A more recent version of this article has been accepted for publication in:
Journal of Industrial Economics, 2013

Strategic Patenting and Software Innovation[1]

Michael Noel[2] and Mark Schankerman[3]

January 28, 2013

[1] **Acknowledgement:** We would like to thank Anne Layne-Farrar for her help at early stages of this project, and the Microsoft Corporation and the Center for Economic Performance at the London School of Economics for financial support. We are very grateful to Bronwyn Hall and Heidi Williams for constructive suggestions, and to Sharon Belenzon, Josh Lerner, Marc Rysman and Manuel Trajtenberg for comments on earlier versions of the paper.

[2] Texas Tech University

[3] London School of Economics and CEPR

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 ncreases the transaction costs of enforcement. We develop a model that incorporates both effects, as well as technology spillovers. Using panel data for 121 firms covering the period 1980-99, we show that strategic patenting and spillovers affect innovation and market value of software firms, that there is a patent premium accounting for 20 percent of the returns to R&D, and that software firms do not appear to be trapped in a prisoner's dilemma of 'excessive patenting'.

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

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

1 Introduction

There is an extensive empirical literature that demonstrates that R&D creates positive knowledge spillovers, which in turn contribute to productivity growth and subsequent innovation. This consensus lies at the heart of modern theories of endogenous growth and is the primary justification for government R&D-support policies.[1] One of the main instruments governments use to increase innovation incentives is the patent system. However, there is growing concern among academic scholars and public policy makers that patent rights are themselves becoming an impediment to the innovation process. The argument is that strategic patenting by firms has created a landscape characterized by a large number of patents, often with fuzzy boundaries and fragmented ownership – so called 'patent thickets'. It is claimed that these fragmented patent rights raise transaction costs, constrain the freedom of action for firms conducting R&D, and expose them to ex post holdup through patent litigation. In this way, it is argued, the growth of patenting has become a drag on innovation and capital investment. These dangers have been prominently voiced in public debates on patent policy in the United States – e.g., National Research Council (2004) and Federal Trade Commission (2011) and – and in the growing concern over the use of injunctive relief in infringement cases, as in the recent eBay decision by the U.S. Supreme Court (eBay Inc. v. MercExchange, L.L.C., 547 U.S. 338 (2006).[2]

These concerns have been intensified by the acceleration in patenting over the past three decades, especially in high technology industries. During the period 1976-1999 the total number of patent applications in the United States (granted by 2010) grew at an average annual rate of 4.4 percent. The growth accelerated sharply from the late-1980s, when there was a pro-

[1] Leading examples include Grossman and Helpman (1991) and Aghion and Howitt (1992). For a recent survey of the litertaure, see Jones (2005). In a recent paper, Bloom, Schankerman and van Reenen (2012) show that R&D also creates negative (pecuniary) externalities through product market rivalry which can lead to over-investment in R&D. But their empirical results confirm that positive externalties dominate, with social returns to R&D exceeding private returns, at least on average.

[2] The eBay decision is generally seen as limiting the use of injunctions in order to prevent hold-up. The dangers were voiced clearly by Justice Kennedy in a concurring opinion:
"In cases now arising trial courts should bear in mind that in many instances the nature of the patent being enforced and the economic function of the patent holder present considerations quite unlike earlier cases. An industry has developed in which firms use patents not as a basis for producing and selling goods but, instead, primarily for obtaining licensing fees...For these firms, an injunction, and the potentially serious sanctions arising from its violation, can be employed as a bargaining tool to charge exorbitant fees to companies that seek to buy licenses to practice the patent."

patent shift associated with the establishment of the specialized Court of Appeals for the Federal Circuit and other developments (Kortum and Lerner, 1999; Jaffe and Lerner, 2004). In the period 1986-1999, aggregate patenting grew at an annual rate of 6.7 percent. This recent growth has been particularly rapid in high tech industries – for example, 9.3 percent in pharmaceuticals, 9.2 in medical instruments, 26.9 in biotechnology, 15.8 in semiconductors and 21.0 percent in software (up to 1996). The rapid growth in software patenting is due in part to judicial decisions during this period that limited the scope of software copyright protection, while at the same time extending the patentability of software (in particular, algorithms not embedded in hardware).[3]

Previous studies have shown 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; Galasso, 2010). The importance of such mechanisms is greatest in 'complex' technology industries where innovation is cumulative and requires the input of a large number of patented innovations from diverse firms (Hall and Ziedonis, 2001; Ziedonis, 2003, 2004). In such industries, fragmented property rights can impede R&D activity by constraining the ability of firms to operate unless they have secured the required licenses of complementary technologies. This position was first enunciated by Heller and Eisenberg (1998), who labelled it the 'problem of the anti-commons.' By increasing the transaction costs of doing R&D, and the possibility that bargaining failures blocks follow-on innovation altogether, patent thickets provide an incentive for firms to develop defensive strategies, which we refer to collectively as strategic patenting. However, there remains sharp disagreement among economic and legal scholars about the scope and severity of this problem.[4]

Strategic patenting encompasses two conceptually distinct issues, which have not always

[3]Key decisions included *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 a good discussion of the changes in the legal environment for software patenting, see Lerner and Zhu (2005) and Hall and MacGarvie (2010).

[4]For opposing views on the dangers of patent thickets in software, see Lessig (2001), Lemley and Shapiro (2007), and Mann (2005). Merges (1996, 1999, 2004) has been a leading voice arguing that firms find ways to contract around patent thickets, and even strategically put some proprietary knowledge in the public domain in order to pre-empt contracting problems. Walsh, Arora and Cohen (2003) and Walsh, Cho and Cohen (2005) present supporting survey evidence in the context of biomedical research activity. In an important set of recent empirical papers, Murray and Stern (2007), Huang and Murray (2009) and Furman and Stern (2010) show that patent thickets have had some impeding effect on the rate of cumulative innovation in the biomedical area.

been sharply distinguished in the literature. The first aspect – which we refer to as defensive patenting – involves the accumulation of patents to use as bargaining chits to preserve the freedom to operate and to improve the bargaining position of the firm in resolving patent disputes when they arise. The key is the link between patent portfolio size and bargaining power. Having a larger patent portfolio puts a firm in a better position to resolve disputes without incurring the high costs of going to court, as well as securing a more favourable outcome in those disputes. Defensive patenting can be costly, but the greater economic concern is that it imposes 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 for other firms of protecting or appropriating the rents from their innovations. In the extreme case, this phenomenon could theoretically create a prisoner's dilemma in which all firms might be better off reducing patenting collectively, but none is willing to do so individually. Some authors claim that this actually occurs in complex technology industries, including semiconductors and software (Bessen and Maskin, 2000; Bessen and Meuer, 2005). However, in this paper we will provide evidence for the software sector that is not consistent with this dire prediction.

The second aspect of strategic patenting involves the link between transaction costs and the number of potential disputants. This is referred to in the literature as the fragmentation of patent rights. 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 about patent thickets, the econometric evidence on their effects is actually quite 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 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 of patent rights among rival firms. Both of these papers focus exclusively on the impact of patent thickets on patenting behaviour. Their impact on R&D investment and the stock market valuation of firms remains unexplored.[5]

In this paper we study the impact of strategic patenting on the R&D, patenting and market value of firms in the computer software industry.[6] Like semiconductors, software is a classic example of a complex technology in which cumulative innovation plays a central role. We develop a model that incorporates both aspects of strategic patenting – portfolio size and the fragmentation of patent rights – as well as knowledge spillovers. The model generates testable predictions about the impact of strategic patenting and knowledge spillovers on R&D, patenting and market value of firms. 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 (2012), using multiple indicators of performance in order to help identify the three types of externalities in which we are interested.[7]

Using panel data on 'software firms' in the U.S. during 1980-99, we find evidence of both strategic patenting and R&D spillovers. First, we find that that greater fragmentation of patent rights – which corresponds to higher transaction costs – is associated with lower market value, but higher levels of patenting and R&D. In the context of the strategic patenting model we develop, the finding that fragmentation increases patenting arises because patent accumulation is more important for resolving disputes when there are more patent holders with whom to deal. The second finding is that patenting by technology rivals reduces the

[5] While 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).

[6] In a recent empirical paper, Hall and MacGarvie (2010) also investigate the effects of software and other patents on the market value of firms in the ICT sectors. However, they do not analyse the effects of strategic patenting.

[7] Bloom, Schankerman and Van Reenen (2012) develop a methodology for distinguishing between the technology spillover and product market rivalry (business stealing) effects of R&D, and apply it to a large panel of U.S. firms. They do not address the impact of stategic patenting, which is the focus of our paper. To keep the framework tractable, we do not incorporate product market rivalry into the model.

firm's market value, patenting and R&D. This finding indicate the importance of bargaining power in resolving patent disputes. Moreover, we show that the impact of strategic patenting is significantly larger in the post-1994 period, when the courts expanded the scope for software patenting. The third key result is that R&D spillovers are important for the software firms in our sample. Spillovers significantly increase patenting and market value, controlling for the firm's stock of R&D. Finally, we also show that there is a large 'patent premium' in the stock market for these software firms, controlling for their stock of R&D and other factors. Using our parameter estimates, we show that this patent premium accounts for about 20 percent of the private return to R&D for these software firms. Our calculations also indicate that firms would not be better off by collectively reducing their levels of patenting – i.e., they do not appear to be trapped in a prisoners' dilemma of high patenting. Whether this is socially desirable, of course, is an entirely different matter.

The paper is organised as follows. Section 2 presents the theoretical model (details in Appendix 1) and summarises the empirical predictions. In Section 3 we describe the construction of the strategic patenting and technology spillover variables. Section 4 describes the data set. In Section 5 we present the econometric specification of the three equations in the model – market value, patenting and R&D. Section 6 presents the baseline empirical results and their implications, and Section 7 summarizes a series of robustness tests. We conclude with a brief summary of key findings and directions for future research.

2 Analytical Framework

We consider a setting with two firms, denoted 0 and τ. We will refer to firm 0 as the focal firm. Each firm produces knowledge by investing in R&D, but it also may benefit from technology spillovers from the other firm, which we will call its technology rival. Each firm recognises that it generates as well as receives technology spillovers. The knowledge production functions for the focal firm and the technology rival are

$$\begin{aligned} k_0 &= \phi^0(r_0, r_\tau) \\ k_\tau &= \phi^\tau(r_\tau, r_0) \end{aligned}$$

We assume that $\phi_1^i > 0$ and $\phi_2^i \geq 0$ and ϕ^i is concave in both arguments, where $i = 0, \tau$ and subscripts 1 and 2 refer to derivatives with respect to the arguments in ϕ^i. If there are knowledge spillovers, $\phi_2^i > 0$, but theory does *not* sign the cross partial ϕ_{12}^i. Knowlege spillovers raise the *average* product of own R&D, but they can raise, lower or leave unchanged the *marginal* product. As we will show later, this implies that the impact of knowledge spillovers on the optimal choice of R&D investment is ambiguous.

