Patents, Thickets and the Financing of Early-Stage Firms: Evidence from the Software Industry

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ABSTRACT

The impact of stronger intellectual property rights in the software industry is controversial. One means by which patents can affect technical change, industry dynamics, and ultimately welfare, is through their role in stimulating or stifling entry by new ventures. Patents can block entry, or raise entrants' costs in variety of ways, while at the same time they may stimulate entry by improving the bargaining position of entrants vis-à-vis incumbents, and supporting a "market for technology" which enables new ventures to license their way into the market, or realize value through trade in their intangible assets. One important impact of patents may be their influence on capital markets, and here we find evidence that the extraordinary growth in patenting of software during the 1990s is associated with significant effects on the financing of software companies. Start-up software companies operating in markets characterized by denser patent thickets see their initial acquisition of VC funding delayed relative to firms in markets less affected by patents. The relationship between patents and the probability of IPO or acquisition is more complex, but there is some evidence that firms without patents are less likely to go public if they operate in a market characterized by patent thickets.

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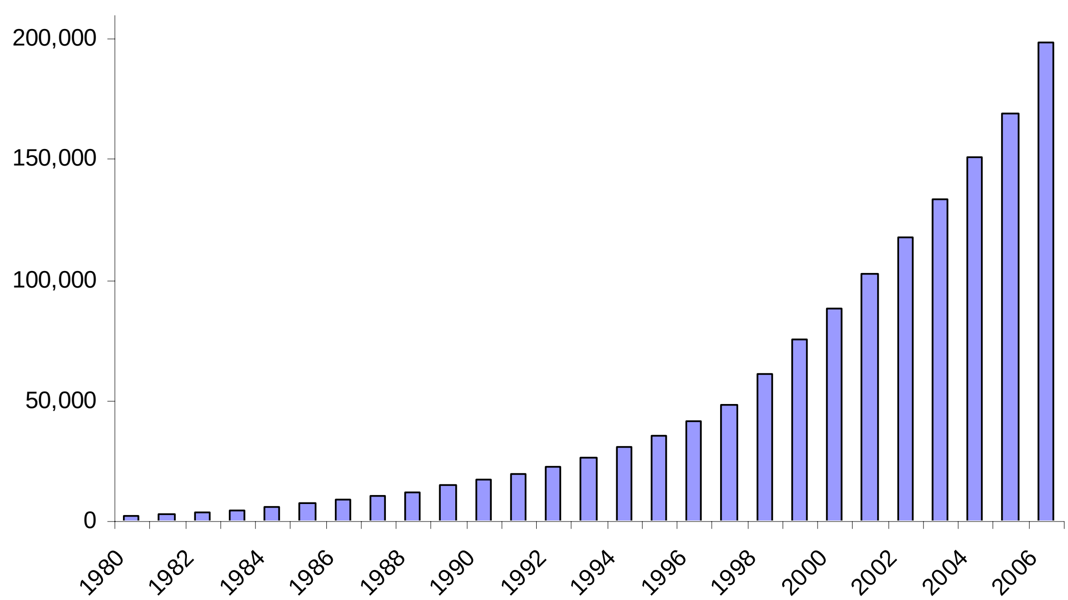
Debate over whether the current U.S. patent system is promoting or hindering innovation has reached a crescendo: reflecting growing skepticism among economists about the overall impact of strengthened and expanded patent rights, Adam Jaffe has stated in testimony before Congress the that "the patent system—intended to foster and protect innovation—is generating waste and uncertainty that hinder and threaten the innovative process."[1] These concerns are particularly acute in industries such as software and semiconductors, where products are highly complex, each embodying thousands of innovations, and where technological progress tends to be incremental and cumulative. In such circumstances, critics argue, any "stimulating" effect of stronger patents on incentives to innovate will be offset, or even swamped, by the "stifling" effect of higher transactions costs, increased threat of litigation, and constraints imposed on the cumulative development of technologies by multiple blocking patents.

Software has been a particularly important locus of innovation in the US economy, yet, notably, much foundational innovation occurred in the absence of strong patent protection, and until relatively recently many leading innovators in the industry, including highly significant firms like Microsoft, filed relatively few patents. But changes in patent law and USPTO practice in the mid-1990s generated a surge in patenting in software that continues unabated. With more than 100,000 software patents issued in the US since 1990, and ever-greater complexity and scale of software products, industry participants face an increasingly forbidding "thicket" of IP. With even quite modest products containing millions of lines of code and thousands or tens of thousand of inter-related component modules, any of which could potentially infringe one or more patents, the cost of "clearing" new products for potential infringement can be very large. Allegedly poor standards of patent examination in this area in the past may also have generated large numbers of patents with inadequate disclosure, and excessively broad claims, raising the

[1] U.S. House of Representatives Oversight Hearing on the Patent System, February 15, 2007.

costs of determining the scope of existing IP, and increasing uncertainty about possible future litigation from competitors and non-competitors alike. Figure 1 shows how dramatic the increase in software patenting has been. The figure plots the total number of patents in force that are relevant to 27 distinct software product markets between 1980 and 2006. Over this period the CAGR of the number of patents outstanding was 29.8%. Over the decade 1994 to 2004 alone, the number of patents in the average market grew by almost 500%, while the number of active firms grew by less than 300%.

Figure 1: Total Patents in Force in 27 Software Markets



By 2006, the average market in this sample had 7370 patents in force, comprising over 145,000 claims. Data such as these suggest that costs associated with patents—such as searching prior art, building patent portfolios, and defending against the threat of patent litigation—have grown very substantially. In software, entrepreneurial firms and independent inventors have played a very significant role in driving technical change, since the impact of these costs is likely to be felt disproportionately by innovators with limited resources, and the pace of innovation may therefore be particularly vulnerable in this industry to the proliferation of patents. To cite just two authoritative observers, Donald Knuth, author of *The Art of Computer Programming* and inventor of TeX, has stated that "I don't think I would have been able to create TeX if the present [patent] climate had existed in the 1970s," while erstwhile entrepreneur Bill Gates has opined that "If people had understood how patents would be granted when most of today's ideas were invented and had taken out patents, the industry would be at a complete standstill today."[2]

"Innovation" is, of course, very difficult to measure consistently over time and across technologies. In software, one useful indicator—recognizing the important role of new ventures in driving innovation in this industry—is market entry and the founding of new firms. In a related paper (Cockburn and MacGarvie (2007)), we find that there are fewer entrants into software markets in which there are more patents, after controlling for the characteristics of the firm and market (including the average importance of patents in the market and the stage of the product lifecycle). Yet it is important to recognize that the "stifling" and "stimulating" effects of patents go hand-in-hand. Patents may limit innovation in particular areas, or make it more costly, but at the same time they may also promote innovation and entry by creating incentives for R&D, by enabling trade in technology, or by facilitating investment in early-stage firms. In Cockburn and MacGarvie (2007) we also found that firms holding patents related to a software market are approximately three times more likely to enter that market than those who do not hold patents—a finding that focuses our attention here on the economic mechanisms through which patents can positively affect incentives to launch new products and new ventures, in particular their impact on the ability of new entrants to secure external financing from various sources.

[2] Pignalberi (2004), Lessig (2002).

In this paper we attempt to characterize the extent to which entrants into a software market at any given point in time face a patent "thicket"—i.e. a "a dense web of overlapping intellectual property rights that a company must hack its way through in order to actually commercialize new technology"[3]—and evaluate the impact of patent thickets on the interaction between new software ventures and capital markets.

We hypothesize that patent thickets affect the ability of software start-ups to raise money from outside investors in two main ways. Firstly, the *transaction costs* of entering a market may be higher when that market has a patent thicket. Patents that block a would-be entrant from producing or selling its product mean that the entrant must either bear additional costs of "inventing around" such patents, pay licensing fees to the patent holder, or accept potentially severe ex post penalties.[4] Noel and Schankerman (2006) provide evidence on the costs imposed by patent thickets from a sample of publicly-traded software firms by showing that market value decreases when patent rights held by a firm's competitors are more fragmented, reflecting the higher costs of negotiating with more parties.

Secondly, the *uncertainty* of the firm's future profit stream may be higher when it faces a patent thicket. Lemley and Shapiro (2006) argue that there are two types of uncertainty associated with patents: uncertainty about the commercial value of the property right granted to the inventor, and uncertainty about the validity and scope of the property right. The latter form of uncertainty may be especially prevalent in software, a field in which patents were until recently not used to protect IP and which saw a dramatic growth of patenting following changes in the USPTO's patentability guidelines in the mid-1990's. The lack of experience with software

[3] Shapiro (2001), p.2

[4] Infringing valid patents can present the entrant with very substantial ex post penalties, such as damages judgments (tripled in the case of "willful infringement") or the loss in value of assets stranded in the wake of an injunction obtained by the patent holder.

patents at the USPTO, combined with the ambiguity associated with what is covered by many patents in this sector, has meant that software developers face significant uncertainty about existing prior art and the possibility of being sued for infringement. Bessen and Meurer (2008) find that software patents are more than twice as likely as other patents to have claim construction appealed to the Federal Circuit, and, which they take as an indicator of elevated uncertainty about the boundaries of patents in software.[5]

We look for evidence of the impact of increased transaction costs and greater uncertainty on new ventures in "thicketed" markets in the following ways. First, higher anticipated transaction costs should affect negatively affect investors' valuations of start-up companies, "raising the bar" for new entrants in terms of meeting minimum levels of profitability required by outside inventors, and thus reducing the number of entrants that receive funding from outside investors. Once a firm becomes an incumbent, the effect of thickets is less clear: thickets may offer protection from entrants, or result in future additional transaction costs, with an ambiguous effect on the value of the enterprise and the probability that a firm goes public, rather than being acquired or wound up (after controlling for the positive effects of the firm's own patent holdings). Second, higher uncertainty about future profits should affect the timing of investments. When investments are irreversible, the opportunity cost of current investment (versus investment at a later date) increases with uncertainty. Thus, increases in uncertainty increase the value of delaying investment. [6] We hypothesize that higher uncertainty over the threat of litigation or other future patent-related costs increases the value of delaying investment.

[5] Brian Kahin (2004) cites the hearings in 2002 on *Competition and Intellectual Property Law and Policy in the Knowledge-Based Economy*, held by the U.S. Federal Trade Commission and the Department of Justice at which Frederick J. Telecky of Texas Instruments stated that: "TI has something like 8000 patents in the United States that are active patents, and for us to know what's in that portfolio, we think, is just a mind-boggling, budget-busting exercise to try to figure that out with any degree of accuracy at all." Kahin notes that, "If a company with TI's resources cannot assess what they have in-house, it is difficult to expect a small company entering a market to evaluate what claims they may be facing."

[6] Arrow (1968), Bernanke (1983), Dixit and Pindyck (1994), among others.

As a result, we expect that, after controlling for firm- and investor-level characteristics, firms operating in markets characterized by denser patent thickets, or markets in which the relevant prior art is less well defined, will see investments delayed. We look for evidence of delay in duration models for the time elapsed until a new venture obtains funding from outside investors (both venture capitalists and corporate investors) for the first time, and in competing hazard models of the time they "exit" from the entrepreneurial phase via IPO or Acquisition. Third, we examine which strategies may help firms succeed when faced with patent thickets. Following Hall and Ziedonis (2003) and Ziedonis (2005), we hypothesize that start-up companies with patents will be able to use them in cross-licensing negotiations to defend themselves against litigation. These patents may then act to reduce the transaction costs associated with operating in a "thicketed" market. These firms should also face less uncertainty, and thus we expect investment will take place earlier.

