, $V_{\rho_0 \rho_\tau} \leq 0$ and $V_{\rho_0 r_\tau} \leq 0$, as indicated above. However, we cannot sign $V_{r_0 r_\tau}$ without further restriction.³² Finally, if $H_{xc} > 0$ then $V_{\rho_0 c} < 0$ but $V_{r_0 c}$ cannot be signed. If $H_{xc} \leq 0$ then $V_{r_0 c} \geq 0$ and $V_{\rho_0 c} \geq 0$.

In addition, using the envelop theorem we get the following results for the value of the firm:

$$\frac{\partial V^0}{\partial \rho_\tau} = \frac{\rho_0 k_0^2}{\rho_\tau^2 k_\tau} H_x \leq 0$$

$$\frac{\partial V^0}{\partial r_\tau} = \frac{\phi_2^0}{\phi_1^0} + \frac{\rho_0 k_0}{\rho_\tau k_\tau^2} H_x \left\{ \frac{\phi_2^0}{\phi_1^0} (k_\tau \phi_1^0 - k_0 \phi_2^\tau) - (k_\tau \phi_2^0 - k_0 \phi_1^\tau) \right\} \geq 0$$

$$\frac{\partial V^0}{\partial c} = -k_0 H_c \geq 0$$

³¹ Using the first order condition for ρ_0 , we obtain

$$V_{r_0 \rho_0} = -\frac{k_0}{\rho_\tau k_\tau^2} (k_\tau \phi_1^0 - k_0 \phi_2^\tau) \{H_x + \frac{\rho_0 k_0}{\rho_\tau k_\tau} H_{xx}\}$$

which is positive if $\phi_1^0 \gg \phi_2^\tau$ and H_{xx} is sufficiently small (i.e., elasticity of H_x is less than unity).

³² If there is no spillover effect ($\phi_2 = \phi_{12} = \phi_{22} = 0$), we get $V_{r_0 r_\tau} > 0$. If we have spillovers but no strategic patenting effect ($H_x = H_{xx} = 0$), we also get $V_{r_0 r_\tau} > 0$, provided diminishing returns in the profit function are not too large.

Appendix 2. Construction of the Sample

We began with two main data sets: the CorpTech data (purchased from Corporate Technology Information Services) and the G06F (‘software’) patent database. The CorpTech data cover more than 15,000 companies (parent companies and subsidiaries) which report some involvement in a software-related activity (product classification) over the period 1990-2002. Of the firms covered by CorpTech, 12 percent are publicly traded firms. We focus exclusively on public firms in order to use market value and other balance sheet information for the empirical analysis.

The first step was to match subsidiaries to their parent companies. Subsidiaries and parent firms are identified in the CorpTech data by ‘type of ownership’ variables. The CorpTech data set includes the firm identifier (CUSIP), but this information was missing for many firms. All public companies with missing CUSIP’s were checked manually (primarily from company websites) and the information was added where available.

The second step was to match the firms in CorpTech (both parents and subsidiaries) to the assignees in the G06F patent database. This first required that we get the CUSIP for the assignee of each G06F patent. This was done by matching the G06F patent number to the NBER database. The next step was to match the G06F patents to the CorpTech database using the company CUSIP. This matching was done under the supervision of Josh Lerner at the Harvard Business School. The matching was done for each CorpTech firm using name recognition software and followed up by two independent rounds of manual checks (one under Josh Lerner and the other by Irina Danilkina of the Law and Economics Consulting Group)..

For this study, we need to match the data for the public firms in CorpTech to all of their patents, not just their G06F patents. In principle, this could be done by matching the CorpTech and NBER patent data, using the CUSIP in each data set. The NBER data include all USPTO patents (up to 1999) and CUSIP numbers from the Hall, Jaffe and Trajtenberg (2004) match, which is based on publicly registered firms in 1989. However, for our purposes this match is antiquated, given the substantial entry and rapid growth of the software industry in the 1990s. We found 1,198 public

firms with CUSIP's in CorpTech that do not show up in the NBER dataset. These are firms that were born or became public after 1989. So while the second step above provides a good match of firms and their G06F patents, there remained no reliable match of firms to their non-software patents. If we were to use this match and include all firms with at least one G06F patent, there would be 70 firms with a total of 18,628 software patents and 127,553 total patents. The vast majority of these firms have very low software to total patent ratios. Using our 45% software to all patent ratio cutoff, we would be left with only 15 firms covering 11,561 software patents and 28,041 total patents. Using the 50% cutoff (which excludes IBM), there would remain 14 firms with 4,905 software patents and 8,736 total patents.