We assume that patent protection (potentially) increases the rents that a firm can earn from its innovations. Let $\rho \in (0, 1)$ denote the fraction of its knowledge that it protects by patenting, which we call the 'patent propensity'. We let $\lambda \geq 1$ represent the amount of rent that can be appropriated from a unit of knowledge if it patented relative to the rents if it is not patented, which we call 'patent effectiveness'. Thus $\lambda - 1$ represents the patent premium. Thus the 'effective unit' of knowledge from an appropriation perspective is given by $\theta_0 = \rho_0\lambda + (1 - \rho_0)$. The focal firm's variable profit function is $\Pi(\theta_0 k_0, w)$, which we assume is increasing and concave in k_0, and decreasing and convex in input prices, w. For notational simplicity we suppress input prices in what follows.

Patenting is costly. The unit cost of a patent includes a fixed administrative (application) fee denoted by c, and a patent enforcement cost denoted by H. Enforcement costs depend on two features of the patenting environment in which the firm operates. The economic literature on patents emphasises that transaction costs of patent enforcement are likely to be higher higher when patent rights are widely dispersed ('fragmented') among different owners, rather than being held by a relatively small number of other firms. When patent rights are more fragmented, it is more 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.' In addition to higher transaction costs, the risk of bargaining failure in the negotiation over the required set of (patented) technological inputs is also greater when there are more distinct patentholders with whom negotiations must be conducted.[8]

The second determinant of enforcement costs is the size of the patent portfolio held by the firm. Using comprehensive data on patent litigation in the U.S., Lanjouw and Schankerman

[8] For discussion and evidence, see Heller and Eisenberg (1996), Ziedonis (2003a), Arora and Cohen (2003), and Walsh, Cho and Cohen (2005).

(2001, 2004) show that the probability of a patent being involved in litigation is much lower when that patent is held as part of a larger portfolio, controlling for observable characteristics of the patent and the patent owner. They argue that these economies of scale in enforcement reflect the ability of larger firms to avoid disputes and to resolve those that do arise in tacitly cooperative ways. In addition, having a larger portfolio size puts the firm in a better bargaining position in negotiations (improving the terms of any agreement), and increases the potential threat to retaliate in the event negotiations of disputes fail. In addition, firms with large patent portfolios avoid litigation through broad cross licensing agreements that preserve their freedom to operate and lower transaction costs (Galasso, 2012). For all these reasons, portfolio size enables firms to reduce the costs of enforcing their patent rights effectively. We refer to this as the 'portfolio size effect'.

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 portfolio size effect), and (2) the degree of fragmentation of patents held by firms in similar technology areas, denoted by f (the patent thicket effect). Formally, we denote the enforcement cost per patent by

$$\begin{aligned} H &= H(x, f) \\ H_x &\leq 0, H_{xx} \geq 0, H_f \geq 0, H_{xf} \lesseqgtr 0 \end{aligned}$$

Relative portfolio size, x, is endogenous since the firm chooses its patent propensity ρ_0. We treat the fragmentation of patents by firms in similar technology areas as exogenous to the firm.

By adopting a specification of the patent portfolio effect that depends on the relative (rather than absolute) number of patents between a firm and its technology rival, we highlight the idea that it might be mutually beneficial for firms to reduce their propensities to patent, putting aside for the moment the lower level of innovation rents that might result if there is a patent premium. In other words, there may be a prisoner's dilemma aspect to strategic patenting, as Bessen and Maskin (2008) emphasize. In the empirical analysis below, we will use our parameter estimates to test whether this prisoner's dilemma actually operates for the software firms in our sample.

The direct effect of higher fragmentation of patents among a firm's technology rivals is to increase its enforcement costs – that is, $H_f \geq 0$. However, there is also an indirect effect because greater fragmentation may change the marginal value of accumulating patents to reduce enforcement costs, which is given by $\mid H_x \mid$. This indirect effect can be either positive or negative – it depends on the sign of H_{xf}. We find it most plausible that greater fragmentation of patent rights increases the marginal value of accumulating patent portfolios, which corresponds to $H_{xf} < 0$, because in such cases firms are less likely to have effective methods of 'tacit cooperation', apart from explicit patent trading arrangements, to resolve disputes with different patent holders without litigation. We will show that this hypothesis implies a testable prediction, which we will examine in the empirical analysis.

Each firm has two decision variables: the level of R&D investment and the patent propensity. The firm chooses these instruments to maximise the market value, which is given by variable profit net of the cost of R&D and patent application and enforcement costs. Focusing on the focal firm, we can write the decision problem as

$$\max_{r_0,\rho_0} V = \Pi(\theta_0\phi^0(r_0,r_\tau)) - r_0 - \{c\rho_0 + H(x,f)\}\phi^0(r_0,r_\tau) \tag{1}$$

Recall that the knowledge production functions $k_0 = \phi^0(r_0, r_\tau)$ and $k_\tau = \phi^\tau(r_\tau, r_0)$ enter the function $H(x, f)$ since $x = \frac{\rho_0 k_0}{\rho_\tau k_\tau}$. In the specification above, we assume that the enforcement cost $H(x, f)$ applies to all units of knowledge, both patented and unpatented. The idea is that if a firm has more bargaining chits in the form of patents, it can also more easily resolve disputes over unpatented innovations.[9]

The first order conditions for the focal firm's maximisation problem are

$$V_{r_0} = \phi_1^0\{\theta_0\Pi_1^0 - c\rho_0 - H\} - (\frac{\rho_0 k_0}{\rho_\tau k_\tau})(k_\tau\phi_1^0 - k_0\phi_2^\tau)H_x - 1 = 0 \tag{2}$$

$$V_{\rho_0} = k_0\{(\lambda-1)\Pi_1^0 - c - (\frac{k_0}{\rho_\tau k_\tau})H_x\} = 0 \tag{3}$$

[9] An alternative specification is to assume that the enforcement cost is higher for patented innovations. We can do this by expressing unit cost as $c\rho_0 + \{(1+\mu)\rho_0 + (1-\rho_0)\}H(x,f)$, where $\mu \geqslant 0$. The qualitative predictions in this specification are similar to those in the text.

where the superscripts on ϕ and Π refer to the firm, while the subscripts denote partial derivatives (1 refers to the single argument in Π, and 1 and 2 refer to the two arguments in ϕ).

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.

For the empirical analysis, we use the model to derive predictions about how R&D and patenting by the technology rival firm τ, and the fragmentation of patent rights, affect the optimal choices of the focal firm 0.[10] Appendix 1 provides the technical details of the analysis. As we make clear in that appendix, we need two key ancillary assumptions to derive these predictions, which we want to bring out here for clarity. These assumptions are:

$A1$: (a) $k_\tau \phi_1^0 - k_0 \phi_2^\tau > 0$ and (b) $k_0 \phi_1^\tau - k_\tau \phi_2^0 > 0$

$A2$: $\frac{x H_{xx}}{|H_x|} < 1$

Assumption A1 says that a firm's R&D has a larger impact on its own knowledge production (in elasticity terms) than it does on its rival's knowledge (part (a) applies to firm 0, part (b) to firm τ).[11] This seems natural since a firm's own R&D is presumably more closely tied to its innovation activity than a rival's (and only a part of the rival's activity may in fact be relevant). As is clear from the second term in equation (2), this assumption ensures that an increase in own R&D has the effect of reducing enforcement costs. Assumption A2 says that the elasticity of the marginal enforcement cost function (H_x) with respect to portfolio size is less than one in absolute value – i.e., that diminishing returns to portfolio accumulation are not 'too strong'.

[10] In this analysis we treat firm $\tau' s$ decisions as exogenous to the focal firm. In the empirical analysis we will show that the results are robust to using lagged internal instruments to account for possible endogeneity issues.

[11] Rearranging part (a) in A1 and multiplying through by r_0, we get $\frac{r_0}{k_0}\phi_1^0 > \frac{r_0}{k_\tau}\phi_2^\tau$. The left hand side is the elasticity of k_0 with respect to r_0 and the right hand side is the elasticity of k_τ with respect to r_0. Analogously, multiplying through part (b) by r_τ, we get $\frac{r_\tau}{k_\tau}\phi_1^\tau > \frac{r_\tau}{k_\tau}\phi_2^0$. The left hand side is the elasticity of k_τ with respect to r_τ and the right hand side is the elasticity of k_0 with respect to r_τ.

Together with Assumptions $A1$ and $A2$, the model generates predictions about how the fragmentation of patent rights, patent propensity of rivals, and technology spillovers affect the market value, patents and R&D of the focal firm. Table 1 summarizes these predictions.

[TABLE 1 ABOUT HERE]

We can summarise the intuition behind these predictions as follows. Starting with the market value equation, greater fragmentation of patent rights among technology rivals means higher transaction costs for a firm in licensing complementary patents and resolving patent disputes. This higher enforcement cost reduces market value unambiguously ($\frac{\partial V_0}{\partial f} < 0$). Second, when the patent propensity of technology rivals is higher, the focal firm incurs greater enforcement costs, since they depend on the relative patent portfolio sizes of the focal firm and its rivals. This also lowers market value ($\frac{\partial V_0}{\partial f} < 0$). Third, a rise in R&D by technology rivals increases knowledge spillovers enjoyed by the focal firm and thus raises its market value ($\frac{\partial V_0}{\partial r_\tau} > 0$).

We consider next the patenting and R&D equations together. First, greater fragmentation of patent rights means higher transaction costs for the focal firm, which has two effects. The direct effect is to raise enforcement costs for the focal firm, which reduces the profitability and thus the optimal level of both R&D and patenting. However, there is also an indirect effect because greater fragmentation changes the marginal incentive to accumulate patents (and the R&D that creates them) in order to reduce enforcement costs. The direction of this effect depends on the sign of H_{xf}. If fragmentation increases the marginal value of accumulating patents (given by$\mid H_x \mid$) – i.e., if $H_{xf} < 0$, which is what we would expect – then the direct and indirect effects work in opposite directions and the impact on R&D and patents is ambiguous. Conversely, if $H_{xf} > 0$, then fragmentation must reduce R&D and patenting. Therefore, if we find that fragmentation has a positive impact on R&D and/or patenting ($\frac{\partial r_0}{\partial f} > 0$, $\frac{\partial \rho_0}{\partial f} > 0$), we can infer that $H_{xf} < 0$.

Second, an increase in the patent propensity of technology rivals raises enforcement costs for the focal firm, and thus reduces the optimal level of R&D and patenting. ($\frac{\partial r_0}{\partial \rho_\tau} < 0$ and $\frac{\partial \rho_0}{\partial \rho_\tau} < 0$).[12] Finally, when technology rivals increase their R&D, this raises the knowledge

[12] There is also an indirect effect at play here: greater patent accumulation by technology rivals reduces the

spillovers enjoyed by the focal firm and thus its innovation output. This increases the the marginal returns to patenting and thus the focal firm's patent propensity ($\frac{\partial \rho_0}{\partial r_\tau} > 0$). However, the effect on its own R&D spending is ambiguous because theory does not determine the impact of spillovers on the marginal productivity of own R&D (i.e., the sign of ϕ_{12} is ambiguous).