We believe this paper makes several contributions to the literature. First, it examines the impact of patent thickets on early-stage firms. Despite the potential importance of such firms as a source of innovation and productivity growth, we are not aware of other empirical research which is has examined these effects on entrepreneurial (in our case, small, young, private) firms. Secondly, we contribute to the literature on entrepreneurship by analyzing a data set that contains both venture- or corporate-funded firms from the SDC universe as well as pre-funding start-ups drawn from the CorpTech database. This allows us to examine how funded firms differ from firms that do not obtain funding, and to analyze determinants of the timing of first investment. While other research has looked at differences between venture-backed and non-venture-backed firms in small samples, we are not aware of other papers that exploit as comprehensive a dataset as the one we use here. Finally, we exploit a methodology inspired by the differences-in-differences approach to isolate the effect of stronger patent rights on entry and financing of early stage firms.

Literature Review

The literature on the “stifling” vs. “stimulating” effects of patents has looked for evidence of the impact of changing patent rights on innovation from quasi-natural experiments associated with legal changes. These changes include the strengthening or instituting of patent systems in countries that previously had weak or non-existent formal IPRs (Sakakibara and Branstetter (2001) for Japan, Lanjouw and Cockburn (1997) for India, Moser (2005) on patent laws in the 19th century), changes in patent rights in confined to specific technologies (Scherer and Weisburst (1995) on pharmaceuticals in Italy), or a variety of other changes to patent law or patent office practice that enhance the strength of patent protection (Lerner (2002)). Hall and Ziedonis (2001) document a surge in strategic patenting in the semiconductor industry following pro-patent policy changes in the 1980s, and Ziedonis (2004) shows that semiconductor firms patent more aggressively when the ownership of complementary patents is more highly fragmented.

Bessen and Maskin (2007) and Bessen and Hunt (2003), have argued that more-and-stronger patent rights have induced a decline in R&D spending in industries affected by software patents. Noel and Schankerman (2006) show that the market value of publicly traded software firms decreases when patent rights held by a firm’s competitors are more fragmented, reflecting the higher costs of negotiating with more parties. Cockburn and MacGarvie (2007) find that software markets in which there are more patents have fewer entrants, after controlling for the characteristics of the firm and market (including the average importance of patents in the market and the stage of the product lifecycle). However, patents also play a role in stimulating entry: this paper finds that firms holding patents related to a software market are approximately three times more likely to enter that market. Hall (2005) shows that patents have a particularly strong correlation with market value for entrants, and suggests that they play a role in helping entrants secure financing. A recent study of patents in the software industry by Mann (2006) shows that software start-ups holding patents receive more investment from venture capitalists than those without patents, consistent with Kortum and Lerner's (2000) finding that venture-backed firms hold more patents than start-ups receiving other types of funding. Arora, Fosfuri and Gambardella (2001), Gans and Stern (2000), Gans, Hsu, and Stern (2002), and others have highlighted the role of patents and other formal IP rights in supporting a "market for technology" which provides an avenue for new entrants to realize value from innovation by licensing, or selling themselves to incumbents. More recently, Gans, Hsu and Stern (2006) show that the resolution of uncertainty over the scope of IP rights associated with the grant of a patent leads to an increase in the probability of licensing for start-up companies, but find that patent grants are less important for licensing in software than in other industries. Hsu and Ziedonis (2007), controlling for a variety of covariates including firm-specific fixed effects, show that a doubling in a start-up firm's patent stock is associated with a 24% increase on average in investors' valuations.

In contrast to the number of papers that use datasets comprised exclusively of venture-backed firms, the literature that models the probability that start-up companies obtain external investment from other sources is relatively sparse. Hellmann and Puri (2002) provide evidence on the impact of VC funding on start-ups, using a sample of venture-backed and non-venture-backed firms. Kortum and Lerner (2000) perform a comparison of venture-backed and non-venture-backed firms in Massachusetts, using the CorpTech directory to identify the set of non-venture-backed firms. Goldfarb et al. (2006) investigate VC's funding decisions using a database of all business plans submitted to a single VC between 1998 and 2002.

Analyses of the role of uncertainty in the duration of investment in start-ups include Gompers (1995) and Guler (2007). Gompers (1995) investigates at the relationship between the staging of venture investment and agency costs in the presence of asymmetric information, arguing that venture capitalists will monitor portfolio companies more frequently when agency costs are higher, leading to more rounds of investment with shorter periods between rounds. Guler (2007) studies the management of investments by venture capitalists as an example of the management of real options, using the number of rounds of financing as an indicator of delayed investment.

Empirical analyses of exits via IPO include Lerner (1994), Gompers (1995), and more recently, Giot and Schwienbacher (2007) and Ljungqvist, Hochberg, and Lu (2007). Factors that have been found to influence the probability of going public include market conditions and industry-specific effects, the stage of development of the firm, the geographical location of the firm, the amount invested and number of investors, and the investors' experience level. Giot and Schwienbacher estimate a competing-risks model that allows for multiple types of exit. We perform a similar analysis in this paper by considering the factors that lead to exit by IPO, acquisition, or liquidation.

Empirical Approach

As in Cockburn and MacGarvie (2007), our approach here is to estimate reduced form regressions in which we look for evidence of an association between measures of patent thickets and indicators of entry and financing of new ventures, controlling for other market characteristics, such as demand, market structure, and the state of technology.

One obvious potential problem is endogeneity: the nature of the patent thicket prevailing in these markets presumably reflects optimizing responses to the competitive environment. We believe that any endogeneity bias is quite limited. First, in all of our regressions we use market fixed effects, so that our identification comes from within-market changes in the patent thicket and the outcomes of interest rather than from purely cross-sectional correlations. Second, while incumbents may endogenously respond to the competitive threat posed by potential entrants by filing additional patents, we believe the influence of this on patent thickets to be quite limited and where it exists it will bias our coefficients toward zero, leading to underestimates rather than overestimates of any causal effect of patents on entry. The timing of incumbents' patent grants (or their ability to obtain patent protection at all) is in large part affected by exogenous changes in resources and policy at the Patent Office. The average time between patent application and grant in our dataset is close to three years.[7] Given the high speed of product cycles and turnover in the software industry, incumbents *filing* patents in response to threats from competitors will in most cases be unable to use the granted patents until well after entry has taken place, and the infringing product has been superseded. Because of this, a substantial portion of the thicket faced by entrants in any market is composed of patents obtained far in the past, and by non-competitors. Thus, after controlling for time-invariant unobserved effects, and a variety of other potential sources of bias (such as confounding growth in the patent thicket with maturity of the technology in a market), endogeneity of our thicket measures created by incumbents' responses to time-varying shocks to the threat of entry appears not to be a major issue. In Cockburn and

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[7] According to the USPTO website, "The length of this delay is determined by many factors, including PTO workload, budget and manpower levels, and patent printing schedules…[for example,] The 1986 patent grant data are lower than would have normally been expected due to a lack of printing funds."

MacGarvie (2007) we used an instrumental variables approach to address the potential endogeneity of patenting by incumbents, and obtained essentially identical estimates.

Here we additionally exploit a series of changes in the legal regime that substantially expanded patentability of software inventions, the number of software patents granted increased dramatically during the 1990s. These changes can be thought of as a quasi-experiment in which the strength of issued patents exogenously increased, raising barriers to entry in markets with more patents relative to markets with fewer patents. This allows us to examine market-level patterns of entry and financing before and after changes in the legal regime using a differences-in-differences approach. In this model, for any there to any bias arising from a correlation between financing/entry and patents induced by omitted variables, the relationship between financing/entry and the omitted variable(s) in question would have to occur simultaneously with the changes in software patentability that took place during our sample. Revisiting Cockburn and MacGarvie (2007), our first key result is that the rate of entry is negatively correlated with the number of patents in a market, and that this correlation intensified following changes in patentability standards. We find similar effects for our financing measures – the correlation with patents in a market becomes more negative following market-specific regime changes in patentability.

This result is provocative, but leaves open the question of why exactly the rate of entry falls, and in particular why young, specialized firms are more affected. One leading hypothesis is that the intensification of patent thickets as barriers to entry reduces the expected profits of early-stage firms, thus reducing the attractiveness of these companies as targets for investment.

We therefore turn to a second hypothesis, that patent thickets affect entry by making it more difficult for early-stage firms to acquire funding. Using the same differences-in-differences approach, we examine the impact of increased patenting on the financing of software ventures at two stages in their life cycle: the period from birth to initial funding by external investors, and the period from first funding by external investors through to exit via IPO or acquisition.

We focus on the following questions:

1. Are start-up firms facing a patent thicket less likely to receive venture capital investment or corporate funding? We hypothesize that firms operating in markets characterized by patent thickets face higher costs of entry (consistent with Noel and Schankerman (2006)), and that investors' expected return on investment in such markets will be lower, leading to a reduction in the likelihood of receiving outside funding

2. Do thickets delay or reduce the likelihood of going public or being acquired, or do they increase the likelihood of acquisition relative to IPO? If patent thickets are a significant barrier to entry or source of increased costs for entrepreneurial firms, we expect that they will reduce investors' expected returns from an IPO and therefore reduce the probability of going public. On the other hand, larger established companies may find it easier to navigate the patent thicket due to deeper pockets or experience with the patent system, so that start-ups facing a thicket may be relatively more likely to be acquired by other companies rather than go public.

3. Do thickets delay and/or reduce investment (through their impact on uncertainty)? With higher uncertainty we expect the option value of delaying an investment to be higher, and therefore see investment take place later in markets with a higher degree of uncertainty about the scope and validity of patents

Recognizing the potential stimulating effects of patents, we also ask whether the above effects of patent thickets are mitigated for start-up firms that themselves hold patents.

Data

Market and firm characteristics

The firms we study are drawn from the CorpTech directory of technology companies, which covers 19,717 public and private firms active in software markets over the period 1990-2004.[8] We know the founding date of the firm, revenues and employment for most (but not all) of the firms in the dataset, the patents held by the firm, information on corporate parents, funding sources, and a number of other variables. To the CorpTech sample, we add data from SDC's VentureXpert database. We use information on the number of rounds received, the amounts invested, the identities of investors, the stage of the investment, the founding date of the venture, and whether the venture ultimately went public or was acquired, and the name of the acquirer when relevant. We also use Compustat data on the sales, employment, and 2-digit SIC codes of corporate investors.

The CorpTech data contains fine-grained information on the product classes in which the firm develops software (the "SOF category"). This self-reported variable can include products under development as well as products already launched. CorpTech reports more than 290 SOF categories, however many of these are quite vaguely defined, or appear to be defined in terms of customer segments rather than in terms of a technology—e.g. "secondary school software, dental practice management software, etc." Furthermore mapping patents to markets is a challenging and resource-intensive task. We therefore focus our analysis on 27 of these SOF-defined markets, listed in Table A.1. These 27 markets were chosen primarily to facilitate subsequent matching to patent data, primarily on the basis of our assessment as to whether the

[8] We define software companies as the firms listed in CorpTech as having at least one product classification beginning with "SOF", which is CorpTech's code for software.

technology/product is reasonably distinctive, and we could define a set of keywords that could be fruitfully searched in the abstract of patent documents.[9]

Tables 1a and 1b show the number of firms of various types in successive CorpTech years and in each market. As can be seen from these tables, there is substantial variation in the cross-section and over time in the size of these markets, in terms of the number of producers, the number of entrants, the number of "new" entrants (i.e. firms founded no more than two years before they appeared as entrants in the CorpTech database) and the fraction of these entrants that receive external funding from either VCs or corporate investors. The number of "new" entrants, as opposed to firms which are new to the market in question, but already have an established presence in other markets, is quite small—averaging 2.2 per market per year over the entire sample—particularly in relation to the number of incumbents, which averages more than 157. (This figure is likely to be an underestimate of the fraction of entrants into these markets that are "new", reflecting issues with the way that CorpTech collects data, and our quite stringent screen for identifying new versus continuing ventures.) Among these new entrants, 16% receive external funding from VCs prior to the year in which they enter the market, while only 6% receive funding from a corporate investor at this point in their lifecycle.