It is clear that the match using the 1989 ownership patterns in the NBER patent database was outdated for our purposes, as many software firms were established or became public after 1989. Thus the third step was to do a new match between the CorpTech and NBER databases. The focus was to identify patents in the NBER database whose assignees were public firms either born or becoming public after 1989. The matching was done manually, as follows. For each of the 1,198 public companies in the CorpTech data with CUSIP numbers that do not appear in the NBER data, we searched the NBER database for matching assignees. This match was done using the 'Soundex' command in SAS to find similar sounding names (including spellings, different abbreviations etc.). This procedure yielded 514 additional name matches. Because many similar sounding names may not be the same firms at all (e.g., Andromedia vs Andromeda, FoundryNetworks vs.FoundryManagement etc.), each name that differed was manually checked (using company websites) to see if the 'matched' companies were in fact the same. Fifty of the 514 provisional matches were discarded, leaving 464 confirmed firm matches. Finally, for all these firms, both the names of the parent and all its subsidiaries were checked in the NBER patent assignee list. This procedure results in the final sample of 445 firms with at least one G06F patent. We then applied the 45% threshold for the ratio of G06F to total patents in order to identify what we call 'software firms'. This yielded the final sample of 121 firms used in the paper.

TABLE 1
PREDICTIONS OF THE MODEL

Exogenous Variable	Endogenous Variable		
	R&D, r_0	Patents, ρ_0	Market value, V_0
Rivals' Patent Propensity, ρ_τ (bargaining power hypothesis)	Negative	Negative	Negative
Patent concentration, c (patent thicket hypothesis)	Ambiguous*	Ambiguous*	Positive
R&D spillovers, r_τ	Ambiguous	Positive	Positive

* If this coefficient is negative, then $H_{xc} > 0$. If the coefficient is positive, we can not infer the sign of H_{xc} .

TABLE 2
DESCRIPTIVE STATISTICS

Variable	Mnemonic	Mean	Median	Standard deviation
Market value, \$m	V	2462	97.0	10,886
Tobin's Q	V/A	6.5	4.3	6.7
R&D flow, \$m	R	188.0	14.7	739
Stock R&D/fixed capital	G/A	5.7	2.2	18.2
Patent flow (positive values only)	P	26.2 (61.9)	0 (2)	162.4 (245.3)
Sales, \$m	S	2891	109.7	12,111
Stock of fixed capital, \$m	A	1189	20.4	5880
Technology spillovers, \$m	Spillover	20,717	20,067	11,615
Patent propensity of technology rivals	Patprop	0.080	0.075	0.064
4-firm patent citation concentration index	Citecon	0.47	0.38	0.25

Notes: The sample is an unbalanced panel covering 121 firms over the period 1980-99. The cells are computed using all non-missing observations over the sample period. Dollar figures are in 1999 values.

TABLE 3
MARKET VALUE EQUATION

	(1)	(2)	(3)	(4)
Dependent variable: Log(V/A)	Baseline 1980-99	Patent Premium 1980-99	Patent Premium 1980-94	Patent Premium 1995-99
Log Spillover _{t-1}	0.167** (.050)	0.187** (.049)	0.168** (.074)	0.155* (.091)
Log Patprop _{t-1}	-0.129* (.074)	-0.122* (.073)	-0.013 (.11)	-0.276** (.12)
Citecon _{t-1}	0.344** (.11)	0.460** (.11)	0.188 (.16)	0.713** (.16)
Log Firm sales _{t-1}	0.185** (.065)	0.196** (.065)	0.021 (.12)	0.253** (.067)
Log Firm sales _{t-2}	-0.178** (.062)	-0.160** (.062)	-0.012 (.12)	-0.183** (.063)
Log TechOpp _{t-1}	2.301** (.70)	2.449** (.70)	5.025** (.95)	0.670 (.84)
Log TechOpp _{t-2}	-2.202** (.68)	-2.377** (.68)	-4.842** (.92)	-0.740 (.80)
(G/A) _{t-1}	0.092** (.013)	0.074** (.014)	0.045** (.024)	0.139** (.035)
(G/A) ² _{t-1}	-0.003** (.0005)	-0.002** (.0004)	-0.002** (.001)	-0.008** (.003)
(G/A) ³ _{t-1} x 10 ³	0.027** (.005)	0.024** (.005)	0.020** (.010)	0.195* (.11)
(G/A) ⁴ _{t-1} x 10 ⁶	-0.109** (.020)	-0.099** (.018)	-0.085** (.038)	-2.330 (1.46)
(G/A) ⁵ _{t-1} x 10 ⁹	0.149** (.027)	0.138** (.025)	0.120** (.046)	10.300 (6.7)
(PS/A) _{t-1}		0.712** (.21)	1.373** (.40)	0.967** (.22)
(PS/A) ² _{t-1}		-0.348** (.16)	-0.846** (.30)	-0.622** (.15)
(PS/A) ³ _{t-1}		0.065* (.039)	0.202** (.079)	0.143** (.038)
(PS/A) ⁴ _{t-1}		-0.005 (.004)	-0.021** (.008)	-0.013** (.003)
(PS/A) ⁵ _{t-1} x 10 ³		0.146 (.11)	0.734** (.29)	0.377** (.10)