We also want to point out that the use of multiple outcomes – market value, patents and R&D – provides a stronger test of the model than we would have from any single indicator. The market value equation provides the unambiguous prediction on the impact of fragmentation (whereas the impact on patents and R&D depend on the sign of H_{xf}). Each of the three equations provides a (complementary) test of the effects of rivals' patent propensity, and thus a stronger overall check on this hypothesis. Finally, we get two tests of the effects of R&D spillovers, one from the market value equation and the other from the patents equation.

3 Measuring strategic patenting and technology spillovers

The software firms in our sample have patenting activity in a variety of technology fields. 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 we use the distribution of a firm's *backward patent citations* across patent classes to measure technological proximity. Our measure of backward citations for a firm includes all of the citations made by that firm in the patents it has been granted up to that year (excluding self-cites). Using citations, rather than patent counts, to construct the proximity measure is appealing because patent citations identify the earlier (patented) technologies that the invention draws upon. The idea is that patent disputes are likely to be associated with these related technologies. Economic research has shown that patent litigation is more likely to arise when

relative patent portfolio of the focal firm, x, which increases the marginal value of patenting by the focal firm since $H_{xx} > 0$. The net effect is revealed by the sign of the cross-derivative $H_{\rho_0 \rho_\tau}$. Using the enforcement cost function $H(x, f)$ where $x = \frac{\rho_0 k_0}{\rho_\tau k_\tau}$, we get sign $H_{\rho_0 \rho_\tau} =$ sign $\{-H_x(1 + xH_{xx}/H_x)\}$. Under Assumption A2, we obtain $H_{\rho_0 \rho_\tau} > 0$, so we get the prediction that greater patenting by rivals reduces the incentive for a firm to accumulate patents.

technological similarity is greater (Lanjouw and Schankerman, 2004). To our knowledge, ours is the first paper to implement a citations-based proximity measure.

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. Self-cites are excluded. Then technology proximity between firm i and j is given by the uncentered correlation coefficient between the citation distributions of the two firms:

$$\tau_{ij} = \frac{W_i{}'W_j}{(W_i'W_i)^{\frac{1}{2}}(W_j'W_j)^{\frac{1}{2}}} \tag{4}$$

where $\tau_{ij} \in [0, 1]$. In the sample, there is large variation in the computed technology distances between firms, with a median of 0.118 but varying all the way from no overlap in citations ($\tau = 0$) to perfect overlap ($\tau = 1$). Among the top five percent of firm pairs in terms of our index of technology proximity are Intel and IBM, Adobe and Apple, and Microsoft and Sun Microsystems. As a robustness check, we also constructed the standard Jaffe measure based on the distribution of patents. The cross sectional correlation between the two technology proximity measures is 0.69, and the econometric results are similar to those reported 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 the technology proximity weights

$$Spillover_{it} = \sum_{j \neq i} \tau_{ij} G_{jt} \tag{5}$$

The R&D stock is constructed by initialising the stock at the beginning of the sample period and using a 15 percent depreciation rate.[13]

To capture the patent portfolio effect of strategic patenting, we compute the weighted average of the 'patent propensity' (measured as the ratio of the patent to R&D stocks) 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 face higher enforcement costs, and be at a greater disadvantage in bargaining over patent disputes.

[13]Initial stock is defined as the intial 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.

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 is

$$Patprop_{it} = \sum_{j \neq i} w_{ij} Z_{jt} \tag{6}$$

where $w_{ij} = \frac{\tau_{ij}}{\sum_{j \neq i} \tau_{ij}}$.[14]

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. The basic idea is that, when a focal firm's patent citations are more fragmented among technology rivals, that firm will incur higher transaction costs in dealing with patent disputes that may arise. Earlier studies of patent thickets employ measures of fragmentation based on how dispersed patenting is across firms in the same technology field as the focal patent field (e.g., Ziedonis, 2004; Galasso and Schankerman, 2010). By contrast, our measure is based on the number of different firms *cited* by the focal firm in its patents. Our fragmentation index is higher captures the degree to which the focal firm cites patents held by diverse firms.

To construct our fragmentation index of patent citations for firm i in year t, we first identify the firm which owns (i.e., patent assignee) each patent that firm i cites in any of the patents in its portfolio in 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. The 4-firm fragmentation measure is equal to one minus the share of these backward cites that go to the top four firms. 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 fragmentation measure is

$$Fragcites_{it} = 1 - \sum_{j=1}^{4} s_{ijt} \tag{7}$$

We also experimented with two alternative measures – an 8-firm fragmentation index and a Herfindahl index, both based on the distribution of backward cites as described above. The econometric results using these measures are similar to those reported in Section 6.

[14] We also experimented with an alternative measure that does not normalise the weights, i,.e, using τ_{ij} rather than w_{ij}. Empirical results are similar to those reported in the text. The non-normalised measure is less conceptually appealing because it results in a higher *Patprop* when there are more technological competitors, for a given level of rivals' patent propensity. As such, the alternative measure blurs the distinction between the effects of patent propensity and concentration in the technology market.

4 Data

Our data set covers the period 1980-1999 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.[15] 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.[16] One approach is to do a keyword search on the USPTO database (this is the approach adopted by Bessen and Hunt, 2003). This can be difficult, and problematic, 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). Fortunately, in a careful discussion of these various alternative approaches, Hall and MacGarvie (2010) conclude that there is considerable overlap in the resulting populations of 'software patents' and that empirical findings are not particularly sensitive to the methodological choice.

Software (G06F) patents are taken out by firms in many diverse industries (Shalem and Trajtenberg, 2009). Moreover, even 'pure' software firms are likely to patent outside G06F, and

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

[16] For a good discussion of different approaches to defining software patents, see Layne-Farrar (2005).

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 also have data on R&D and market value. 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.[17] 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.

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

[17] In 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.

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 percent 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 provides some basic descriptive statistics. The sample firms are large and R&D intensive, but with considerable heterogeneity in market value, patents and R&D. 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. There is substantial variation in the patent propensity of technology rivals ($Patprop$). Patent citations are not dramatically fragmented – the sample mean of $Fragcites$ is 0.53, which implies (in the symmetric case) that on average a firm cites about eight other firms. It is also worth noting (not reported in the table) that the average value of $Patprop$ rose sharply after 1994 (then courts expanded the scope for software patenting) – it was 0.028 in 1980-94 and 0.133 in 1995-99. However, the fragmentation index does not change much between the pre- and post-1994 periods, despite the sharp increase in software patenting.

[TABLE 2 ABOUT HERE]

5 Econometric Specification

5.1 Market Value Equation

In the empirical specification, we follow the approach of Bloom, Schankerman and Van Reenen (2012) 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):

$$\ln (V/A)_{it} = \ln \kappa_{it} + \ln (1 + \gamma^{v} (G/A)_{it}) \tag{8}$$

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.[18] 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 of κ_{it}. We parameterize the latter as

$$\begin{aligned} \ln \kappa_{it} &= \beta_1^v \ln Patprop_{it-1} + \beta_2^v \ln Fragcites_{it-1} + \beta_3^v \ln Spillover_{it-1} \\ &\quad + X_{it-1}^{V\prime} \beta_4^v + \xi_I^v + \eta_t^v + \upsilon_{it}^v \end{aligned} \tag{9}$$

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 υ_{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 $\ln 1 + \gamma^v (G/A)_{it}$ by $(G/A)_{it}$, but this will not be adequate for many high tech firms (Hall and Oriani, 2004). Therefore, we approximate $\ln\left(1 + \gamma^v \left(G/A\right)_{it}\right)$ 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

$$\begin{aligned} \ln\left(V/A\right)_{it} &= \Phi((G/A)_{it-1}) + \beta_1^v \ln Patprop_{it-1} + \beta_2^v \ln Fragcites_{it-1} \\ &\quad + \beta_3^v \ln Spillover_{it-1} + X_{it-1}^{v\prime} \beta_4^v + \xi_I^v + \eta_t^v + \upsilon_{it}^v \end{aligned} \tag{10}$$

The predictions of the model are as follows: $\beta_1^v < 0, \beta_2^v < 0, \beta_3^v > 0$ and the marginal stock market valuation of R&D, computed from the coefficients of the polynomial $\Phi(G/A)$, should be positive.

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

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

as equation (10) except that we incorporate a (fifth) order polynomial in the ratio of the firm's patent stock to fixed assets, $\Psi(PS/A)$.[19] This version allows us to compute the market patent premium from the coefficients of the polynomial $\Psi(PS/A)$.

Since the software firms in our sample are classified into different SIC industries, we include four-digit industry dummies in the market value equation 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.[20] 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).[21]

In the market value equation, as in the patent and R&D specifications described below, 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 and patenting 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 variables, which should also reduce

---

[19] We 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.

[20] Strictly speaking, under the efficient market hypothesis the market value in period t should not be predictable with information publicly available at $t-1$.

[21] Using a larger sample of firms from a broader set of manuafacturing industries, Bloom, Schankerman and Van Reenen (2012) are able to estimate a market value equation with fixed firm effects, but in the current study we are not able to do so.

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.

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.[22] Finally, we construct a measure of technological opportunity defined as the total patenting in a technology class weighted by a firm's closeness to that class, as captured 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.[23]

5.2 Patent Equation

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

$$\begin{aligned} E(P_{it}|X_{it}) \quad = \quad & \exp\{\beta_1^p \ln Patprop_{i,t-1} + \beta_2^p \ln Fragcites_{i,t-1} + \beta_3^p \ln Spillover_{i,t-1} \\ & + X_{it}^{p\prime}\beta_3^p + \xi_i^p + \eta_t^p\} \end{aligned} \tag{11}$$

The predictions of the model are $\beta_1^v < 0, \beta_2^v \gtrless 0$, and $\beta_3^v > 0$. Writing $E(P_{it}|X_{it}) = \exp(x_{it}'\beta^p)$ 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 constrains the mean and variance to be the same, corresponding to the special case $\alpha = 0$, whereas 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 pre-

[22] We 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 which is available for the sub-period 1993-2001. Results using this control are similar to those reported in Section 6.