Tables 2a and 2b provide some further summary statistics on the markets into which these firms are entering. We do not have market-level sales data, but we construct a proxy based

[9] Clearly there is some potential for selection bias to influence our results, however we believe that the criteria used to choose these markets are independent of entry and exit dynamics and the sample of 27 SOFs does not appear to be markedly different from the other 262 in terms of firm characteristics and entry and exit rates (see the Appendix). One area in which our sample differs, however, is in terms of the average number of patents held by firms active in the market. The average firm active in one of the sample markets has 29 patents, while the average firm in a market omitted by the sample has only 18 patents, and this difference is statistically significant. Note though that this difference arises by construction: it is difficult, if not impossible to identify patents related to many of the more vaguely defined markets. In our judgment, therefore, this subset of markets is reasonably representative of software products in general.

on the sales of firms active in a market.[10] On average, markets in this sample have a total of $1.7bn in annual sales, with substantial growth over time. Markets range widely in size, from less then $70MM per year in sales to over $6.5BN.

Patents

Identifying the set of patents relevant for firms operating in a particular market is not a trivial task. Cockburn and MacGarvie (2007) describe the process used to match USPTO patent classifications to the CorpTech SOF categories.[11] In short, we used a combination of text searching and reading the manual of patent classification to identify the set of key patents associated with each market. Using the mapping between patent classes and CorpTech product markets described above, we obtained all the relevant patents in these classes from the NBER Patent Database. Table 3 shows the annual count of patents that meet these criteria, by grant date and application date. There is a striking increase in the number of patents over time: annual patent grants relevant to this set of 27 product markets increased more than 40-fold between 1980 and 2006. The table also shows the number of patents expiring each year, either because they have reached full term, or because the assignee has failed to pay maintenance fees. These expirations represent a non-trivial fraction of the total number of patents in force: in the late 1990s, for example, new patents were being added to the sample at a rate of about 7000 per year, while about 1200 were being removed from the "patent stock." (Once patents expire, they are excluded from our subsequent calculations.)

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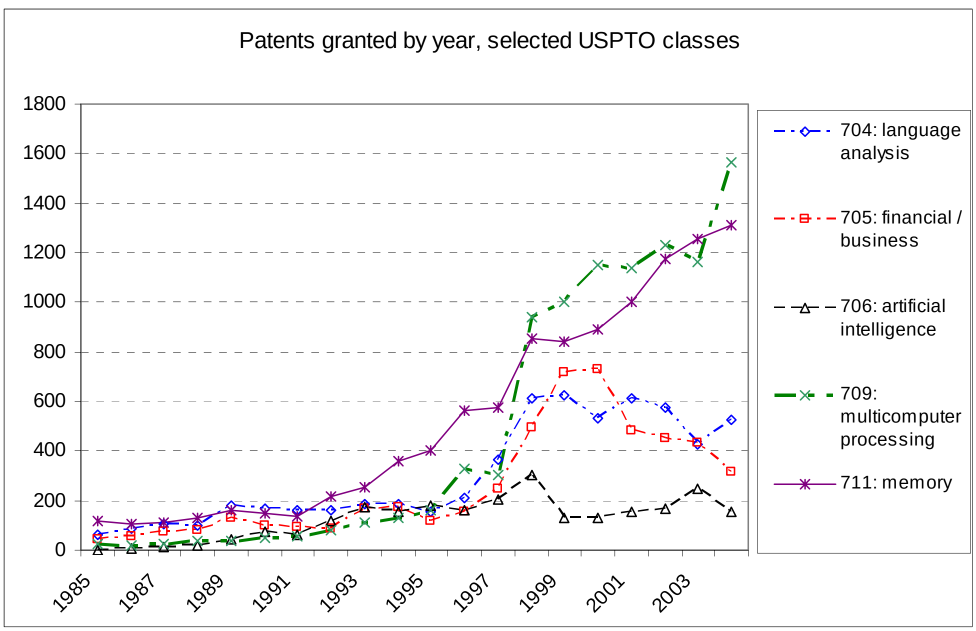
[10] For firm i active in in market j as well as n other markets, we compute average sales per market in market j as $SALES_i/n$ (the total sales of the firm divided by the number of markets in which it is active). We then add up the average sales per market for all firms active in the market. CorpTech contains a numerical sales variable as well as a categorical variable that indicates the range in which the firm's revenues fall. A significant portion of observations on the former are missing, and we fill in these observations with the mid-point of the range indicated by the categorical sales variable.

[11] Arora et al (2007) use a related approach to create a comprehensive concordance between USPTO classes and software product categories.

Tables 4a and 4b present statistics on the characteristics of the 108,863 patents issued since 1977 that we have determined to be relevant to one or more the 27 product markets considered here. As can been seen in Table 4a, there are very large changes over time in patent characteristics such as the average number of claims, which doubles between 1980 and 2006, the average number of backward citations, which almost triples over this period, and the average number of citations to non-patent literature, which increase 10-fold. While some of the growth in citations reflects growth in the pool of references available to be cited, these figures also suggest significant changes in the nature of the patent rights being awarded and the stringency of patent examination.

As Figure 2 shows, there is substantial variation the numbers of patents issued in different technology classes as well as in trends in patenting in different technology classes

Figure 2



After mapping these classes to product markets this variation is reflected in substantial cross-sectional and time series differences between these markets in the number of patents granted. As can be seen in Table 4b, in some markets only a few hundred patents met our search criteria, while in others there are more than 16,000 patents issued over the sample period. Less substantial differences are also apparent in the average number of claims and in the amount of patent and non-patent prior art that is cited. (Note though that ANOVA F-tests strongly reject the hypothesis of equality of means across markets for all of these measures.)

Markets also differ in the extent to which the patent thicket has grown over time. As shown in Table 4a, the compound annual growth rate of patents in force between 1980 and 2006 is positive for all markets, but ranges from 12% per year to 31%.

Quantitative measures of patent thickets

Patents that block a would-be entrant from producing or selling its product can clearly be a significant barrier to entry. The entrant must either bear additional costs of "inventing around" such patents, pay licensing fees to the patent holder, or accept potentially severe *ex post* penalties.[12] As a first step towards characterizing the patent "landscape" in a market, we therefore compute the cumulative stock of patents in the markets in which each ventures operates, as an indicator of the overall amount of intellectual property faced by the venture.[13]

However, it may not be just the absolute *number* of patents in an area that can deter entry, but also the extent to which those patents form a "thicket" in the sense of generating transactions costs above and beyond simple blocking power. As Shapiro (2001) puts it, "a patent thicket is a

[12] Infringing valid patents can present the entrant with very substantial ex post penalties, such as damages judgments (tripled in the case of "willful infringement") or the loss in value of assets stranded in the wake of an injunction obtained by the patent holder.

[13] We do this in two ways. Following the literature, we compute a stock of patents based on the flow of patents relevant to each market that issued each year, using the perpetual inventory method and the "Griliches constant" 15% depreciation rate. Alternatively, we also total the number of patents relevant to the market that are in force in any given year, assuming a 17 year term, and taking account of patents that expire earlier due to failure to pay maintenance fees.

dense web of overlapping intellectual property rights that a company must hack its way through in order to actually commercialize new technology. With cumulative innovation and multiple blocking patents, stronger patent rights can thus have the perverse effect of stifling, not encouraging, innovation."[14]

Ziedonis (2004) and Noel and Schankerman (2006) argue that a key factor driving transactions costs may be the degree to which ownership of patent rights is fragmented. Suppose a prospective entrant were to obtain licenses from holders of blocking patents. The factors determining the total cost of obtaining licenses to allow entry are complex. All else equal, we expect that the more patents that must be licensed, the higher the total cost of entry. However, particularly in complex technologies, patents are frequently bundled or pooled, or jointly licensed, thus total costs of entry may not have a simple linear relationship to the number of patents blocking the would-be entrant. Another salient feature of "thickets" is the higher costs associated with negotiating with many parties. To the extent that there are fixed costs of conducting a negotiation, having to conduct more negotiations will drive up costs. In addition, the outcome of a complex bargaining process conducted with many licensors, each of whom has some holdup power, may result in higher total costs—i.e. the height of the "royalty stack" may rise non-linearly in the number of its components.

Following Ziedonis and Noel and Schankerman we capture this second effect by measuring the concentration of IP ownership in each market using patent citations.[15] Patent citations are references to existing patented technologies, listed in the patent document.[16] Since these citations delimit the property rights represented by a patent by describing related claims

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[14] P. 2

[15] In Cockburn and MacGarvie (2007) we use an alternative measure, a count of the number of cited assignees in each market.

[16] "Prior art" is not confined to patents, indeed most forms of printed publication describing the claimed invention can constitute prior art, as can public knowledge, use, or sale of the technology.

contained in other patents, citations made by a patent give an indication of the extent to which a technological area is already covered by intellectual property rights and is thus (in principle) foreclosed to entrants who do not obtain a license. Assuming that the share of citations received by an assignee proxies the importance of negotiating with that assignee, we postulate that in a market which has many cited assignees but where citations go disproportionately to a small number of firms, entry costs may actually be lower than in a market with fewer assignees each of which receives a similar share of total citations. To capture this effect, we calculate the Herfindahl index of citations over assignees for each market in each year.[17] Table 5 shows the mean values of this measure over time and for each market in our sample.

Some of these patent measures will be correlated with the maturity of the technology. Gort and Klepper (1982), for example, document an increase in patenting as technologies reach the late stages of the product life cycle. We want to separate the effects of increased patenting at any given stage of the technology life cycle from the natural accumulation of larger patent stocks as time passes. To control for the average maturity of technology in the product market, we use the modal citation lag. Since the number of citations to a patent is a function of the number of potential citations, we estimate the modal lag using a framework that adjusts for this effect. For each product class and citing-cited year pair, we compute the citation frequency, or ratio of actual to potential citations (see Jaffe and Trajtenberg (1999)), and then identify the citation lag (citing year – cited year) with the highest citation frequency for a given product class and citing year.[18] If the modal lag in a product category is short, it implies that the most highly cited

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[17] We also experimented with using the Herfindahl index of citations across assignees to measure concentration of patent rights, but obtained very similar results to those based on the four-assignee concentration index. These results are available from the authors upon request.

[18] We compute the citation frequency as the ratio of the number of observed citations to the number of potential citations. That is, if Ckgd is the number of citations made to patents in market k in citing year g to patents granted in market k in cited year d, Pkg is the number of patents granted in class k in year g, and Pkd is the number of patents granted in class k in year d, the citation frequency is Ckgd/(Pkg Pkd)

patents in that market were granted recently, which suggests that the market is at a relatively early stage of the product cycle.[19] Average values by year are listed in Table 2a.

Quantitative measures of uncertainty about patent rights

Capturing market participants' ex ante uncertainty about the scope and validity of the patents that they face is clearly a substantial challenge. Based on discussions with practitioners and our reading of the ongoing debates about "patent quality" we identify two aspects of patents that may signal that their scope and validity may be difficult to assess. First, we look at the number of non-patent references cited as prior art. Software patent applications (and their review by the patent office) have been widely criticized for failing to recognize or consider relevant prior art in the form of articles in professional journals, trade press, widely circulated product manuals and the like, which could potentially have sharply reduced the scope of claims allowed. According to this view, patents with very few citations to this type of prior are more likely to be held invalid if subjected to legal challenge. (Of course, it may be that these patents reflect truly innovative inventions for which no prior art existed.) Arguably, therefore, markets with many of such patents are ones in which the degree to which the technology space is "covered" is particularly hard to assess.

Secondly, we compute the average number of claims per patent in a market. Arguably that the difficulty of assessing the scope of a patent is increasing in the number of claims. One of the USPTO's recent initiatives to improve patent quality has been to limit the number of claims in a patent to no more than 25 (with no more than 5 independent claims.) Further, Allison et al. (2004) show that patents with larger numbers of claims are more likely to be litigated, and while the likelihood of litigation is undoubtedly related to the value of the patent, it is also more likely

[19] The usefulness of this variable as an indicator of the stage of the product cycle obviously depends on the assumption that the key inventions are patented, or at least that the patented inventions

to occur when parties disagree over the validity or scope of the patent—i.e. when there is greater uncertainty.[20] We calculate the ratio of the number of claims allowed on a patent to the number of patents (both US and foreign) cited. Our reasoning is that patents with a very large number of claims and very few citations to prior art are whose validity and scope are likely to be particularly difficult to assess. (Such patents are sometimes referred to by practitioners as "problem patents.")