Industry dummies (p-value: zero effects)	Yes (<.01)	Yes (<.01)	Yes (<.01)	Yes (<.01)
Year dummies (p-value: zero effects)	Yes (.066)	Yes (.073)	Yes (.47)	Yes (.10)
No. observations	865	865	399	466
R ²	0.49	0.51	0.61	0.52

Notes: Tobin's Q is defined as market value of equity plus debt, divided by the stock of fixed capital. Estimation is by OLS. Newey-West standard errors (in brackets) are robust to heteroskedasticity and first-order serial correlation. Dummy variables are included for observations where Citecon or lagged R&D stock is zero. * denotes significance at the 10% level, ** at the 5% level.

TABLE 4
PATENT EQUATION

Dependent variable: Patent Count	(1) No initial conditions 1980-99	(2) Initial conditions 1980-99	(4) Initial conditions 1980-94	(5) Initial conditions 1995-99
Log Spillover _{t-1}	0.106 (.096)	0.637** (.12)	0.542** (.15)	1.040** (.23)
Log Patprop _{t-1}	0.210 (.24)	-0.453** (.22)	-0.808** (.33)	-0.501 (.41)
Citecon _{t-1}	-2.540** (.38)	-2.553** (.34)	-2.171** (.42)	-2.785** (.47)
Log R&D Stock _{t-1}	0.761** (.036)	0.599** (.043)	0.578** (.065)	0.626** (.052)
Log TechOpp _{t-1}	-4.238** (2.07)	-6.328** (1.83)	-9.394** (3.14)	-6.686** (2.21)
Log TechOpp _{t-2}	4.593** (2.08)	5.982** (1.80)	9.627** (3.06)	5.386** (2.04)
Log Pre-sample patents		0.368** (.052)	0.346** (.076)	0.272** (.073)
Over-dispersion, α	1.161** (.14)	1.336** (.12)	1.005** (.15)	1.423* (.17)
Industry dummies (p-value: zero effects)	Yes (<.01)	No	No	No
Year dummies (p-value: zero effects)	Yes (<.01)	Yes (<.01)	Yes (.028)	Yes (<.01)
No. observations	991	991	472	519
Pseudo R ²	0.27	0.26	0.27	0.27

Notes: 'IC' denotes the pre-sample control for initial conditions. Estimation is based on the Negative Binomial model. Standard errors (in brackets) are robust to heteroskedasticity. Dummy variables are included for observations where Citecon or lagged patent flow is zero. The initial conditions in columns (2)-(4) are estimated with 'pre-sample mean scaling approach' of Blundell, Griffith and Van Reenen (1999). * denotes significance at the 10% level, ** at the 5% level.