[23] We also experimented with measures using patent flows rather than stocks. Empirical results were similar to those reported in the text.

sample scaling approach developed by Blundell, Griffith and Van Reenen (1999) – this uses pre-sample information on patents to control for heterogeneity. The alternative approach using conditional maximum likelihood (Hausman, Hall and Griliches, 1984) 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

$$\begin{aligned}\ln R_{it} &= \varphi^r \ln R_{it-1} + \beta_1^r \ln Patprop_{it-1} + \beta_2^r \ln Fragcites_{it-1} \\ &\quad + \beta_3^r \ln Spillover_{it-1} + X_{it-1}^{r\prime}\beta_3^r + \xi_i^r + \eta_t^r + \upsilon_{it}^r \qquad (12)\end{aligned}$$

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 υ_{it}^r is an idiosyncratic error term. The predictions of the model are $\beta_1^r < 0, \beta_2^r \gtreqless 0$, and $\beta_3^r \gtreqless 0$. In the R&D equation we include fixed firm effects to capture unobserved heterogeneity.[24] 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.

6 Empirical Results

6.1 Market Value Equation

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 the firm's (lagged) R&D stock is strongly related to its market value. Using the estimated coefficients on the polynomial in G/A, we find that a 10 percent increase in the R&D stock is associated with a 8.4 percent increase in value. Evaluated at the sample means, this implies that an extra dollar of R&D generates an increase of 96 cents in market value.[25] This estimate

[24] The time dimension of the company panel is relatively long (mean number of annual observarions is 9.1), so the 'within groups bias' on weakly endogenous variables is likely to be small (Nickell, 1981).

[25] We 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 $\frac{\partial V}{\partial G} = \frac{V}{A}\Phi'(\frac{G}{A})$.

is similar to the one found by Hall and MacGarvie (2010) in their study of software patents (though they use a different scheme for identifying software patents). It is also in line with Hall, Jaffe & Trajtenberg (2005), who study a broader sample of firms in diverse industries and 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 also is a large indirect return in the form of a patent premium.

[TABLE 3 ABOUT HERE]

Second, we find that technology spillovers strongly affect the stock market value. The estimated coefficient on *Spillover* is positive and statistically significant, and implies 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 a dollar of additional *Spillover* is associated with an increase in market value of 13 cents. In other words, an extra dollar of technology spillovers 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, 2012), which is consistent with the widely-held view that cumulative innovation is particularly important in software.

Third, our findings strongly support the model's predictions about strategic patenting – there is evidence that both fragmentation of property rights (transaction costs) and relative patent portfolio size (bargaining power) affect the market value of firms. Firms that face a more fragmented set patent rights among rivals have significantly lower market value. This finding is consistent with the hypothesis that higher fragmentation increases the transactions costs of settling patent disputes. The coefficient on $Fragcites$ 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) raises market value by 1.7 percent. We also find that firms which face technology rivals with higher patent propensities have lower market value. The estimated coefficient on $Patprop$ is negative and statistically significant, and implies that a 10 percent increase in the patent propensity of rivals reduces a firm's value by 1.3 percent.

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 a more encompassing measure of knowledge than simply using patents. However, as Schankerman (1998) emphasized, there may also be a patent premium for those innovations the firm chooses to patent – i.e., their private value would be less if not patented. This is a particularly contentious issue in software, and other sectors where technology is fast-moving and cumulative. Some commentators have suggested that patenting in such sectors does not contribute to private value, and may even reduce it (e.g., Bessen and Meuer, 2005).

To investigate this hypothesis for software firms, we augment the empirical specification with 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. If there is a patent premium, the patent stock should affect market value after controlling for the stock of R&D. The results in column 2 shows clear evidence of a patent premium. Using the estimated coefficients on the polynomial in PS/A (evaluating at sample means), we obtain a statisticallly significant elasticity of market value with respect to the stock of patents equal to 0.32 (standard error = 0.084). We denote this elasticity by $e_{V,PS}$. Thus a 10 percent increase in the patent stock is associated with a 3.2 percent rise in market value, holding the stock of R&D constant.[26] In this extended specification, we also can compute the elasticity of market value with respect to the R&D stock, denoted by e_{VG}. The point estimate is 0.71. Taken together, these findings imply constant returns to scale with respect to innovation in the value equation – a 10 percent increase in *both* the stocks of R&D *and* patents is associated with about a 10.3 percent increase in market value. Nonetheless, allowing for a patent premium in the specification of the market value equation

[26]We compute this elasticity as $e_{V,PS} = \frac{PS}{A}\Psi'(\frac{PS}{A})$ where Ψ' is the derivative of the polynomial Ψ.

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 and the indirect return through the patent premium. Formally, we can express the total elasticity of market value with respect to R&D stock as follows: $E_{VG} = e_{VG} + e_{V,PS}\ e_{PS,G}$. 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 the stock of 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: $E_{VG} = 0.71 + 0.32\ x\ 0.60 = 0.90$. In other words, the direct effect of a 10 percent increase in the R&D stock raises market value by 7.1 percent, but once we account for the effect through the patent premium, the market value gain rises to 9.0 percent.

From this we conclude that the patent premium accounts for 21 percent of the total elasticity effect of R&D.[27] This finding shows that patents are important as a means of appropriating innovation rents in software. This is noteworthy because of the frequent claims to the contrary.

One cautionary remark is in order. We interpret the patent premium as reflecting the fact that patents enhance the ability of the firm to appropriate rents from any given innovation output, relative to alternative methods of protection. It is also possible that patents are simply serving as a (noisy) indicator of R&D success, but do not affect the firm's ability to appropriate innovation rent. Since patenting is costly we expect firms to take out patents only on their more valuable innovations, so the patent premium we estimate from the market value equation may reflect the higher profit stream associated with successful, above-average quality R&D. Unless one had an independent indicator of R&D success, this second interpretation cannot be ruled

[27] We 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.

It is interesting to note that, in their study of software, Hall and MacGarvie (2010) found that the elasticity of market value with respect to patents per R&D (controlling for R&D stocks) is 0.30. This is similar to our computed patent premium.

out. However, our estimated patent premium is broadly in line with estimates, for a variety of industries, which are based on methodologies that are not subject to this interpretation problem.[28] For this reason, we conclude that software patent rights do in fact generate private value.

One other important implication comes out of the empirical results. 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, 2008) argue that patent regimes in complex technology industries create a prisoner's dilemma in which firms could be better off by collectively reducing their levels of patenting. We can test this conjecture using our parameter estimates. Suppose that all firms were to increase their patenting proportionally. If they are trapped in a prisoners' dilemma, this scaling up of patenting would be expected to reduce the market value of all firms, holding their R&D constant. In particular, the conjecture implies that the sum of the coefficient on $Patprop$ in the market value equation and the elasticity on own patent stock (computed from the polynomial in PS/A) should be negative. Our parameter estimates do not support this claim. Using the estimates from column 2, we compute the sum of these elasticities as $-0.12 + 0.32 = 0.19$ (standard error = 0.11), which is significantly different from zero at the 10 percent level. This result indicates that a proportional increase in patenting by the firms in our sample *increases* the market value of firms.[29] To our knowledge, this is the first attempt to subject the prisoners' dilemma claim to an empirical test. While a definitive conclusion for software, and other complex technology sectors, must await further studies to confirm or refute our finding, the evidence here should raise doubts about the empirical relevance of the claim.

As discussed in the introduction, the scope of software patent protection was gradually increased, and software copyright protection reduced, in a series of court decisions during the 1980s and early 1990s. These decisions made it increasingly desirable for firms to protect

[28] These include patent renewal models that estimate the value of patent rights from the willingness of patentees to pay maintaince fees (Schankerman and Pakes, 1986; Pakes, 1986; and Schankerman 1998), and structural models using survey data of R&D and patenting (Arora, Ceccagnoli and Cohen, 2008).

[29] In our robustness analysis in Section 7, we also make this computation in an extended specification of the patents and market value equations that adds a control for product market concentration. In that specification, the sum of the estimated coefficient on $Patprop$ and the elasticity of own patent stock is even larger, 0.280 (standard error = 0.12), and statistically significant at the 0.05 level.

software algorithms using patents rather than by copyright as they had done previously. We want to investigate whether the shift in patent policy, and the associated intensification of software patenting, had any discernible impact on the market valuation of R&D and patents for our software firms, or the effect of strategic patenting variables on market value. It is sometimes claimed that these policy changes made strategic patenting in software more important. To examine this, we break the sample into two sub-periods, 1980-94 and 1994-99, and estimate the market value equation separately for each period.[30]

Columns 3 and 4 in Table 3 presents the results. Two striking findings emerge. First, we find no evidence that the shadow price of the R&D stock changed as a result of the change in patent regime (the coefficients are not reported, for brevity). We cannot reject the null hypothesis that the coefficients on the polynomial in G/A are the same in both periods (p-value = 0.20). Second, although we do reject the hypothesis that the coefficients on the polynomial in PS/A remained constant over the two periods (p-value $< .01$), the implied shadow price of the patent stock does not change very much between periods. We estimate it 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.

Second, we find that the impact of the strategic patenting variables on the market value of firms increased substantially in the post-1994 period. Neither the fragmentation of patent rights nor the patent propensity of rivals has any significant effect on market value in the earlier period. After the policy shift, however, both fragmentation and the patenting by technology rivals reduce market value, as the estimated coefficients on $Fragcites$ and $Patprop$ are negative and statistically significant.

One last point warrants mention. We interpret the strategic patenting variables $Fragcites$ and $Patprop$ as capturing aspects of the costs of enforcing patent rights as depicted in the model. However, one might worry that our measures may simply be proxies for product market competition. Greater fragmentation may proxy for low concentration (thus greater competition) in the product market, which one would expect to reduce market value. Similarly, $Patprop$

[30]There 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.

might be picking up the effect from patenting by product market competitors (who may also be technology rivals). However, if this were the case, we would expect to see their impacts on market value in both periods. The fact that *Fragcites* and *Patprop* have no signficant effect in the first period suggests that they are not just serving as proxies for product market competition. We conduct an additional check of this alternative interpretation in Section 7.

In summary, we conclude that the change in patent regime was associated with a sharp increase in the importance 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 R&D or 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. While this may at first seem surprising, it is what we would expect to see if firms face roughly the same cost of capital in both periods and are optimally adjusting their R&D and patenting decisions to equalize the marginal private returns and costs from these investments.

6.2 Patent Equation

Table 4 presents the results for the patent equation.[31] 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.[32] Also note that the coefficients on our measures of technological opportunity (*Techopp*)

---

[31] Two points should be noted. First, In 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. Second, we also estimated the model using citation-weighted 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.

[32] The 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, the decision to patent will depend on the incremental profits from patenting relative to protecting those

are surprising – they suggest that the growth in 'technological opportunity' reduces current patenting (the coefficients are about equal in magnitude and opposite in sign). Since *Techopp* measures the aggregate patent activity in the patent classes in which the firm operates, the estimated coefficients suggest 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.[33] But some caution is warranted here, in view of our earlier finding that the growth in *Techopp* increased the market value of firms.