Mean values of these measures for each market in our sample are shown in Table 5. The average patent has 2.15 patent citations per claim, with industry averages ranging from 1.67 to 2.72. Variation in this ratio across markets is statistically significant: an ANOVA F-test strongly rejects the hypothesis of equal industry means ($P<0.0001$).

RESULTS

I. Impact of patent thickets at the market-level

Tables 6 and 7 give estimates of the impact of patent thickets on market level measures of activity by new software ventures. In Table 6, the dependent variable in the regressions in the number of new entrants in each market in each sample year. In Table 7 we look at the impact of patent thickets on three measures of financing activity: the number of firms receiving an initial round of funding from external investors in that market-year, the median amount invested per firm in that market-year, and the number of IPOs in that market/year.

In each of these regressions we focus on the number of patents in force as an explanatory variable, controlling for market size, market structure and demand using market and year fixed effects, the number of incumbents (and its square), the growth rate of sales, for the quality of

[20] See also Bessen and Meurer (2006).

patents in the market using the average number of forward citations received per patent in force, and for the maturity of the technology in the market using the modal citation lag.

As discussed above, we also present "differences-in-differences" estimates that make use of the fact that the expansion of software patentability took place at different times for different types of software. Though driven to some extent by pressure from patent applicants, arguably these changes are exogenous to the extent of the patent thicket in a particular market. Briefly, these regime changes were as follows. In 1972, the Supreme Court's ruling in *Gottschalk v. Benson* held that because software is essentially a collection of algorithms, it could not be patented. However, in 1982 in the *Diamond v. Diehr* ruling, the court allowed for patenting of software tied to physical or mechanical processes, such as the program implemented in the method for curing rubber at issue in the case. While patents were granted during the 1980s for inventions with a substantial software component, and the distinction between patentable and non-patentable subject matter in this area was progressively shifted and weakened by various court decisions and creative drafting of patent claims, the effectiveness of patent protection for software was far from clear, with many leading software companies filing only limited numbers of applications, or eschewing software patents altogether. This uncertainty was resolved in the mid 1990s, when the 1994 Federal Circuit decision *In re Alappat* drew a definitive distinction between unpatentable software in the form of "a disembodied mathematical concept…which in essence represents nothing more than a 'law of nature,' 'natural phenomenon,' or 'abstract idea'" and patentable software that is "rather a specific machine to produce a useful, concrete, and tangible result."[21] A series of further court decisions in 1994 and 1995 following *Alappat* culminated in a new set of guidelines, issued by the Commissioner of Patents in May of 1996,

[21] *In re* Alappat, 33 F.3d 1526, 1544 (Fed. Cir. 1994), quoted in Sterne and Bugaisky, p. 222

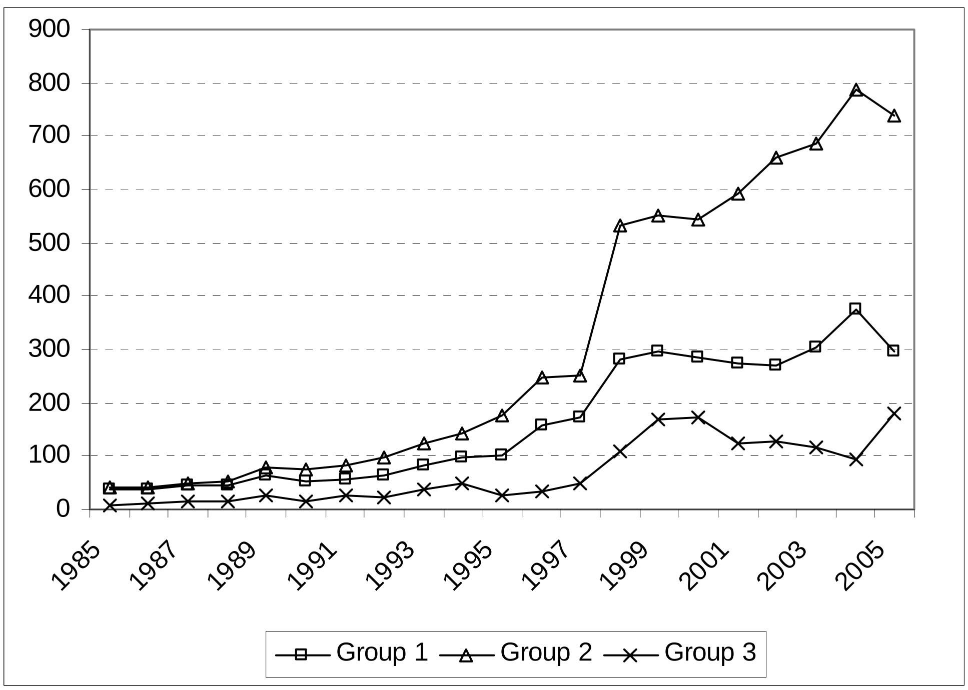
which allowed inventors to patent any software embodied in physical media.[22] Further expansion of software patentability came in 1998 with the *State Street Bank & Trust vs. Signature Financial Corp. ("State Street")* decision, which eliminated the requirement that the software algorithm be tied to a "physical transformation."

As a result of this evolution of legal and administrative doctrine over the 1980s and 90s, some categories of software patents became more clearly obtainable, and more easily enforceable before others. While, software used in manufacturing or "embedded" in hardware devices was covered prior to the 1996 change in guidelines, software more generally was covered after 1996, and financial or business methods software became clearly patentable after *State Street* in 1998. The markets in our sample fall into three groups that were affected by these "regime changes" at different times: those for which software was patentable before 1996 (manufacturing software), those for which it became patentable in 1996 (other types of software not including those affected by *State Street*), and those for whom patentability increased in 1998 (financial software and internet-related software). Using the standard differences-in-differences specification, we therefore we include in the regression the log of the number of patents in a market, the regime-change dummy, and the interaction of the latter two variables. The coefficient on this interaction term gives the change in the effect of the market's patents on the dependent various following the expansion of the strength of patents that are relevant to the market. Figure 3 shows the average number of patents granted in each market, grouped by the applicable regime change. As the figure shows, changes in the volume of patenting and the timing of these changes behave quite differently across the three groups, reflecting the differential impact of the regime changes in 1996 and 1998. Group 1, the set of software markets characterized by manufacturing applications, shows a stable increase over time. Group

[22] Sterne and Bugaisky, p. 223

2, the set we classify as primarily affected by the legal decisions following *Alappat* and the change in USPTO guidelines as of 1996, see a dramatic jump after 1996 followed by a return to trend. Markets in the third group, which were affected by *Alappat* but also by *State Street* in 1998, see an increase after 1996 and continue to grow until 2000, when the USPTO began performing more rigorous examinations of business methods patents (the "second pair of eyes"). This change would seem to account for the dip in the number of patents granted in group 3 after 2000.

Figure 3: Patents granted by year and type of software



Group 1: Automatic teller machine software, Robotic software, Quality control software, Peripheral device drivers
Group 2: Voice technology software, Natural language software, Neural network software, Fax software, Internet tools, Wide area network software, Local area network software, File management software, Hierarchical DBMS software, Relational DBMS software, Database query language software, 3D representation software, Electronic message systems software, Desktop publishing software, Artificial intelligence R&D, Geographic information systems software, Disaster recovery software, Security/auditing software, Performance measuring software
Group 3: Invoicing/Billing Software, Tax preparation and reporting software, Inventory management software, Order entry/processing software

Patents and entry

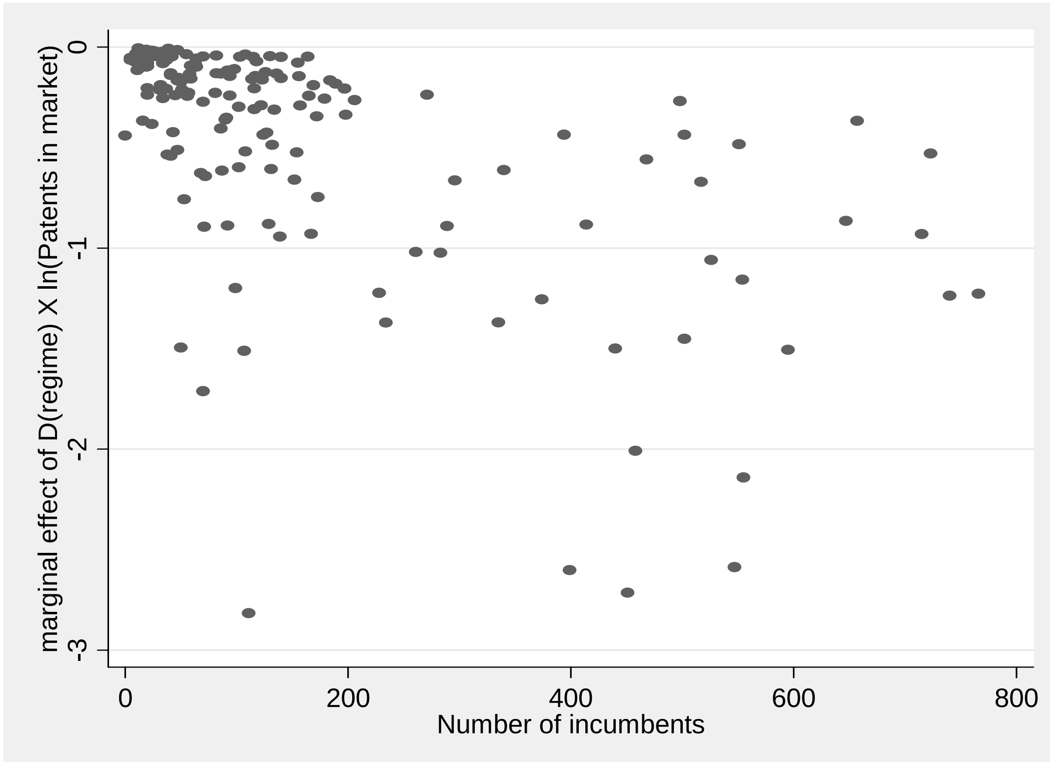
Table 6 reports coefficient estimates from Poisson regressions on the number of entrants in each market-year. Standard errors are clustered by market. Column (1) of Table 6 confirms the findings reported in Cockburn and MacGarvie (1997)—after controlling for market structure, demand etc, the number of patents in force in the market has a substantial negative and significant effect on the number of entrants with an elasticity of -0.438. In Column (2) we include measures of uncertainty about the scope of patent rights, and the negative and significant coefficient on the number of claims per patent citation suggests that markets in which there are a preponderance of such "problem patents" see less entry. Column (3) of Table 6 gives the "differences-in-differences" estimates. Interestingly, there was an overall increase in entry following the regime change (see the positive and significant coefficient on the dummy indicating a market was post-regime-change). However, the negative and significant coefficient on the interaction term indicates that markets with more patents saw larger reductions in entry following the regime change when compared with other post-regime-change markets with fewer patents as well as pre-regime-change markets. In columns (3) and (4) we report results estimated separately for "de novo" entrants versus "diversifiers" (entry into new product markets by firms that are already established in other markets. The marked difference in the estimated coefficients on the number of patents in force and on the interaction term suggest that these negative effect of patent thickets on entry is largely driven by the impact on the *de novo* entrants.

This finding is provocative because it suggests that small, specialized firms are more affected by increases in the strength of IP rights than established firms. One mechanism through which this effect may operate is the financing of early-stage firms. If increases in barriers to entry reduce the expected profitability of entrants, they will also reduce their attractiveness to investors and may make it more difficult for *de novo* entrants to raise capital.