TABLE 5
R&D EQUATION

Dependent variable: Log R&D	(1) Static, no firm effects 1980-99	(2) Dynamic, no firm effects 1980-99	(3) Static, firm effects 1980-99	(4) Dynamic firm effects 1980-99
Log Spillover _{t-1}	0.214** (.096)	0.104** (.036)	-0.156 (.14)	-0.102 (.096)
Log Patprop _{t-1}	-0.033 (.10)	-0.060 (.056)	-0.091 (.075)	-0.075 (.059)
Citecon _{t-1}	-1.016** (.17)	-0.198** (.095)	-0.281* (.17)	-0.124 (.14)
Log R&D _{t-1}		0.756** (.033)		0.410** (.058)
Log firm sales _{t-1}	0.952** (.078)	0.467** (.048)	0.709** (.075)	0.496** (.075)
Log Firm sales _{t-2}	-0.219** (.069)	-0.284** (.039)	0.029 (.065)	-0.077* (.048)
Log TechOpp _{t-1}	0.906 (1.03)	-0.161 (.54)	-0.070 (.82)	-0.283 (.63)
Log TechOpp _{t-2}	-1.162 (1.04)	0.087 (.51)	-0.074 (.77)	0.173 (.61)
Industry dummies (p-value: zero effects)	Yes (<.01)	Yes (<.01)	No	No
Firm dummies (p-value: zero effects)	No	No	Yes (<.01)	Yes (<.01)
Year dummies (p-value: zero effects)	Yes (.88)	Yes (.52)	Yes (.70)	Yes (.71)
No. observations	866	866	866	866
R ²	0.90	0.96	0.96	0.97

Notes: Estimation is by OLS. Newey-West standard errors (in brackets) are robust to heteroskedasticity and first-order serial correlation. The sample includes only firms which performed R&D continuously in at least two adjacent years. A dummy variable is included for observations where Citecon is zero. * denotes significance at the 10% level, ** at the 5% level

TABLE 6
COMPARISON OF EMPIRICAL RESULTS WITH MODEL'S PREDICTIONS

	Partial correlation of:	Theory	Empirics	Consistency
$\partial V_0/\partial \rho_\tau$	Market value with Patprop	Negative	-0.12*	Yes
$\partial V_0/\partial c$	Market value with Citecon	Positive	0.50**	Yes
$\partial V_0/\partial r_\tau$	Market value with Spillover	Positive	0.19**	Yes
$\partial k_0/\partial \rho_\tau$	Patents with Patprop	Negative	-0.45**	Yes
$\partial k_0/\partial c$	Patents with Citecon	Ambiguous	-2.59**	N/A
$\partial k_0/\partial r_\tau$	Patents with Spillover	Positive	0.64**	Yes
$\partial r_0/\partial \rho_\tau$	R&D with Patprop	Negative	-0.091	Yes
$\partial r_0/\partial c$	R&D with Citecon	Ambiguous	-0.28**	N/A
$\partial r_0/\partial r_\tau$	R&D with Spillover	Ambiguous	-0.16	N/A

Notes: The empirical results are taken from the market value equation with a patent premium (column 2, Table 3), the patent equation with the pre-sample control (column 2, Table 4), and the static R&D equation with fixed firm effects (column 3, Table 5). * denotes significance at the 10% level, ** at the 5% level.

APPENDIX TABLE
LIST OF SAMPLE FIRMS (FIRST HALF)

Cusip	SIC	Company Name	Cusip	SIC	Company Name
004334	3663	Accom, Inc.	205638	7372	Compuware Corp.
004930	7372	Activision, Inc.	206186	7372	Concord Communications, Inc.
00651F	3661	Adaptec, Inc.	206710	3571	Concurrent Computer Corp.
00724F	7372	Adobe Systems, Inc.	208547	7372	Consilium, Inc.
00826M	7372	Affinity Technology Group, Inc.	232462	7372	CyberCash, Inc.
036384	7372	Ansoft Corp.	233326	7372	DST Systems, Inc.
037833	7372	Apple Computer, Inc.	238016	3625	Data Translation, Inc.
037935	3829	Applied Microsystems Corp.	253798	3577	Digi International, Inc.
043412	3661	Asante Technologies, Inc.	25387R	3577	Digital Video Systems, Inc.
04362P	7372	Ascential Software Corp.	281667	7372	J.D. Edwards & Company
045327	7372	Aspen Technology, Inc.	292475	3669	Emulex Corp.
052754	7379	Auto-trol Technology Corp.	36227K	7372	GSE Systems, Inc.
052769	7372	Autodesk, Inc.	362555	3669	Gadzoox Networks, Inc.
05367P	7372	Avid Technology, Inc.	370253	7372	General Magic, Inc.
055921	7372	BMC Software, Inc.	40425P	7372	HNC Software Inc.
073308	7375	Be Free, Inc.	451716	7372	IKOS Systems, Inc.
073325	7372	BEA Systems, Inc.	45666Q	7372	Informatica Corp.
079860	7379	BellSouth Information Systems	45812Y	7371	Integrated Surgical Systems, Inc.
109704	7372	Brio Technology, Inc.	458140	3674	Intel Corp.
111412	7372	BroadVision, Inc.	458153	7372	IntelliCorp, Inc.
12487Q	7375	CCC Information Services Inc.	458176	7372	Starfish Software, Inc.
126349	7372	CSG Systems, Inc.	458683	7371	Intergraph Corp.
127387	7372	Cadence Design Systems, Inc.	459200	7372	IBM Corp.
14167A	7372	MCS-Simione Central, Inc.	46060X	7372	Internet Security Systems, Inc.
162813	7372	CheckFree Corp.	461202	7372	Intuit, Inc.
17275R	3669	Cisco Systems, Inc.	46145F	7372	ITG, Inc.
177376	7372	Citrix Systems, Inc.	465754	7372	i2 Technologies, Inc.
204493	3571	Compaq Computer Corp.	514913	7372	Landmark Graphics Corp.
20482G	7375	CompuServe Interactive Services	51506S	7372	Landmark Systems Corp.
204912	7372	Computer Associates International	524651	7372	Legato Systems, Inc.
204925	7372	Computer Network Tech Corp.	530129	7372	Liberate Technologies