[TABLE 5 ABOUT HERE]

Turning now to the key variables of interest, the empirical results support the hypothesis that both strategic patenting variables and technology spillovers affect the decision to patent. First, there is strong evidence that greater fragmentation (higher transaction costs) affects the decision to patent. Higher fragmentation is associated with a statistically significant increase in patenting. This finding is consistent with the earlier evidence on semiconductor firms in Ziedonis (2004). In the context of our model, this finding implies that greater fragmentation increases the marginal value of accumulating a patent portfolio in order to enforce patent rights (in the model, $H_{xf} < 0$). 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 – e.g., 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.

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

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.

[33] We 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 probabilty 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.

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 reduces their 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, knowledge spillovers strongly affect patenting once we control for unobserved firm heterogeneity (column 2). The coefficient on *Spillover* is positive and highly significant. The spillover effect is large: a ten percent increase in spillovers is associated with a 6.4 percent increase in patenting, holding the firm's own R&D stock constant.

Finally, we test whether the policy shift toward software patentability increased the impact of patent portfolios or fragmentation on the patenting behaviour of firms. 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 $Fragcites$ are larger in the later sub-period, and the coefficient on $Patprop$ is smaller, the differences are not statistically significant.

6.3 R&D Equation

Table 6 presents the parameter estimates for the R&D equation. Overall, the results are weaker than for the market value and patent equations. The main result is that R&D investment is higher when patent rights are more fragmented. The effect is statistically significant in the static model without fixed effects (column 1), and holds up when we introduce dynamics or fixed firm effects in the regression (columns 2 and 3, respectively). In the static specification with fixed effects, the estimates imply an elasticity of R&D with respect to fragmentation about 0.14 – a 10 percent increase in fragmentation only raises raises R&D by about 1.4 percent. When we introduce both fixed effects and dynamics in column 4, the point estimate is broadly similar but no longer statistically significant.

As explained in Section 2, the effect of fragmentation on R&D is ambiguous, and depends on how fragmentation affects the marginal value of patent accumulation as a means to reduce enforcement costs (i.e., on the sign of H_{xf}). Our finding that fragmentation increases R&D

implies that $H_{xf} < 0$, which is consistent with what we found in the patent equation. This means that having a larger patent portfolio is more valuable when patent rights are more fragmented among rival firms. This finding is consistent with our expectations, since tacit forms of cooperation are less likely to develop in such cases, making a large patent portfolio more important to avoid and resolving disputes.

[TABLE 6 ABOUT HERE]

We do not find much evidence that the patent propensity of technology rivals affects R&D. 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.

Finally, we find that knowledge spillovers do not affect the R&D decision, once we control for firm fixed effects. While the coefficient on the *Spillover* variable is positive when we include only industry fixed effects, the point estimate becomes negative but statistically insignificant once we add firm fixed effects (column 3). The latter is the preferred specification, as the firm fixed effects are highly significant (p-value $<.001$). This does not contradict the model, however. The predicted impact of spillovers on R&D is ambiguous, as it depends on the sign of the cross derivative in the knowledge production function, ϕ_{12}. Taken at face value, the finding here suggests that spillovers do not materially affect the *marginal* product of own R&D, even though our earlier findings that spillovers strongly increase the number of patents and market value show that spillovers do raise the *average* product of the recipient firm's R&D.

Finally, we note that the coefficients of the time dummies (not reported) show no evidence that R&D changed systematically over the sample period. We cannot reject the hypothesis that these coefficients are jointly zero in any of the specifications. This indicates 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, at least up to the end of our sample period. This finding contradicts the claim by Bessen and Hunt (2003) that the expansion of software patenting led firms to *reduce* R&D over this period. Of course, whether the stronger patent rights for software will intensify innovation in this area remains an open question.

7 Robustness Analysis

We conducted a series of robustness checks on the baseline results. In this discussion we focus on the market value and patent equations, where the baseline results were much sharper and more significant than in the R&D equation.

Our sample includes both 'software' companies specialising in packaged software (SIC7372) and 'hardware' firms classified in other related sectors (e.g. computers) but doing significant levels of software patenting. The incentives for strategic patenting may differ for these two types of firms – hardware firms that are vertically integrated into software patenting (e.g., semiconductor firms) are more likely to have large capital investments in plant and equipment that are exposed to ex post hold in the even of patent litigation, and thus particularly inclined to accumulate patents to defend against this danger and preserve freedom to operate in R&D (Hall and MacGarvie, 2010). We run two separate checks to examine robustness of our baseline results.

First, we check whether our findings are skewed by the presence of a few dominant firms active in software patenting but not specializing in packaged software. The top four of these firms – Cisco, Compaq, IBM and Intel –account for 82 percent of all patents, and 71 percent of software patents, in our sample. We re-estimate the baseline specifications of the market value and patent equations including both firms in packaged software and other sectors, but excluding these four companies (they are kept in for purposes of measuring the pool of technology spillovers for all firms, however). The results in Panel A of Table 6 show that the baseline results hold up. The sign and magnitudes of the estimated coefficients on the strategic patenting variables and knowledge spillover variables are similar to the baseline estimates in column 2 of Tables 3 and 4.

Second, we check whether there are significant differences in the role of strategic patenting and knowledge spillovers between the 'software' companies specialising in packaged software and the 'hardware' firms classified in other sectors. To do this, we re-estimate the baseline specifications but now add interactions of the key variables of interest – $Fragcites$, $Patprop$ and $Spillover$ – with a dummy variable for software (SIC7372) firms.[34] Panel B in Table

[34] It is interesting to note that the 'software' firms do not more heavily specialize in software patents (patent

6 reports the presents the results. The negative impact of fragmentation on market value is not statistically different for hardware and software firms. Moreover, patenting for both type of firms is strongly and positively related to fragmentation, as in the baseline estimates, implying that patent accumulation reduces enforcement costs more when fragmentation is greater ($H_{xf} < 0$). However, consistent with the hypothesis above, we find that patenting by rivals reduces a firm's market value for hardware firms while the effect for software firms is smaller and not statistically significant (due to the positive interaction coefficient for software firms). But the negative effect of *Patprop* on patenting is the same for both software and hardware firms. Finally, we find that knowledge spillovers are much stronger for hardware firms than for those specializing in packaged software. In fact, we find significant knowledge spillovers in the market value only for hardware firms, and though they are present in the patent equation for both types of firms, they are much larger for hardware companies.

The third robustness exercise it to check whether the sharp bubble in the stock market that occurred at the end of our sample period skews the results, especially for market value. During the two years 1998-99, the mean value of firms in our sample rose by 20.8 percent, which is more than 37 percent of its total change over the entire 19 year sample period. To check this, we re-estimate the baseline specification dropping the years 1998 and 1999. Panel C in Table 6 shows that the estimated coefficients are generally robust. The main difference is that the negative coefficient on *Patprop* in the market value equation declines and is no longer statistically significant.

Fourth, we examine whether the estimates are robust to allowing for the potential endogeneity of the patent propensity of rivals and R&D spillovers. In the baseline regressions we use the lagged values of these measures ($Patprop_{t-1}$ and $Spillover_{t-1}$) in order to remove the effect of contemporaneous shocks. Nonetheless, there could be serial correlation in the shocks driving patenting and market value that might still contaminate the estimates. To address this, we re-estimate the model using the second lags of *Patprop* and *Spillover* as instrumental variables

class G06F) than the 'hardware' firms in our sample. Software patents account for 39 and 42 percent of total patenting for the two types of firms, respectively. Ideally, we would like to be able to disaggregate each firm's patents into software and other patents and to incorporate both types into the analysis. Unfortuntately, the data were not rich enough to allow us to get informative results with this approach.

for their lagged values. We use an IV Poisson model for this purpose.[35] As Panel D in Table 6 shows, the IV estimated coefficients of $Fragcites$ and $Spillover$ for both the market value and patent equations are very similar to the baseline coefficients in Tables 3 and 4. However, using IV we find there is no longer any significant effect of $Patprop$ on either the market value or patenting behaviour of firms.

The final issue involves the role of product market competition. The model in this paper focuses on how fragmentation of patent rights and patent portfolio accumulation by rivals affect patent enforcement costs, and thereby the firm's market value, patenting and R&D. However, the impacts we find for our strategic patenting variables could be due, at least in part, to the effects of product market competition rather than patent enforcement costs. For example, we find that high concentration of patent rights (low $Fragcites$) increases market value. But this effect could be due instead to high concentration of sales (less intense product market competition), if the concentration of patent rights is positively correlated with the concentration of sales. Our finding that greater fragmentation increases the patenting might also be explained in this way if patent accumulation is more important where product market competition in more intense. The effects we find for $Patprop$ could also be explained by product market competition, since we would expect patenting by rivals to reduce the firm's market value, and lower its patenting (if rivals' patents are a strategic substitute).

To address this alternative interpretation, we need to control for product market competition in the baseline regressions. To this end, we construct a measure of sales concentration ($SalesCon$) for each firm in each year, which is equal to a weighted average of the four-firm sales concentration in each of the four-digit SIC classes in which the firm operates. The sales concentration data are taken from the U.S. Bureau of the Census. The weights are constructed from Compustat information on the distribution of firm sales across lines of business which are reported by firms from 1993 onwards.[36]

[35] The appropriate lag depends on the form of the serial correlation in the market value (or patent) equation. If it is an $MA(1)$ process, using the second lag as an instrument will be consistent. To check further, we tried using the third lag as the instrument, which would be appropriate if the error is an $MA(2)$ process. The results are similar to those reported in the table. We use the IV Poisson model for this experiment because there is no readily available software for the IV Negative Binomial model.

[36] For details of the line of business data, see Bloom, Schankerman and van Reenen (2013). For this computation we need to assume that distribution of a firm's sales across lines of business in 1993 applies to the earlier 1980-92

Panel E in Table 6 reports the coefficients on the main variables from the baseline specifications with this new control variable. The key finding here is that the estimated coefficients on the strategic patenting variables, $Fragcites$ and $Patprop$, and R&D spillovers in the market value and patent equations are very similar to (and not statistically different from) the baseline coefficients in column 2 in Tables 3 and 4. This indicates that our conclusions about the role of strategic patenting and spillovers are not simply picking up the effects of variations across firms in product market competition.[37] In addition, the positive coefficient on sales concentration in the patent equation indicates that patents are, perhaps surprisingly, *more important* for appropriating innovation rents when the market is more concentrated. Lastly, the coefficient on sales concentration is negative and significant in the market value equation. The most plausible explanation is that entry (which reduces concentration) occurs in more profitable lines of business and that, despite our demand-side controls, we may not be fully accounting for their unobserved 'potential profitability.'

8 Concluding Remarks

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 to capture the firm's bargaining power in patent disputes and licensing, and fragmentation of patenting among rivals to capture the transaction costs of enforcing those patent rights. Using panel data

period. The four-digit SIC concentration data are taken from the U.S. Censuses of Manufacturing, Retail Trade and Whole Trade. Some censuses were missing data for selected SICs (due to redefinitions of sectors), in which cases we interpolated. For details, see Appendix 2.