Note that coefficient on the interaction term (the "treatment effect" from strengthening patent rights in the market) is the *average* treatment effect measured in terms of elasticities. Though it is negative and statistically significant at the 5% level, this coefficient conceals substantial differences in the marginal "treatment effect" measured in numbers of entrants computed for each observation. In Table 6 we report estimates of the marginal effect of the interaction term at the 25th, 50th, and 75th percentiles of the market size distribution.[23] As Figure 4 shows, while the estimated marginal interaction effects are all negative, some are quite small and not statistically distinguishable form zero. As Figure 4 also shows, there appears to be a relationship between the magnitude of marginal interaction effects and market size that is not fully captured by the control variables in the regression. Larger marginal effects tend to be found in markets with more incumbent firms, suggesting a more complex relationship between the patent landscape and competition than is captured by this simple regression model.

[23] These effects were obtained by calculating the pre- and post-regime change difference in the partial derivative with respect to the log of patents in the market, using Stata's *predictnl* command. This command computes standard errors via the delta method.

Figure 4:
Marginal effect of interaction of regime change dummy and the log of patents in market plotted against the size of the market



Patents and initial funding

Turning to the impact of patent thickets on financing, the first two columns of Table 7a present results from Poisson regressions on the number of new ventures receiving their first round of financing from external investors.[24] As before, standard errors are clustered by market, and all regressions have market and year fixed effects. The dependent variable is the number of firms in market j who have not previously received external financing and who obtain such investment for the first time in year t. (The following section describes in greater detail how this indicator is constructed, and performs a comprehensive analysis of the probability a firm receives

[24] See the discussion of firm level results below for details on the construction of this variable.

initial investment by a given year. Here we present a preview of these findings by examining the broad market-level patterns in initial financing episode and patenting in the market.)

The number of firms in a market receiving investment for the first time in year t will depend on a) the number of firms “at risk” (i.e. the number of early stage firms that haven’t previously received investment), b) the stage of development of firms in the market (the average age of the firms), and c) the expected profitability of the entrants. We use the same variables as in the entry regressions to control for demand and market structure, but also include a count of the number of firms “at risk” which is the total number of new ventures identified as being present in the previous sample year.

In column (1) the coefficient on the number of patents in force is large and negative, implying that software ventures that enter markets with larger patent thickets see are less likely to receive funding from outside investors. In this regression the estimated coefficient is only marginally significant, though when the market structure variables are excluded the estimated coefficient is -1.07 and strongly significant. In column (2) we use the differences-in-differences specification, and here a large and strongly significant coefficient is estimated on both the dummy for change in regime and the interaction term. We conclude that patent-intensive markets saw a reduction in initial investment by external parties in early-stage firms relative to low-patent markets following the expansion of software patentability in the 1990s.

In Table 7b we include measures of the uncertainty of patent rights. As can be seen in columns (1) and (2) these have little effect on the result for number of patents in force, but we find a negative and significant effect on entry of the mean share of non-patent references in the citations made by patents in the market. (In the differences-in-differences specification in column (2) the estimated coefficient is larger and more significant. In specifications where we include interaction terms with the uncertainty variables they are not significant.) This result is consistent with idea that markets in which patents have relatively more references to the technical literature—i.e. are more clearly distinguished from the prior art, and perhaps more likely to be held valid—appear to make new ventures less attractive to outside investors.

Patents and funding levels

Columns (3) and (4) of Tables 7a and 7b report regression results where the dependent variable is the amount of financing received by firms active in each market in year. Here we use the log of the median amount invested across all transactions in a given market/year as the dependent variable. When we use the log of the total amount invested in all transactions (or try to model the amount received by each venture in a firm-level regression) the regression performs very poorly. We believe that this reflects the very high level of measurement error in the amount of financing received at the transaction level, which creates some very large and influential outliers, as well as difficulties in adequately capturing heterogeneity across different rounds and unobserved aspects of individual transactions.

In Table 7b we find the opposite "main effect" of patent thickets on funding levels than was the case for the volume of entry: the coefficient on the number of patents in the market is positive and significant, with an elasticity around +1. We attribute this to a strong selection/threshold effect, whereby the higher entry costs associated with patent thickets result in smaller firms requiring lower amounts of external investment being denied funding. As before, however, the "treatment effect" of strengthening patent rights is negative and significant: relative to markets with fewer patents in force, strengthening patent rights in markets with a large thicket results in a leftwards shift in the distribution of external investments in software ventures. The uncertainty variables (columns (3) and (4) of Table 7b) have no significant effect on funding amounts, and controlling for these subtler aspects of the patent landscape in each market has little impact on the estimated effect of the number of patents in force.

Patents and IPOs

Finally, columns (5) and (6) in Tables 7a and 7b present results from a Poisson regression on the number of IPOs in each market/year. Consistent with patent thickets being, on net, beneficial to incumbent firms in Table 7b we find a large, positive main effect of the number of patents, but with a negative and significant interaction term. Relative to markets with fewer patents, strengthening patent rights in markets with a large number of patents in force appears to make software enterprises less attractive to investors in public markets. However the very large positive coefficient estimated on the regime change dummy points to possible difficulties in identifying this effect separately from other factors affecting IPOs. For example, the "tech stock" bubble of the late 1990s is somewhat coincident with the changes in legal regime. We experimented with using the level of the NASDAQ index and the book-to-market ratio in the ICT industry as control variables but found that their inclusion did not substantially alter the main findings and we concluded that the influence of aggregate forces such as these were better captured by the year dummies included in these regressions.

Including the uncertainty measures in these regressions (columns (5) and (6) of Table 7b) has a substantial impact on the estimated effect of the number of patents. The coefficients lose significance, while the estimated effect of the uncertainty measures are large and significant. Taken at face value, the estimates suggest that investors in public markets are less willing to invest in firms operating in markets where there are more "problem patents" with a high ratio of claims to citations made, but more willing to invest in firms operating in markets where the average patent cites a larger amount of technical literature as opposed to other patents.

II. Impact of patent thickets at the firm level

The market level results, though provocative, do not permit any investigation of our other hypotheses about the effect of uncertainty about patent-related costs being to delay investment. By looking at firm-level data, we can measure the timing of investments and test for any impact of patent thickets and our other measures of uncertainty about the scope of patent rights. We can also control for the degree to which investors concerns about patent thickets are mitigated by new ventures holding their own patents. (See Gans, Hsu, and Stern.) Cockburn and MacGarvie (2007) find a substantial positive effect of own patent holdings on the probability of entry into a market, suggesting that this may also be an important factor in funding decisions.

Receipt of initial funding from VCs and corporate investors

As discussed above we hypothesize that, if patent thickets reduce a venture's expected profits, investors faced with two otherwise identical companies will choose the one operating in a less "thicketed" market.

In order to test this hypothesis, we would ideally have a dataset comprised of firms that sought external funding and were either granted or denied such funding. While this type of data is very difficult to find, we have created what we believe to be a reasonable approximation of such a dataset using a sub-sample of firms extracted from the CorpTech directory. CorpTech lists more than 19,000 software companies active at some point between 1992 and 2004, but is unlikely to capture the entire population of software firms. To the extent that firms that appear on CorpTech have passed some threshold of success that warrants their inclusion in the directory, our sample may not be entirely representative of the universe of entrepreneurial companies. Inference based on firm-level census data would allow for unbiased estimates of the effects of patent thickets on investment in early stage firms. Lacking such data, our estimates may therefore provide a lower bound for the effects of interest.

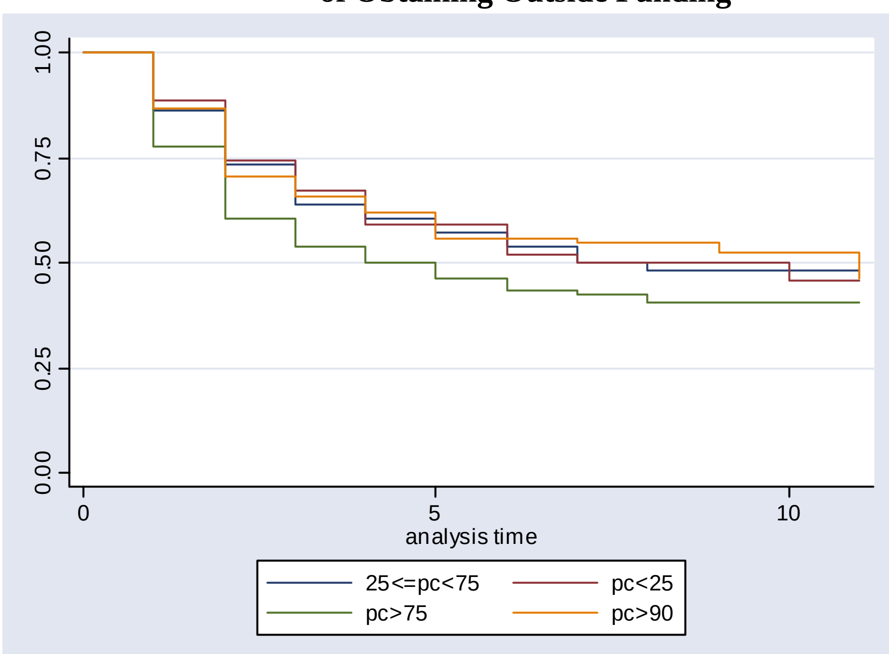
From the CorpTech sample we select firms founded in 1990 or later that are active in no more than one of our 27 product classes. For firms that appear in CorpTech more than one year after being founded, we extrapolate the firm-level data on firm size backwards. We eliminate firms that have already gone public or been acquired.

CorpTech reports the initial source(s) of capital for the firm, for all smaller firms founded between 1992 and 2002. This variable allows us to construct a database comprised of firms that obtain funding at an early stage from venture capitalists or corporate investors and firms that do not obtain such funding. We use CorpTech to identify the set of firms that did and did not receive funding, and we use VentureXpert to identify the *timing* of first investment. Kaplan, Sensoy and Stromberg (2002) show that VentureXpert omits 15% of financing rounds and 20% of financing committed. To ensure that we do not mistakenly classify firms that receive external funding but are not listed on VentureXpert, we drop from the sample 290 firms that are listed on CorpTech as having VC or corporate investment prior to 2002 but that do not appear on VentureXpert. We also drop firms for which no information is available from CorpTech on initial sources of capital. We are left with a sample of 951 firms, of which 475 receive external funding for the first time between 1992 and 2002.

Using information on the first round of investment from VentureXpert, we create a dummy variable equal to 1 if firm *i* receives venture or corporate financing for the first time in year *t*, 0 before year t, and missing after year t. This variable takes on a value of zero in all years for firms that never receive funding before 2002. We then perform duration analysis using the Cox Proportional Hazard model.[25]

Figure 5a gives the Kaplan-Meier survival curves estimated from these data for firms grouped by where their target market falls in the distribution of the numbers of patents in force. (Here "survival" means failure to attract outside funding.)