**APPENDIX TABLE
LIST OF SAMPLE FIRMS (SECOND HALF)**

Cusip	SIC	Company Name	Cusip	SIC	Company Name
545700	7372	Lotus Development Corp.	826565	7372	Sigma Designs, Inc.
553903	3572	MTI Technology Corp.	827056	7371	Silicon Graphics, Inc.
555904	7372	GLOBEtrotter Software, Inc.	827068	7372	Silicon Valley Research, Inc.
556100	7372	Macromedia, Inc.	834021	3571	SofTech, Inc.
587200	7372	Mentor Graphics Corp.	852192	7372	Spyglass, Inc.
589378	7371	Mercury Computer Systems, Inc.	859205	7372	Sterling Commerce, Inc.
589405	7372	Mercury Interactive Corp.	86211A	7372	Storage Computer Corp.
589981	7372	Merge Technologies Inc.	862685	3577	Stratasys, Inc.
594918	7372	Microsoft Corp.	866810	3572	Sun Microsystems, Inc.
604567	7371	MIPS Technologies, Inc.	871130	7372	Sybase, Inc.
641074	7372	Nestor, Inc.	871503	7372	Symantec Corp.
64108P	7375	Netcentives Inc.	871607	7372	Synopsys, Inc.
641149	7372	Netscape Communications Corp.	871926	7372	SystemSoft Corp.
64120N	3577	Network Computing Devices, Inc.	879101	8742	IEX Corp.
669937	7372	Novadigm, Inc.	879516	7372	Telescan, Inc.
670006	7372	Novell, Inc.	885535	3669	3Com Corp.
68370M	7372	Open Market, Inc.	88553W	7372	3DO Co. (The)
68389X	7372	Oracle Corp.	887336	7372	Timeline, Inc.
699173	7372	Parametric Technology Corp.	895919	3577	Trident Microsystems, Inc.
705573	7372	Pegasystems, Inc.	896121	3669	Tricord Systems, Inc.
712713	7372	PeopleSoft, Inc.	903891	3571	Ultradata Systems, Inc.
719153	7372	Phoenix Technologies Ltd	923429	7372	Verifone, Inc.
741379	7372	Preview Systems, Inc.	923436	7372	VERITAS Software Corp.
743312	7372	Progress Software Corp.	92343C	7372	Verity, Inc.
74838E	7372	Quickturn Design Systems, Inc	92672P	7372	Viewpoint Corporation
750862	3577	Rainbow Technologies, Inc.	973149	7372	Wind River Systems, Inc.
75409P	7372	Rational Software Corporation	980903	7372	Workgroup Technology Corp.
811699	3663	SeaChange International, Inc.	984149	7372	Xybernaut Corp.
813705	7372	Secure Computing Corp.	G8846W	7372	3Dlabs, Inc.
815807	7372	Segue Software, Inc.			

The SIC codes are defined as follows: 3571 Electronic Computers, 3572 Computer Storage Drives, 3577 Computer Peripheral Equipment, 3625 Relays and Industrial Controls, 3661 Telephone and Telegraph Apparatus, 3663 Radio & Television Broadcasting and Communications Equipment, 3669 Communication Equipment, 3674 Semiconductors and Related Devices, 3829 Measuring and Controlling Devices, 7371 Computer Programming Services, 7372 Pre-packaged Software, 7375 Information Retrieval Services, 7379 Computer Related Services, 8742 Management Consulting Services.