[37] Two points are worth noting. First, our measures of product market concentration ($SalesCon$) and fragmentation of patent rights ($Fragcites$) is very low, only -0.06. Second, following Bloom, Schankerman and Van Reenen (2012), we also use the information on the distribution of sales across SIC industries to construct a measure of product market distance between firm pairs in our sample. This is constructed as the uncentered correlation between the sales distributions of firm pairs (as in equation 4, with W_i defined as the distribution of firm $i's$ sales across SIC industries). The correlation across firm pairs between the technology and product market distance measures is only 0.17, confirming that the technology distance measure used in the construction of our *Patprop* and *Spillover* measures does not simply reflect product market interaction.

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, patenting by technology rivals reduces the firm's R&D investment, patenting and market value. Third, greater fragmentation of patent rights increases both R&D and patenting by the firm – reflecting greater need to have an arsenal of patents to resolve disputes when there are many players – but it lowers market value because transaction costs are higher. Finally, 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.

These findings show that, contrary to often-heard claims, patenting in software appears to be valuable for firms. Our evidence suggests that software firms in our sample are not trapped in a bad equilibrium of high patenting, and that collective action to reduce patenting would not raise their market value. However, the welfare implications of our results are not clear-cut. Insofar as strategic patenting imposes negative externalities on other firms – by increasing the fragmentation of patent rights and the need to patent defensively – the level of patenting may well be *socially inefficient*. Recent research offers some evidence that patenting impedes cumulative innovation, at least in the specific, but important, field of human genetic research (Murray and Stern, 2007; Huang and Murray, 2009; Furman and Stern, 2010). Unfortunately, we are still a long way off from having a full assessment of how these social costs stack up against the incentive effects of stronger patent rights.

References

Aghion, Philippe and Peter Howitt (1992), “A Model of Growth through Creative Destruction,” *Econometrica, 60*: 323-351

Allison, John and Emerson Tiller (2003), “Internet Business Method Patents,” in Wesley Cohen and Stephen Merrill, eds., *Patents in the Knowledge-Based Economy* (Washington D.C.: National Academies Press): 259-284

Arora, Ashish , Marco Ceccagnoli and Wesley Cohen (2008), “R&D and the patent premium,” *International Journal of Industrial Organization*, 26(5): 1153-1179

Bessen, James and Robert Hunt (2003), “An Empirical Look at Software Patents,” Research on Innovation, Working Paper No. 03-17/R, available at http://www.researchoninnovation.org/swpat.pdf

Bessen, James and Eric Maskin (2009), “Sequential Innovation, Patents and Imitation,” R*AND Journal of Economics*, 16(2): 237-252

Bloom, Nick, Mark Schankerman, and John Van Reenen (2013), “Identifying Technology Spillovers and Product Market Rivalry,” forthcoming in *Econometrica.* Earlier version available as CEPR Discussion Paper 3916 (Revised March 2012)

Blundell, Richard, Rachel Griffith, and John Van Reenen (1999) “Market Shares, Market Value and Innovation in a Panel of British Manufacturing Firms,” *Review of Economic Studies*, 66: 529-554

Federal Trade Commission (2011), “The Evolving IP Marketplace: Aligning Patent Notice and Remedies with Competition,” (Washington D.C.: Government Printing Office)

Furman, Jeff and Scott Stern (2010), “Climbing Atop the Shoulders of Giants: The Impact of Institutions on Cumulative Research,” *American Economic Review,*

Galasso, Alberto (2012), “Broad Cross-License Negotiations” *Journal of Economics and Management Srategy*, 21: 873-911.

Graham, Stuart and Mowery, David (2003) "Intellectual Property Protection in the U.S. Software Industry," in Wesley Cohen and Steven Merrill, eds., *Patents in the Knowledge Based Economy* (Washington D.C.: National Academies Press): 220-258

Griliches, Zvi (1981), "Market Value, R&D and Patents," *Economics Letters*, 7: 183-187

Grossman, Gene and Elhanan Helpman (1991), *Innovation and Growth in the Global Economy* (Cambridge, MA: MIT Press)

Hahn, Robert and Scott Wallsten (2003), "A Review of Bessen and Hunt's Analysis of Software Patents," *AEI-Brookings Joint Center for Regulatory Studies,*Working Paper (November)

Hall, Bronwyn and Raffaele Oriani (2006), "Does the Market Value R&D Investment by European Firms? Evidence from a Panel of Manufacturing Firms in France„ Germany and Italy," *International Journal of Industrial Organization*, 24(5): 971-993

Hall, Bronwyn, Adam Jaffe, and Manuel Trajtenberg (2005), "Market Value and Patent Citations," *RAND Journal of Economics,* 36(1): 16-38

Hall, Bronwyn and Megan MacGarvie (2010), "The Private Value of Software Patents," *Research Policy, 39(7): 994-1009*

Hall, Bronwyn and Rosemarie Ziedonis (2001), "The Patent Paradox Revisited: An Empirical Study of Patenting in the Semiconductor Industry, 1979-1995," *RAND Journal of Economics* 32(1): 101-128

Hausman, Jerry, Bronwyn Hall, and Zvi Griliches (1984), "Econometric Models for Count Data and an Application to the Patents-R&D Relationship," *Econometrica*, 52: 909-938

Heller, Michael and Rebecca Eisenberg (1998), "Can Patents Deter Innovation? The Anticommons in Biomedical Research," *Science,* 280 (May): 698-701

Huang, Kenneth and Fiona Murray (2009), "Does Patent Strategy Shape the Long-Run Supply of Public Knoweldge? Evidence from Human Genetics," *Academy of Management Journal*, 52(6): 1193-1221

Jaffe, Adam (1986), "Technological Opportunity and Spillovers of R&D: Evidence from Firms' Patents, Profits and Market Value," *American Economic Review* 76: 984-1001

Jaffe, Adam (1988), "Demand and Supply Influences in R&D Intensity and Productivity Growth," *Review of Economics and Statistics,* 70 (3): 431-437

Jaffe, Adam and Josh Lerner (2004), *Innovation and Its Discontents* (Princeton: Princeton Universtiy Press)

Jaffe, Adam, Manuel Trajtenberg, and Rebecca Henderson (1993), "Geographic Localisation of Knowledge Spillovers as Evidenced by Patent Citations," *Quarterly Journal of Economics* 108 (3): 577-598

Jones, Charles (2005), "Growth and Ideas," in Philippe Aghion and Stephen Durlaff, eds., *Handbook of Economic Growth* (Amsterdam: Elsevier Press)

Kortum, Sam and Josh Lerner (1999), "What is Behind the Recent Surge in Patenting?" *Research Policy:* 1-22

Layne-Farrar, Anne (2005), "Defining Software Patents: A Research Field Guide," *American Enterprise Institute-Brookings Joint Center for Regulatory Studies*, Working Paper 05-14 (August)

Lessig, Lawrence (2001), *The Future of Ideas: The Fate of the Commons in a Connected World* (New York: Vintage)

Lerner, Josh and Feng Zhu (2005), "What is the Impact of Software Patent Shifts: Evidence from Lotus v. Borland," NBER Working Paper 11168

Manski, Charles (1991), "Identification of Endogenous Social Effects: The Reflection Problem," *Review of Economic Studies* 60 (3): 531-42

Mann, Ronald (2005), "Do Patents Facilitate Financing in the Software Industry?" *Texas Law*

Review, vol. 83, no. 4 (March): 961-1030

Merges, Robert (1996), "Contracting into Liability Rules: Intellectual Property Rights and Collective Rights Organizations," *California Law Review*, 84(5): 1293-1393

Merges, Robert (1999), "Institutions for Intellectual Property Transactions: The Case of Patent Pools," Boalt Hall School of Law Working Paper, University of California, Berkeley

Merges, Robert (2004), "A New Dynamism in the Public Domain," *University of Chicago Law Review*, 71(1): 183-203

Murray, Fiona and Scott Stern (2007), "Do Formal Intellectual Property Rights Hinder the Free Flow of Scientific Knowledge? An Empirical Test of the Anti-Commons Hypothesis," *Journal of Economic Behavior and Organization*, 63: 648-687

National Research Council (2004), *A Patent System for the 21st Century,* Report by the Committee on Intellectual Property Rights in the Knowledge-Based Economy, Board of Science, Technology and Economic Policy (Washington.: The National Academies Press)

Nickell, Steven (1981), "Biases in Dynamics Models with Fixed Effects," *Econometrica,* 49: 1417-1426

Pakes, Ariel (1986), "Patents as Options: Some Estimates of the Value of Holding European Patent Stocks," *Econometrica, 54(4)*: 755-84

Schankerman, Mark (1998), "How Valuable is Patent Protection?" *RAND Journal of Economics,* 29(1): 77-107

Shalem, Roy and Manuel Trajtenberg (2009), "Software Patents, Inventors and Mobility" SSRN Paper No. 1547276

Shapiro, Carl (2001), "Navigating the Patent Thicket: Cross Licenses, Patent Pools, and Standard Setting," in Adam Jaffe, Josh Lerner and Scott Stern, eds., *Innovation Policy and the Economy*, 1: 119-150

Softletter (1998), “The 1998 Softletter 100”. Softletter Trends & Strategies in Software Publishing,” 14: 1-24

Walsh, John, Ashish Arora and Wesley Cohen (2003), “Effects of Research Tool Patents and Licensing on Biomedical Innovation,” in Wesley Cohen and Stephen Merrill, eds., *Patents in the Knowledge-Based Economy* (Washington D.C.: National Academies Press): 285-340

Walsh, John, Charlene Cho and Wesley Cohen (2005), “View from the Bench: Patents and Material Transfers,” *Science*, vol. 309, Issue 5743: 2002-2003

Ziedonis, Rosemarie (2003), “Patent Litigation in the U.S. Semiconductor Industry,” in Wesley Cohen and Richard Levin, eds., *Patents in the Knowledge-Based Economy* (Washington D.C.: National Academies Press): 180-212

Ziedonis, Rosemarie (2004), ”Don’t Fence Me In: Fragmented Markets for Technology and the Patent Acquisition Strategies of Firms,” *Management Science*, 50(6): 804-820

Appendix 1. Analysis of the Model's Predictions

We use the model to derive predictions about how R&D and patenting by the technology rival firm τ, and the fragmentation of patent rights, affect the optimal choices of the focal firm 0. The firm makes two decisions: the level of R&D investment and the patent propensity. The decision problem is

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

Recall that $k_0 = \phi(r_0,r_\tau)$ and $k_\tau = \phi(r_\tau,r_0)$ also enter the function $H(x,f)$ since $x = \frac{\rho_0 k_0}{\rho_\tau k_\tau}$. The first order conditions for the focal firm are

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

where superscripts on the functions Π and ϕ refer to the firm, the subscripts denote partial derivatives with respect to the arguments in Π (one argument only), H and ϕ.