Figure 5a:
Kaplan-Meier Estimates of Survival Functions for the Hazard of Obtaining Outside Funding

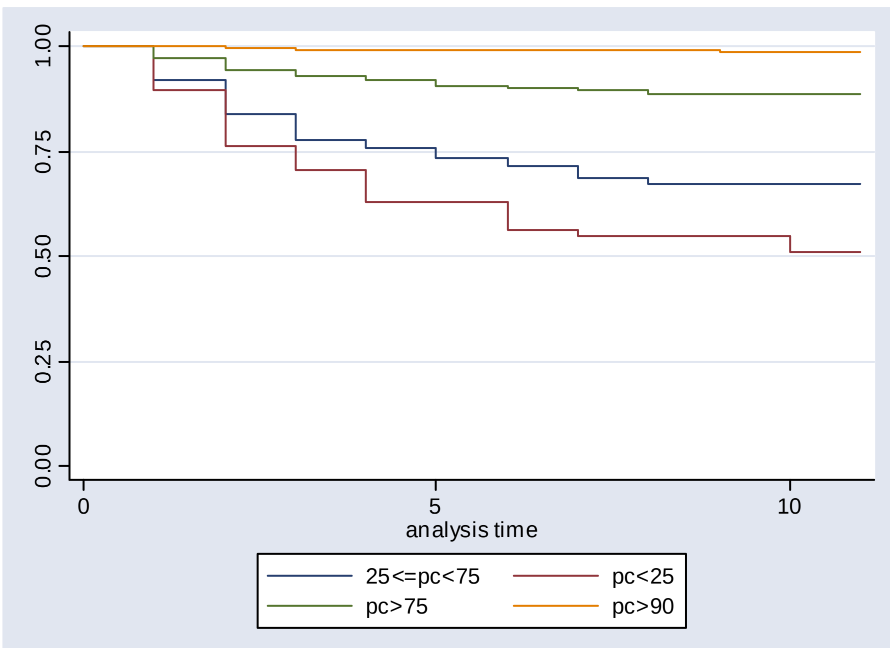


There is no obvious difference across these groups, but once the survival functions are adjusted for the size of the market (number of incumbents and number of incumbents squared,

[25] Essentially similar results are obtained using logit Discrete-Time Hazard models.

we see quite striking differences in the impact of patent thickets.[26] As can be seen in Figure 5b, the Kaplan-Meier estimates show that software ventures in the most thicketed markets have a very small probability of obtaining outside funding, while there are marked differences in the survival curves across markets corresponding to differences in the quartiles in the patenting distribution, with the likelihood of funding at any given duration falling as we move from lower to higher percentiles (after adjusting for market size).

Figure 5b:
Kaplan-Meier Estimates of Survival Functions for the Hazard of Obtaining Outside Funding, Adjusted for the Number of Incumbents in Each Market



These results show the importance of controlling for market characteristics, and in the hazard models, our explanatory variables include year and product market fixed effects, and the modal citation lag for patents in the market. Other market-level controls relating to profitability

[26] These graphs were created using Stata's *sts graph* command, which estimates separate Cox regressions for each percentile group. Adjusting for the number of incumbents means that the number of incumbents and the number of incumbents squared were included as covariates in the Cox regression.

in the firm's target market include the number of incumbents in the market and the number of incumbents squared, and the growth of sales in the market.[27] Variables relating to the patent landscape include the log of the patent stock in the market and the Herfindahl over assignees of citations made by patents in the market.[28] Firm-level explanatory variables include the aforementioned dummies for firm size range, implicitly the age of the firm (since the "duration" variable is years since the birth of the firm), and the number of patents granted and pending.

Table 8 contains results from these regressions, reported as hazard ratios. Looking at the control variables, relative to baseline, the hazard of receiving funding is significantly higher (and thus delays in funding are shorter) in faster growing markets. In general the hazard of funding is nonlinearly related to the number of competitors in the market, with an initial increase and then decrease, first rising with the this measure of the size of the market—presumably reflecting an increase in expected profits due to a reduction in the market power of incumbents or a reduction of barriers to entry created by network effects—then falling as the number of incumbents increases, which could reflect the fact that large numbers of incumbents indicate more mature, more crowded, and less attractive markets. The dummies for the range of firm size (not reported, but available upon request) display a concave relationship between firm size and the hazard of initial funding. These results are somewhat sensitive to the selection of control variables, but adding or dropping control variables has little effect on the estimated coefficients on the patent variables.

[27] The inclusion of a proxy for the CR4 of sales in the market was rejected by a likelihood ratio test. The same is true of the log of the number of forward citations per patent in the market.

[28] This is computed by taking patents associated with a given market (SOF) in application year t, and calculating the share of their backward citations received by each of a set of assignees. Assignee names were cleaned using a combination of an algorithm and manual inspection. Backward citations to patents granted no more than ten years previously are omitted.

The “patent landscape” variables display a pattern consistent with several of our hypotheses. In all of the regressions, increases in the total number of patents in the market are associated with a substantial and statistically significant reduction in the hazard of receiving funding (or, equivalently, longer delays in receiving funding). Conversely, we find a positive and significant effect on the hazard of receiving funding for software ventures that have their own patents. Consistent with the idea that investors are forward-looking (and with anecdotal evidence) a much larger and statistically significant effect is found for the number of patents pending than for the number of patents granted.

In column (2), the differences-in-differences specification shows that the negative effect of patent thickets is larger in markets where patent rights were strengthened relative to those where it was not. Comparing columns (1) and (2) with (3) through (5), a one standard deviation increase in the number of patents in the market is associated with a reduction in the hazard of being funded on average of 0.01 (one percentage point). After 1996, this increases to approximately a reduction in the hazard of funding by 0.04 for a one standard deviation increase in the patent stock in the market. Given that the mean probability of obtaining funding in a given year is 0.085 overall and 0.102 after 1996, this effect appears to be of considerable importance. The significance of these results are robust to clustering at the market level. The “average treatment effect” implied by the interaction term is statistically significant. However, though the marginal effect computed for each observation is always negative, it is not always significant. Table 8 gives the average marginal interaction effect, and the average standard error, estimated from a logit discrete-time version of the Cox continuous time model.[29]

[29] These marginal effects are again computed using Stata’s *predictnl* command. See Ai and Norton (2003) for more on the estimation of interaction terms in nonlinear discrete choice models.

Comparing estimates using the full sample of data to those obtained for the sub-sample of observations after 1996 (the major shift in the legal regime governing software patentability) shows that the impact of patent thickets was much larger during this period. Consistent with the quite large negative interaction term effect in column (2), the hazard of receiving funding is substantially lower for this subsample than for the full sample. The marginal effect of the number of patents in force is almost four times larger after 1996 than for the full sample.

Column (4) of Table 8 reports results from including measures of bargaining costs. In Cockburn and MacGarvie (2007) we found that these had a significant effect on entry. (We report results only for the post-1996 subsample. Coefficients were insignificant but of the same sign and similar magnitude when the same specification was used on the full sample.) Consistent with the hypotheses about bargaining costs and the concentration of patent ownership discussed above, we find a positive effect of the Herfindahl of patent citations over assignees within each market on the hazard of receiving initial funding. In other words, an initial round of funding by external investors is more likely to be obtained by software ventures operating in markets were IP ownership is more concentrated. Our alternative measure of bargaining costs, a quadratic in the number of cited assignees, is insignificant.

Exits

Table 9 presents results of a model of the probability that a new venture ultimately exits from the "entrepreneurial phase" by going public, being acquired by another firm, or is liquidated or truncated in the dataset. The unit of observation for this analysis is a calendar year, and we use a competing risks discrete time hazard model in which we use a multinomial logit for probability of each of these mutually exclusive outcomes being observed in each year. The dependent variable is equal to 0 in each year prior to exit via IPO or acquisition, 1 in the year that the firm goes public, and 2 when the firm exits via acquisition. Firms that are censored or liquidated take on a value of zero in all periods. (Competing risks can be estimated using this type of multinomial logit model provided the competing risks are independent, see Allison (1982).) The market-level variables are as described above. We also include controls for characteristics of the investors in each venture (total patents held by investors, the number of investments from corporate investors as opposed to VCs, and the cumulative number of IPOs by firms in which investors had previously invested) and of the venture itself (total amount invested to date, and number of patents held.) The sample is restricted to firms from the sample used in the initial funding regressions that received at least one round of funding. Characteristics of investors are measured only in years in which the firm receives a round of investment, and a dummy variable is included to indicate years in which the firm received investment.[30]

Consistent with the market level results on IPOs, the multinomial logit regressions reported in columns (1) and (2) of Table 9 indicate that the hazard of going public or being acquired is higher in markets with more patents, though the coefficient is not significant. We also find that the hazard of exiting from the sample in these ways is increasing in the number of patents owned by the venture (a strongly significant effect) and increasing in the total amount of outside investment to date (though only marginally significant.)

In the differences-in-differences specification in columns (3) and (4) we also obtain a result consistent with the market-level findings: a significant positive effect of the number of patents in the market on the probability of exiting via IPO, although the interaction effect with the legal regime change is negative. Again, we interpret this as evidence that patent thickets tend

[30] The coefficient on this variable is not reported but is available upon request. We also estimated models in which an observation was a firm-round, rather than a firm-year, and obtained comparable results.

to protect incumbents, but only up to a point. When patents are strengthened by changes in the legal regime, the effect is smaller (though not significantly so). The effect on the hazard of exiting via acquisition is negative, but not significant, and because the data are ill-conditioned (due to sparse cell counts) we are unable to obtain stable estimates of the regime dummy interaction effect for the exit via acquisition outcome. The impact of patent thickets is very apparent when we estimate the model on the subset of firms that did not obtain any patents of their own. As can be seen in columns (5) and (6), these firms are much less likely to exit via IPO, relative either to liquidation/censoring or to acquisition, in markets with a large patent thicket. This finding is striking in light of the fact that only a minority of the firms in our sample (22%) hold patents by the time of exit. An important question for future research is why, given the apparent differences in success rates between patent-holding and non-patent holding firms, relatively few firms in these markets filed patents during this time period.

Summary and Conclusions

The impact of stronger intellectual property rights in the software industry is controversial. One often under-emphasized means by which patents can affect technical change, industry dynamics, and ultimately welfare, is through their role in stimulating or stifling entry by new ventures. The mechanisms through which patents can impact this process are, as ever, complex. Patents can block entry, or raise entrants' costs in variety of ways, while at the same time they may stimulate entry by improving the bargaining position of entrants vis-à-vis incumbents, and supporting a "market for technology" which enables new ventures to license their way into the market, or realize value through trade in their intangible assets. Some of the impact of patent thickets may therefore be felt in the interaction of new ventures with the capital markets, and here we find evidence that the extraordinary growth in patenting of software has had a variety of effects on the financing of software companies.

Our analysis of an unusually complete data set that contains information on software ventures that do not obtain outside funding as well as those that do attract VC and corporate investments provides evidence that patents significantly affect the likelihood of obtaining funding for early-stage firms. Interestingly, the number of a firm's patents pending is positively and significantly related to the probability a firm obtains initial funding, while the number of patents already granted is not—outside investors appear to be focused on these firms' "pipeline" of IP assets under development. . The estimated effect is quite large: each additional patent pending increases the hazard of funding by around 10%. Start-up software companies operating in markets characterized by denser patent thickets see their initial acquisition of VC or corporate funding delayed relative to firms in markets less affected by patents. This effect does not appear to be present on average once funding has been obtained and new ventures have become incumbents. If anything, our market-level estimates of the conditional correlation between the number of IPOs in a market and the patents in force there suggest that firms operating in markets with a large number of patents may be more attractive to investors in public markets, stimulating IPO activity and thus the payoff to early-stage investors. We do however find that changes in the legal regime that strengthen patent rights significantly lower the correlation between patents in a market and the number of IPOs. In a firm-level analysis that controls for additional characteristics of pre-IPO firms, these results are maintained, but they are statistically weak (the estimated coefficients are have the same sign but rarely significant) and again the effect only works up to a point. Interestingly, we find a significant negative correlation between the hazard of going public and the number of patents in a market for the start-up firms that do not themselves hold patents. Firms without patents operating in thicketed markets are also significantly more likely to be acquired than to have an IPO. Measures of uncertainty about of the scope and validity of patents also appear to play a role in investment decisions, though our results are less robust. We find that there is less entry into markets where patents have a higher ratio of claims made to the amount of prior cited. We also find a statistically significant association between our measures of patent-related uncertainty and the number of IPOs in a market in a given year. Investors in public securities appear to be more willing to invest in software companies operating in markets in which there are fewer “problem patents” and in which patents cite more non-patent prior art. However we find no evidence for our hypothesized relationship between higher levels of uncertainty and delays in the timing of initial financing of new software companies by venture capitalists and corporate investors.