To simplify notation, we supress the arguments in functions. Differentiating totally we obtain

$$\begin{bmatrix} V_{r_0r_0}..V_{r_0\rho_0} \\ V_{\rho_0r_0}..V_{\rho_0\rho_0} \end{bmatrix} \begin{bmatrix} dr_0 \\ d\rho_0 \end{bmatrix} = -\begin{bmatrix} V_{r_0\rho_\tau}...V_{r_0c}...V_{r_0r_\tau} \\ V_{\rho_0\rho_\tau}...V_{\rho_0c}...V_{\rho_0r_\tau} \end{bmatrix} \begin{bmatrix} d\rho_\tau \\ df \\ dr_\tau \end{bmatrix}$$

Second order conditions imply $V_{r_0r_0} < 0$, $V_{\rho_0\rho_0} < 0$, and $A = V_{r_0r_0}\,V_{\rho_0\rho_0} - V_{r_0\rho_0}^2 > 0$.

In order to sign some of the predictions (details below), we make two assumptions:

*A*1: (a) $k_\tau\phi_1^0 - k_0\phi_2^\tau > 0$ and (b) $k_0\phi_1^\tau - k_\tau\phi_2^0 > 0$

*A*2: $\frac{xH_{xx}}{|H_x|} < 1$

Assumption A1 says that a firm's R&D has a larger impact on its own knowledge production (in elasticity terms) than it does on its rival's knowledge (part (a) applies to firm 0, part (b) to firm τ). This seems natural since a firm's own R&D is presumably more closely tied to its innovation activity than a rival's (and only a part of the rival's activity may in fact be relevant). Assumption A2 says that the elasticity of the marginal enforcement cost function

(H_x) with respect to portfolio size is less than one – i.e., that diminishing returns to portfolio accumulation are not 'too strong'.

From the first order conditions, and assumptions A1 and A2, we can derive the following expressions:

$$\begin{aligned} V_{r_0\rho_0} &= (\lambda-1)\theta_0 k_0 \phi_1^0 \Pi_{11}^0 - \frac{k_0}{\rho_\tau {k_\tau}^2}(k_\tau \phi_1^0 - k_0\phi_2^\tau)H_x\{1+x\frac{H_{xx}}{H_x}\} \\ &> 0 \ \text{ provided that } \Pi_{11}^0 \text{ is not 'too large'} \end{aligned}$$

$$V_{r_0\rho_\tau} = \frac{\rho_0 k_0}{(\rho_\tau^2 k_\tau)}\phi_1^0 H_x + \frac{\rho_0 k_0}{(\rho_\tau k_\tau)^2}(k_\tau \phi_1^0 - k_0\phi_2^\tau)H_x\{1+x\frac{H_{xx}}{H_x}\} \leq 0$$

$$V_{\rho_0\rho_\tau} = \frac{k_0^2 k_\tau}{(\rho_\tau k_\tau)^2}H_x\{1+x\frac{H_{xx}}{H_x}\} \leq 0$$

$$V_{\rho_0 r_\tau} = (\lambda-1)\theta_0 k_0 \phi_2^0 \Pi_{11}^0 - \frac{k_0}{\rho_\tau {k_\tau}^2}(k_\tau \phi_2^0 - k_0\phi_1^\tau)H_x\{1+x\frac{H_{xx}}{H_x}\} < 0$$

$$V_{r_0 f} = -\phi_1^0 H_f - \frac{k_0\rho_0}{\rho_\tau {k_\tau}^2}(k_\tau \phi_1^0 - k_0\phi_2^\tau)H_{xf} \lesseqgtr 0$$

$$V_{\rho_0 f} = -\frac{k_0^2}{\rho_\tau k_\tau}H_{xf} \lesseqgtr 0$$

$$V_{r_0 r_\tau} = \frac{\phi_{12}^0}{\phi_1^0} + \phi_1^0\phi_2^0\Pi_{11}^0 - AH_x - \frac{\rho_0^2 k_0}{\rho_\tau^2 k_\tau^4}(k_\tau\phi_2^0 - k_0\phi_1^\tau)H_{xx} \lesseqgtr 0$$

where $A = -\frac{\rho_0}{\rho_\tau k_\tau^2}\{k_0^2(\frac{\phi_{12}^0\phi_2^\tau - \phi_{21}^\tau\phi_1^0}{\phi_1^0}) - 2k_0(\phi_2^0\phi_2^\tau + \phi_1^\tau\phi_1^0) + 2k_0(\phi_1^0\phi_2^0 + \frac{1}{k_\tau}\phi_2^\tau\phi_1^\tau)\}$.

Using Cramer's rule and the cross derivatives derived above, we get the following predictions:

$$\frac{\partial r_0}{\partial \rho_\tau} = -A^{-1}(V_{r_0\rho_\tau}V_{\rho_0\rho_0} - V_{r_0\rho_0}V_{\rho_0\rho_\tau}) < 0$$

$$\frac{\partial r_0}{\partial f} = -A^{-1}(V_{r_0 f}V_{\rho_0\rho_0} - V_{r_0\rho_0}V_{\rho_0 f}) \gtrless 0$$

$$\frac{\partial r_0}{\partial r_\tau} = -A^{-1}(V_{r_0 r_\tau}V_{\rho_0\rho_0} - V_{r_0\rho_0}V_{\rho_0 r_\tau}) \gtrless 0$$

$$\frac{\partial \rho_0}{\partial \rho_\tau} = -A^{-1}(V_{r_0 r_0}V_{\rho_0\rho_\tau} - V_{r_0\rho_0}V_{\rho_0\rho_\tau}) < 0$$

$$\frac{\partial \rho_0}{\partial f} = -A^{-1}(V_{r_0 r_0}V_{\rho_0 f} - V_{r_0\rho_0}V_{r_0 f}) \gtrless 0$$

$$\frac{\partial \rho_0}{\partial r_\tau} = -A^{-1}(V_{r_0 r_0}V_{\rho_0 r_\tau} - V_{r_0\rho_0}V_{r_0 r_\tau}) \gtrless 0$$

Finally, using the envelope theorem we get

$$\frac{\partial V_0}{\partial \rho_\tau} = \frac{\rho_0 k_0^2}{\rho_\tau^2 k_\tau} H_x \leq 0$$

$$\frac{\partial V_0}{\partial r_\tau} = \frac{\phi_2^0}{\phi_1^0} + \frac{\rho_0 k_0}{\rho_\tau {k_\tau}^2} H_x \{ \frac{\phi_2^0}{\phi_1^0}(k_\tau \phi_1^0 - k_0 \phi_2^\tau) - (k_\tau \phi_2^0 - k_0 \phi_1^\tau) \} \gtrless 0$$

$$\frac{\partial V_0}{\partial f} = -k_0 H_f \leq 0$$

Two final remarks on the predictions are in order. First, as indicated above, we cannot unambiguously sign $\frac{\partial r_0}{\partial f}$ and $\frac{\partial \rho_0}{\partial f}$because they depend on the sign of H_{xf}. This reflects the fact that a rise in fragmentation has two effects: 1) it increases the level of enforcement costs and thus reduces the profit from any given level of R&D and patenting, but 2) it changes the marginal value of accumulating patents and thus the incentive to do R&D and patenting (this latter effect depends on the sign of H_{xf}). However, using the cross partials $V_{\rho r f}$ and $V_{\rho_0 f}$, we can show that $\frac{\partial r_0}{\partial f} > 0$ implies $H_{xf} < 0$, and similarly $\frac{\partial \rho_0}{\partial f} > 0$ implies $H_{xf} < 0$. We use this fact in the analysis of the empirical results in the paper. However, we cannot infer the sign of H_{xf} if $\frac{\partial r_0}{\partial f} \leq 0$ or $\frac{\partial \rho_0}{\partial f} \leq 0$.

Second, the impact of technology rival's R&D on the market value of the firm focal firm, $\frac{\partial V_0}{\partial r_\tau}$, is ambiguous because a rise in the rival's R&D has two countervailing effects: 1) it increases knowledge spillovers for the focal firm, raising its market value, but 2) the increase in the rival's kowledge (and patents) raises enforcement costs for the focal firm and reduces its market value. In the econometric specification, however, we control for rivals' patent propensity (ratio of patent to R&D stocks) – turning off the second effect. Thus our empirical prediction is $\frac{\partial V^0}{\partial r_\tau} > 0$.

A similar argument applies to the impact of technology rival's R&D on patenting by the firm focal firm, $\frac{\partial \rho_0}{\partial r_\tau}$. This effect is ambiguous because the rise in rival's R&D increases knowledge spillovers for the focal firm (which increases its patenting), but also raises enforcement costs for the focal firm, reducing the profitability of patenting. In the econometric specification, however, we control for rivals' patent propensity, so we get only the first effect operating. Thus our empirical prediction is $\frac{\partial \rho_0}{\partial r_\tau} > 0$.

Appendix 2. Data Construction

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.

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. One could do so in principle by matching the CorpTech and the 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, this match is antiquated, especially when considering the software industry which grew so rapidly 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 (many software firms were established or became public after 1989), so 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.

Construction of the Sales Concentration Measure

To calculate $SalesCon$ we use both Compustat data on the self-reported sales of each firm in different lines of business, and U.S. Census data on SIC-level concentration ratios. A line of business as reported by Compustat may correspond to a single four digit SIC industry or multiple SICs. The available data set lists up to two SICs for each line of business. Following Bloom, Schankerman and van Reenen (2013), if two SICs are listed we attribute 75% of the firm's sales to the primary SIC and 25% to the secondary SIC. For each SIC industry 's', we calculate the sales of firm i in line of business s in year t, y_{ist}, total firm sales, $y_{it} = \sum_s y_{ist}$, and define $\beta_{ist} = \frac{y_{ist}}{y_{it}}$ which is the share of firm $i's$ sales that fall into industry s in year t ($\sum_s \beta_{ist} = 1$).

Data are available from 1993, so for earlier years we use 1993 shares. We then obtain the four firm concentration ratio for each SIC industry, $C4_{st}$, as reported in the U.S. Censuses of Manufacturing, Services, Wholesale Trade, and Retail Trade (distinct publications) for the years 1982, 1987, 1992 and 1997. Since the industry classification system in 1997 changed from SIC to NAICS, we use the concordance provided by the Census for imputation. We interpolate values for intermediate years.

We then calculate $SalesCon$ for firm i in year t as the weighted average of the four firm concentration ratios across the SICs in which the firm participates

$$C4_{it} = \sum_s \beta_{ist} C4_{st}$$

Table 1. Predictions of the Model

Variable:	Fragmentation, f	Rival's Patent Propensity, $\rho\tau$	Rival's R&D, r_τ
Market Value, V_0	$\partial V_0/\partial f < 0$	$\partial V_0/\partial \rho_\tau < 0$	$\partial V_0/\partial r_\tau > 0$
Patent Propensity, ρ_0	$\partial \rho_0/\partial f \lesseqgtr 0$ [a]	$\partial \rho_0/\partial \rho_\tau < 0$	$\partial \rho_0/\partial r_\tau > 0$
R&D, r_0	$\partial r_0/\partial f \lesseqgtr 0$ [b]	$\partial r_0/\partial \rho_\tau < 0$	$\partial r_0/\partial r_\tau \lesseqgtr 0$

[a.] If $\partial \rho_0/\partial f > 0$, we can infer that $H_{xf}<0$. If $\partial \rho_0/\partial f < 0$, one cannot infer the sign of $H_{xf.}$

[b.] If $\partial r_0/\partial f > 0$, we can infer that $H_{xf}<0$. If $\partial \rho_0/\partial f > 0$, one cannot infer the sign of $H_{xf.}$

Table 2. Descriptive Statistics

Variable:	Mnemonic	Mean	Median	Std. Dev.
Market Value	V	2,462	97	10,886
Tobin's Q	V/A	6.5	4.3	6.7
R&D	R	188.0	14.7	739.0
R&D Stock/Assets	G/A	5.7	2.2	18.2
Patents (> 0)	P	61.9	2.0	245.3
Patent Stock/Assets	PS/A	0.62	0.17	1.44
Fragmentation Index	Fragcites	0.53	0.62	0.25
Rivals' Patent Propensity	Patprop	0.080	0.075	0.064
R&D Spillovers	Spillover	20,717	20,067	11,615

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

Table 3. Market Value Equation

Dependent Variable: log(V/A)	(1) Baseline 1980-99	(2) Patent Premium 1980-99	(3) Patent Premium 1980-94	(4) Patent Premium 1995-99
$Fragcites_{t-1}$	-0.344**	-0.460**	-0.188	-0.713**
	(0.11)	(0.11)	(0.16)	(0.16)
log $Patprop_{t-1}$	-0.129*	-0.122*	-0.013	-0.276**
	(0.074)	(0.073)	(0.110)	(0.120)
log $Spillover_{t-1}$	0.167**	0.187**	0.168**	0.155*
	(0.050)	(0.049)	(0.074)	(0.091)
log Firm $Sales_{t-1}$	0.185**	0.196**	0.021	0.253**
	(0.065)	(0.065)	(0.120)	(0.067)
log Firm $Sales_{t-2}$	-0.178**	-0.160**	-0.012	-0.183**
	(0.062)	(0.062)	(0.120)	(0.063)
log $TechOpp_{t-1}$	2.301**	2.449**	5.025**	0.670
	(0.70)	(0.70)	(0.95)	(0.84)
log $TechOpp_{t-2}$	-2.202**	-2.377**	-4.842**	-0.740
	(0.68)	(0.68)	(0.92)	(0.80)
$(G/A)_{t-1}$	0.092**	0.074**	0.045**	0.0139**
	(0.013)	(0.014)	(0.024)	(0.035)
$(G/A)_{t-2}$	-0.003**	-0.002**	-0.002**	-0.008**
	(0.0005)	(0.0004)	(0.001)	(0.003)
$(G/A)^3_{t-1} \times 10^3$	0.027**	0.024**	0.020**	0.195*
	(0.005)	(0.005)	(0.010)	(0.110)
$(G/A)^4_{t-1} \times 10^6$	-0.109**	-0.099**	-0.085**	-2.330
	(0.020)	(0.018)	(0.038)	(1.46)
$(G/A)^5_{t-1} \times 10^9$	0.149**	0.138**	0.120**	10.300
	(0.027)	(0.025)	(0.046)	(6.70)
$(PS/A)_{t-1}$		0.712**	1.373**	0.967**
		(0.21)	(0.40)	(0.22)
$(PS/A)^2_{t-1}$		-0.348**	-0.846**	-0.622**
		(0.16)	(0.30)	(0.15)
$(PS/A)^3_{t-1}$		0.065*	0.202**	0.143**
		(0.039)	(0.079)	(0.038)
$(PS/A)^4_{t-1}$		-0.005	-0.021**	-0.013**
		(0.004)	(0.008)	(0.003)
$(PS/A)^5_{t-1} \times 10^3$		0.146	0.734**	0.377**
		(0.11)	(0.29)	(0.10)
Industry dummies	Yes	Yes	Yes	Yes
(p-values)	(<0.01)	(<0.01)	(<0.01)	(<0.01)
Year dummies	Yes	Yes	Yes	Yes
(p-values)	(0.066)	(0.073)	(0.47)	(0.10)
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 Fragcites or lagged R&D stock is zero. * denotes significance at the 5% level, ** at the 1% level.

Table 4. Patent Equation

Dependent Variable: Patent Count	(1) No Initial Conditions 1980-99	(2) Initial Conditions 1980-99	(3) Initial Conditions 1980-94	(4) Initial Conditions 1995-99
Fragcites_{t-1}	2.540**	2.553**	2.171**	2.785**
	(0.38)	(0.34)	(0.42)	(0.47)
log Patprop_{t-1}	-0.210	-0.453*	-0.808*	-0.501
	(0.24)	(0.22)	(0.33)	(0.41)
log Spillover_{t-1}	0.106	0.637**	0.542**	1.040**
	(0.10)	(0.12)	(0.15)	(0.23)
log R&D Stock_{t-1}	0.761**	0.599**	0.578**	0.626**
	(0.036)	(0.043)	(0.065)	(0.052)
log TechOpp_{t-1}	-4.238*	-6.328**	-9.394**	-6.686**
	(2.07)	(1.83)	(3.14)	(2.21)
log TechOpp_{t-2}	4.593*	5.982**	9.627**	5.386**
	(2.08)	(1.80)	(3.06)	(2.04)
log Presample Patents		0.368**	0.346**	0.272**
		(0.052)	(0.076)	(0.073)
Overdispersion	1.161**	1.336**	1.005**	1.423**
	(0.14)	(0.12)	(0.15)	(0.17)
Industry dummies	Yes	No	No	No
(p-values)	(<0.01)			
Year dummies	Yes	Yes	Yes	Yes
(p-values)	(<0.01)	(<0.01)	(0.028)	(<0.01)
No. Observations	991	991	472	519
Pseudo R^2	0.27	0.26	0.27	0.27

Notes: Estimation is based on the Negative Binomial Model. Standard errors (in brackets) are robust to heteroskedasticity. A dummy variable is included for observations where Fragcites is zero. The initial conditions in columns (2)-(4) are estimated with the 'pre-sample mean scaling approach' of Blundell, Griffith and Van Reenan (1999). * denotes significance at the 5% level, ** at the 1% 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
Fragcites_{t-1}	1.016**	0.198**	0.281**	0.124
	(0.17)	(0.10)	(0.17)	(0.14)
log Patprop_{t-1}	-0.033	-0.060	-0.091	-0.075
	(0.100)	(0.056)	(0.075)	(0.059)
log Spillover_{t-1}	0.214**	0.104**	-0.156	-0.102
	(0.096)	(0.036)	(0.140)	(0.096)
log $\text{R\&D}_{t-1}$		0.756**		0.410**
		(0.033)		(0.058)
log Firm Sales_{t-1}	0.952**	0.467**	0.709**	0.496**
	(0.078)	(0.048)	(0.075)	(0.075)
log Firm Sales_{t-2}	-0.219**	-0.284**	0.029	-0.077*
	(0.069)	(0.039)	(0.065)	(0.048)
log TechOpp_{t-1}	0.906	-0.161	-0.070	-0.283
	(1.03)	(0.54)	(0.82)	(0.63)
log TechOpp_{t-2}	-1.162	0.087	-0.074	0.173
	(1.04)	(0.51)	(0.77)	(0.61)
Industry dummies	Yes	Yes	No	No
(p-values)	(<0.01)	(<0.01)		
Firm dummies	No	No	Yes	Yes
(p-values)			(<0.01)	(<0.01)
Year dummies	Yes	Yes	Yes	Yes
(p-values)	(0.88)	(0.52)	(0.70)	(0.71)
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 yearrs. A dummy variable is included for observations where Fragcites is zero. * denotes significance at the 5% level, ** at the 1% level.

Table 6. Robustness Checks

Panel A. Exclude Top Four Patenting 'Hardware' Firms

Equation:	Fragcites	Patprop	Spillover
Market Value	-0.465**	-0.131*	0.139*
	(0.110)	(0.072)	(0.063)
Patents	2.342**	-0.489*	0.797**
	(0.39)	(0.25)	(0.20)

Panel B. Hardware vs. Software Firms

Equation:	Fragcites		Patprop		Spillover	
	Hardware	Software	Hardware	Software	Hardware	Software
Market Value	-0.344**	-0.157	-0.145*	0.107*	0.129*	0.117
	(0.14)	(0.19)	(0.073)	(0.049)	(0.620)	(0.084)
Patents	2.795**	-0.718	-0.603*	0.027	0.638**	-0.493
	(0.55)	(0.63)	(0.26)	(0.13)	(0.15)	(0.26)

Panel C. Exclude Stock Market Bubble, 1998-1999

Equation:	Fragcites	Patprop	Spillover
Market Value	-0.306**	-0.011	0.179**
	(0.12)	(0.084)	(0.056)
Patents	2.268**	-0.631*	0.604**
	(0.38)	(0.26)	(0.10)

Panel D. Instrumental Variables Estimates

Equation:	Fragcites	Patprop	Spillover
Market Value	-0.447**	0.038	0.184**
	(0.092)	(0.110)	(0.040)
Patents	3.016**	0.203	0.443*
(Poisson)	(0.40)	(0.53)	(0.21)

Panel E. Control for Product Market Concentration

Equation:	Fragcites	Patprop	Spillover	Salescon
Market Value	-0.459**	-0.076	0.184**	-1.235**
	(0.110)	(0.072)	(0.051)	(0.30)
Patents	2.251**	-0.333	0.600**	3.318**
	(0.37)	(0.24)	(0.13)	(0.63)

Table A. 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.
36384	7372	Ansoft Corp.	233326	7372	DST Systems, Inc.
37833	7372	Apple Computer, Inc.	238016	3625	Data Translation, Inc.
37935	3829	Applied Microsystems Corp.	253798	3577	Digi International, Inc.
43412	3661	Asante Technologies, Inc.	25387R	3577	Digital Video Systems, Inc.
04362P	7372	Ascential Software Corp.	281667	7372	J.D. Edwards & Company
45327	7372	Aspen Technology, Inc.	292475	3669	Emulex Corp.
52754	7379	Auto-trol Technology Corp.	36227K	7372	GSE Systems, Inc.
52769	7372	Autodesk, Inc.	362555	3669	Gadzoox Networks, Inc.
05367P	7372	Avid Technology, Inc.	370253	7372	General Magic, Inc.
55921	7372	BMC Software, Inc.	40425P	7372	HNC Software Inc.
73308	7375	Be Free, Inc.	451716	7372	IKOS Systems, Inc.
73325	7372	BEA Systems, Inc.	45666Q	7372	Informatica Corp.
79860	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

Table A. 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.