One of the most statistically robust (and provocative) findings of this paper is the importance of new ventures obtaining their own patents. Firms that have higher numbers of patents and patent applications pending are more likely to receive funding from outside investors, and more likely to subsequently “exit” from the entrepreneurial phase through IPO or acquisition. These findings may in part reflect the value to outside investors of the ability to obtain patents as signal of the quality of a new venture’s technology and/or management. Hsu and Ziedonis (2007) show that larger numbers of patent applications are associated with higher valuations of early stage semiconductor companies, and attribute this in part to factors other than the information about a firm’s technology that is provided by patents. Beyond this “capabilities” argument, we suggest that when faced with a patent thicket, patents also confer significant competitive advantages on entrant firms in minimizing transactions costs associated with incumbents' patent holdings. But despite these facts, only 16% of the firms in our regression sample (and only 22% of the firms that ultimately got funding) ever filed for a patent during our sample period. If the benefits from holding patents are as substantial as our results suggest, it is puzzling why more of the firms that were active in these markets during this period did not obtain them. One explanation may be that causality between funding and patent applications runs in the opposite direction: it may be that investors require early stage firms to file patent applications as a condition of receiving funds, or that applications are observed disproportionately by firms that get funding and are more able to support the substantial costs of patent prosecution. In these data we only observe applications that are subsequently granted, so this may be a significant source of bias if large numbers of unobserved applications are abandoned by firms who are not funded.

This paper documents a number of mechanisms through which patents confer private benefits to software companies. These benefits appear to have been substantial, and are reflected in the extraordinary surge in patenting in this industry. However these incentives to obtain patents may ultimately become collectively self-destructive. Our differences-in-differences estimates of the relative impact of strengthening patent rights show a generally negative effect on entry and financing of software firms in the most heavily thicketed markets. Continued accumulation of patents may therefore result in the "stifling" effects identified here swamping the offsetting "stimulating" effect on innovation.

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Table 1a: Number of firms per market – mean by firm type and year

Year	Incumbents	All entrants	Diversifiers	Number of new entrants	Share of new entrants VC-funded	Share of new entrants Corporate-funded
1994	82.63	9.81	8.89	0.93	0.04	0.04
1996	109.22	15.74	13.30	2.44	0.14	0.02
1998	132.00	19.07	16.74	2.33	0.12	0.05
2000	176.59	13.74	12.22	1.52	0.17	0.04
2002	200.85	7.81	4.41	3.41	0.26	0.09
2004	243.48	23.41	20.93	2.48	0.25	0.11
All	157.46	14.93	12.75	2.19	0.16	0.06

Table 1b: Number of firms per market – mean by firm type and SOF

SOF	Incumbents	All entrants	Diversifiers	Number of new entrants	Share of new entrants VC-funded	Share of new entrants Corporate-funded
ac_b	489.83	24.67	21.00	3.67	0.11	0.08
ac_t	117.00	6.33	6.17	0.17	0.00	0.00
ai_a	73.50	7.00	6.33	0.67	0.17	0.00
ai_l	13.50	2.00	1.33	0.67	0.08	0.08
ai_n	17.00	2.00	1.67	0.33	0.00	0.00
ba_a	25.00	1.67	1.33	0.33	0.17	0.00
cs_f	88.17	12.50	10.83	1.67	0.04	0.00
cs_i	377.67	51.17	40.67	10.50	0.34	0.14
cs_l	142.00	13.00	11.17	1.83	0.21	0.04
cs_w	67.83	9.83	9.00	0.83	0.25	0.08
Dm_f	373.00	44.17	38.67	5.50	0.21	0.13
dm_mh	39.83	4.00	3.33	0.67	0.17	0.08
dm_mr	167.17	12.67	10.50	2.17	0.13	0.04
dm_q	103.00	16.17	14.33	1.83	0.25	0.08
ma_c	12.17	1.00	1.00	0.00	0.00	0.00
ma_q	74.33	17.00	15.33	1.67	0.08	0.00
oa_gd	121.00	10.00	7.83	2.17	0.26	0.17
oa_me	142.17	15.33	12.67	2.67	0.28	0.18
oa_p	51.33	4.50	3.67	0.83	0.17	0.00
sv_ar	34.00	0.83	0.83	0.00	0.00	0.00
ts_er	109.67	9.33	8.50	0.83	0.04	0.00
ut_h	80.17	7.33	7.00	0.33	0.08	0.00
ut_r	54.17	7.67	6.67	1.00	0.33	0.17
ut_x	279.00	28.33	23.33	5.00	0.39	0.14
ut_y	192.00	28.67	23.33	5.33	0.24	0.05
Wd_i	593.50	35.33	31.17	4.17	0.11	0.00
wd_o	413.50	30.67	26.50	4.17	0.28	0.06
All	157.46	14.93	12.75	2.19	0.16	0.06

Table 2a: Market Characteristics – by year

Year	Total Sales $MM	CR4 for Sales	Modal backward citation lag
1994	316	0.73	3.15
1996	461	0.71	4.15
1998	662	0.68	5.37
2000	4,825	0.50	6.04
2002	1,903	0.59	7.30
2004	2,025	0.50	7.70
All	1,699	0.62	5.62

Table 2b: Market Characteristics – by market

SOF	Total Sales $MM	CR4 for Sales	Modal backward citation lag
ac_b	2,073	0.34	5.33
ac_t	853	0.66	3.50
ai_a	1,138	0.66	6.50
ai_l	254	0.95	7.17
ai_n	219	0.93	7.17
ba_a	465	0.80	5.33
cs_f	867	0.62	4.67
cs_i	6,577	0.28	4.67
cs_l	3,610	0.50	4.67
cs_w	1,357	0.67	4.67
dm_f	3,550	0.30	5.00
dm_mh	266	0.86	5.50
dm_mr	2,160	0.53	5.50
dm_q	1,302	0.54	5.50
ma_c	68	0.95	5.50
ma_q	723	0.62	6.00
oa_gd	1,842	0.61	4.67
oa_me	1,371	0.50	6.00
oa_p	528	0.72	6.50
sv_ar	1,324	0.92	5.33
ts_er	1,761	0.70	4.50
ut_h	1,410	0.73	4.33
ut_r	805	0.68	5.67
ut_x	4,366	0.45	7.00
ut_y	2,729	0.54	6.33
wd_i	2,692	0.29	7.50
wd_o	1,554	0.36	7.17
All	1,699	0.62	5.62

Table 3: Patent Counts by year				
Year	Grants	Applications	Expirations	Total patents in force
1980	366	680	.	2359
1981	394	755	.	2987
1982	491	859	.	3797
1983	552	860	.	4659
1984	739	861	.	5870
1985	851	920	.	7307
1986	873	1096	.	8759
1987	1091	1363	.	10557
1988	1076	1567	.	12296
1989	1632	1856	.	14900
1990	1463	2116	.	17272
1991	1595	2237	.	19816
1992	1735	2569	.	22882
1993	2095	2805	.	26702
1994	2400	3738	439	31162
1995	2688	5694	774	35775
1996	3497	7032	734	41892
1997	3676	8693	1049	48219
1998	6706	9523	974	61406
1999	7149	10753	1290	75457
2000	7049	12270	1259	88718
2001	7561	11634	1435	102808
2002	7777	9200	1795	118032
2003	8219	5121	2091	133597
2004	9123	2070	2131	150981
2005	10781	590	2017	169093
2006	16285	36	2669	199191
All	107864	108898	18660	

Table 4a: Patent Characteristics – by year

Grant Year	# Patents Granted	Mean # of claims	Mean # of US patents cited	Mean # Foreign patents cited	Mean # non-patent references	Mean # forward cites within 5 years
1977	382	12.35	6.06	0.03	0.27	4.07
1978	351	14.15	5.98	0.04	0.35	4.03
1979	266	12.24	6.26	0.12	0.50	4.02
1980	366	12.65	6.79	0.18	0.49	4.87
1981	394	12.39	7.24	0.25	0.58	4.85
1982	491	12.54	7.37	0.32	0.68	5.24
1983	552	12.69	7.35	0.42	0.73	5.58
1984	739	11.93	7.24	0.38	1.00	6.19
1985	851	11.70	7.51	0.41	0.78	6.35
1986	873	11.85	7.38	0.58	0.79	5.84
1987	1091	11.63	7.54	0.41	0.86	6.86
1988	1076	12.18	7.57	0.61	1.16	6.17
1989	1632	13.56	8.18	0.86	1.34	6.38
1990	1463	13.47	8.36	0.76	1.69	6.45
1991	1595	13.40	7.96	0.75	1.50	6.73
1992	1735	14.45	8.92	0.94	2.08	7.85
1993	2095	14.50	8.56	0.95	2.07	9.06
1994	2400	14.58	8.91	1.05	2.40	9.67
1995	2688	14.52	9.66	1.11	2.32	9.53
1996	3497	16.01	10.76	1.20	3.03	10.87
1997	3676	17.13	11.35	1.18	3.72	10.77
1998	6706	18.89	11.48	1.27	3.53	10.81
1999	7149	20.44	12.23	1.29	4.03	10.54
2000	7049	20.95	12.83	1.19	4.05	9.44
2001	7561	20.76	14.22	1.53	4.22	9.34
2002	7777	22.10	13.76	1.57	4.06	.
2003	8219	22.38	14.82	1.66	4.28	.
2004	9123	22.84	14.95	1.61	4.08	.
2005	10781	22.79	16.00	1.99	5.34	.
2006	16285	22.44	19.11	2.21	6.98	.
All	108863	19.79	13.44	1.47	4.09	9.12

Table 4b: Patent Characteristics by Market

SOF	Total # Patents Granted	CAGR of # patents in force 1980-2006	Mean # of claims	Mean # of US patents cited	Mean # of Foreign patents cited	Mean # of non-patent references	Mean # of forward cites within 5 years
ac_b	189	21.6%	26.06	17.48	2.07	17.17	16.79
ac_t	41	14.0%	17.24	9.85	0.63	6.59	4.36
ai_a	8385	16.1%	19.64	9.98	1.22	4.68	6.63
ai_l	2981	13.8%	19.09	10.00	1.32	4.10	6.29
ai_n	1482	26.5%	19.24	10.65	0.93	10.11	6.40
ba_a	1242	15.7%	19.36	18.88	2.38	2.59	8.64
cs_f	13629	25.5%	22.36	17.52	1.35	4.98	15.32
cs_i	13629	25.5%	22.36	17.52	1.35	4.98	15.32
cs_l	13629	25.5%	22.36	17.52	1.35	4.98	15.32
cs_w	13629	25.5%	22.36	17.52	1.35	4.98	15.32
dm_f	8943	22.1%	22.81	13.30	0.92	5.36	13.41
dm_mh	10169	219%	23.54	13.46	0.92	5.60	13.21
dm_mr	10169	21.9%	23.54	13.46	0.92	5.60	13.21
dm_q	10169	21.9%	23.54	13.46	0.92	5.60	13.21
ma_c	1055	16.8%	17.38	13.84	2.09	4.53	6.37
ma_q	332	31.2%	20.51	13.37	1.57	2.28	7.70
ma_tc	16809	13.7%	17.56	10.98	1.01	2.40	7.09
oa_gd	6057	15.5%	19.20	10.62	1.66	3.51	6.20
oa_me	742	31.5%	23.45	18.38	1.49	5.64	18.68
oa_mv	724	12.7%	16.82	9.84	3.48	1.89	6.57
oa_p	3126	18,7%	20.29	13.64	1.06	5.08	9.75
sv_ar	2261	28.5%	20.05	10.51	0.86	9.48	6.86
ts_er	13445	16.1%	16.82	12.00	2.16	1.33	7.39
ut_2	1166	21.2%	23.59	12.13	0.75	5.00	11.65
ut_h	13164	14.8%	17.59	13.18	1.01	2.08	8.34
ut_o	12508	22.4%	23.32	13.62	0.94	5.50	13.09
ut_r	15536	14.7%	18.73	13.63	1.07	2.77	9.50
ut_x	3092	22.5%	23.32	18.83	2.72	8.42	14.75
ut_y	16811	13.7%	17.56	10.98	1.01	2.39	7.09
wd_i	1681	19.0%	20.02	16.50	1.84	3.77	9.26
wd_o	5076	20.1%	23.66	17.94	2.15	8.84	13.00
All	227684		20.69	14.01	1.28	4.38	10.53

Table 5a: Thicket Measures – by year

year	# of claims per patent citation	Mean # of non-patent references	# of cited assignees	HHI index of citations	CR4 of citations
1994	2.29	2.09	189.96	0.05	0.34
1996	2.11	2.66	331.65	0.05	0.33
1998	2.04	3.26	564.78	0.04	0.29
2000	2.16	4.67	683.07	0.04	0.28
2002	2.13	4.91	869.93	0.03	0.25
2004	2.17	5.29	1054.70	0.03	0.27
All	2.15	3.81	617.45	0.04	0.29

Table 5b: Thicket Measures – by Market

SOF	# of claims per patent citation	Mean # of non-patent references	# of cited assignees	HHI index of citations	CR4 of citations
ac_b	2.13	15.88	55.33	0.14	0.51
ac_t	1.67	3.63	14.80	0.12	0.51
ai_a	2.22	3.80	548.33	0.02	0.24
ai_l	2.21	3.07	301.83	0.02	0.25
ai_n	1.92	7.23	217.83	0.03	0.27
ba_a	2.62	1.81	272.33	0.05	0.31
cs_f	2.29	3.14	1274.67	0.03	0.27
cs_i	2.29	3.14	1274.67	0.03	0.27
cs_l	2.29	3.14	1274.67	0.03	0.27
cs_w	2.29	3.14	1274.67	0.03	0.27
dm_f	2.09	4.01	859.83	0.04	0.32
dm_mh	2.18	4.09	993.17	0.04	0.32
dm_mr	2.18	4.09	993.17	0.04	0.32
dm_q	2.18	4.09	993.17	0.04	0.32
ma_c	1.80	2.46	153.33	0.03	0.29
ma_q	1.77	1.04	67.83	0.05	0.31
oa_gd	2.20	2.28	562.00	0.02	0.21
oa_me	2.72	3.37	195.00	0.05	0.33
oa_p	2.34	3.59	378.67	0.04	0.33
sv_ar	2.04	7.14	294.67	0.03	0.26
ts_er	1.68	1.03	757.00	0.02	0.21
ut_h	1.93	1.48	892.83	0.03	0.24
ut_r	1.97	2.51	589.67	0.03	0.25
ut_x	2.31	4.30	404.67	0.04	0.31
ut_y	2.16	2.01	810.83	0.02	0.20
wd_i	2.29	2.56	366.17	0.04	0.28
wd_o	2.28	4.97	749.50	0.05	0.29
All	2.15	3.81	617.45	0.04	0.29

Table 6: Market-level results on entry

Poisson regressions with year and market fixed effects and standard errors clustered by market

	(1) Entrants	(2)	(3)	(4) De novo	(5)	(6) Diversifiers	(7)
Key Patent Variables							
Ln(Market's patents)	-0.438	-0.493	-0.411	-0.570	-0.465	-0.365	-0.358
	(0.140)***	(0.137)***	(0.139)***	(0.290)**	(0.304)	(0.143)**	(0.139)**
Average claims per cite in market		-0.371					
		(0.182)**					
Non-patent share of prior art		0.089					
		(0.358)					
D(Regime change)			0.687		1.779		0.473
			(0.283)**		(0.894)**		(0.230)**
D(Regime change)*ln(market’s patents)			-0.068		-0.231		-0.039
			(0.035)**		(0.126)*		(0.025)
Control Variables							
Ln(Avg Quality of market’s patents)	-1.043	-0.927	-0.849	-0.653	0.010	-1.111	-1.012
	(0.324)***	(0.346)***	(0.346)**	(0.810)	(0.750)	(0.349)***	(0.366)***
Incumbents (in hundreds)	0.869	0.953	0.902	1.207	1.240	0.791	0.816
	(0.111)***	(0.116)***	(0.102)***	(0.231)***	(0.236)***	(0.087)***	(0.082)***
Incumbents (in hundreds) squared	-0.067	-0.075	-0.070	-0.105	-0.108	-0.059	-0.060
	(0.013)***	(0.015)***	(0.012)***	(0.024)***	(0.024)***	(0.011)***	(0.010)***
Growth of revenues	0.143	0.145	0.188	0.166	0.206	0.114	0.156
	(0.072)**	(0.079)*	(0.072)***	(0.112)	(0.131)	(0.076)	(0.077)**
Modal citation lag	-0.028	-0.048	-0.033	0.001	-0.004	-0.020	-0.023
	(0.013)**	(0.015)***	(0.014)**	(0.037)	(0.037)	(0.014)	(0.014)*
Constant	6.604	7.023	5.589	1.794	-1.589	6.747	6.234
	(1.651)***	(1.818)***	(1.780)***	(3.620)	(3.413)	(1.752)***	(1.839)***
Observations	162	162	162	162	162	162	162
Log likelihood	-422.8	-419.5	-418.4	-231.5	-229.4	-383.5	-381.2

Median marginal effects of interaction terms

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
D(Regime change)*ln(market’s patents)			-1.539		-0.47		-0.883
median standard error			0.793		0.433		0.503
median p-value			0.04		0.271		0.083
Average effect below 25th percentile of market size			-0.651		-0.309		-0.342
Average effect above 75th percentile of market size			-5.93		-1.815		-3.4

Robust standard errors in parentheses
* significant at 10%; ** significant at 5%; *** significant at 1%

Table 7a: Market-level results on financing and IPOs

Estimation method	Poisson		OLS		Poisson	
Dependent variable	Number of firms in market j receiving initial funding in year t		Log of the median amt invested in firms in market j in year t		# of IPOs in market j in year t	
	(1)	(2)	(3)	(4)	(5)	(6)
Patent variables						
Ln(Market's patents)	-0.704	-0.788	0.911	1.171	2.446	3.181
	(0.418)*	-0.61	(0.517)*	(0.463)**	(1.315)*	(1.417)**
D(regime change)		-2.759		2.919		6.554
		(2.80)***		(1.008)***		(1.697)***
D(regime change) X ln(patents in market)		-0.395		-0.423		-0.712
		(4.100)***		(0.079)***		(0.230)***
Control Variables						
Ln(Avg Quality of market’s patents)	-0.334	0.935	-0.142	0.445	5.727	8.135
	(0.563)	-1.099	(0.847)	(0.755)	(1.796)***	(1.798)***
Modal citation lag	0.100	0.010	0.010	-0.018	-0.241	-0.289
	(0.060)*	(0.044)	(0.044)	(0.053)	(0.247)	(0.260)
Incumbents (in hundreds)	-0.001	0.000	0.000	0.000	-2.032	-1.650
	(0.002)	-0.41	(0.000)	(0.000)	(0.793)**	(0.841)**
Incumbents (in hundreds) squared	-0.000	0.002	-0.007	-0.002	0.179	0.140
	(0.000)	-0.75	(0.005)	(0.004)	(0.125)	(0.130)
Growth of revenues	-0.164	-0.27	-0.146	0.006	-0.060	-0.112
	(0.173)	-0.01	(0.155)	(0.137)	(0.599)	(0.658)
# firms "at risk"	0.010	0.017	0.019	0.014	0.024	0.023
	(0.003)***	(0.004)***	(0.012)	(0.011)	(0.014)*	(0.013)*
average age of firms "at risk"	-0.995	-1.016	-0.008	-0.009	-0.091	-0.126
	(0.126)***	(0.174)***	(0.031)	(0.029)	(0.053)*	(0.060)**
Constant	5.334	-6.032	3.397	-1.559	-41.305	-59.849
	(5.349)	-10.683	(1.707)*	(8.069)	(13.943)***	(13.745)***
Observations	231	231	206	206	168	168

All regressions include market and year fixed effects.
Robust standard errors clustered by market in parentheses.
* significant at 10%; ** significant at 5%; *** significant at 1%

Table 7b: Market-level results on financing and IPOs

Estimation method	Poisson		OLS		Poisson	
Dependent variable	Number of firms in market j receiving initial funding in year t		Log of the median amt invested in firms in market j in year t		# of IPOs in market j in year t	
	(1)	(2)	(3)	(4)	(5)	(6)
Patent variables						
Ln(Market's patents)	-0.667	-0.962	0.959	1.165	1.855	1.618
	(0.430)	(0.530)*	(0.558)*	(0.466)**	(1.462)	(1.377)
Average claims per cite in market	-0.238	-0.100	0.938	0.359	-2.849	-3.002
	(0.595)	(0.582)	(0.709)	(0.641)	(1.404)**	(1.354)**
Share of non-patent references	-0.991	-1.869	0.969	0.186	4.698	7.101
	(0.516)*	(0.391)***	(0.539)*	(1.043)	(1.320)***	(3.288)**
D(regime change)		-1.959		2.616		-4.617
		(2.044)		(1.419)*		(4.053)
D(regime change) X ln(patents in market)		-0.542		-0.378		0.302
		(0.138)***		(0.078)***		(0.288)
Control Variables						
Ln(Avg Quality of market’s patents)	-0.799	-0.451	0.112	0.441	8.413	8.563
	(0.806)	(0.786)	(0.789)	(0.817)	(2.201)***	(2.248)***
Modal citation lag	0.102	0.059	0.004	-0.016	-0.375	-0.375
	(0.061)*	(0.049)	(0.039)	(0.050)	(0.251)	(0.248)
Incumbents (in hundreds)	-0.001	0.003	0.000	0.000	-1.217	-1.185
	(0.002)	(0.002)	(0.000)	(0.000)	(0.766)	(0.753)
Incumbents (in hundreds) squared	-0.000	-0.000	-0.009	-0.004	0.096	0.094
	(0.000)	(0.000)*	(0.005)*	(0.004)	(0.113)	(0.111)
Growth of revenues	-0.181	-0.244	-0.079	0.016	-0.147	-0.225
	(0.176)	(0.169)	(0.125)	(0.144)	(0.658)	(0.658)
# firms "at risk"	0.009	0.006	0.020	0.015	0.027	0.028
	(0.003)***	(0.003)**	(0.012)	(0.012)	(0.013)**	(0.013)**
average age of firms "at risk"	-1.027	-1.174	-0.015	-0.012	-0.139	-0.123
	(0.151)***	(0.141)***	(0.034)	(0.031)	(0.066)**	(0.059)**
Constant	10.970	8.400	0.899	-0.877	-51.164	-53.484
	(6.968)	(7.003)	(7.501)	(6.763)	(18.460)***	(16.581)***
Observations	231	231	206	206	168	168

All regressions include market and year fixed effects.
Robust standard errors clustered by market in parentheses.
* significant at 10%; ** significant at 5%; *** significant at 1%

Table 8: Hazard model of initial funding episode

Dummies for Year, Market and Employment size range category included.
Standard errors clustered by firm.

	(1)	(2)	(3)	(4)	(5)	(6)
Patent variables		*Full sample*		*Post-regime change*		*Discrete-time**
Ln Patents in Market	0.708	0.791	0.140	0.124	0.153	1.221
	(0.259)	(0.276)	(0.111)**	(0.100)***	(0.124)**	(0.176)
Firm's patents pending	1.112	1.117	1.103	1.102	1.099	1.145
	(0.059)**	(0.056)**	(0.055)**	(0.055)*	(0.055)*	(0.073)**
Firm's patents granted	0.996					
	(0.047)					
D(Regime Change)		3.261				3.105
		(2.727)				(2.726)
D(Regime Change) X ln (Patents in Market)		0.765				0.754
		(0.096)**				(0.101)**
Herfindahl of citations in market				1.148		
				(0.062)***		
Average claims per citation in market					3.282	
					(3.236)	
Share of non-patent prior art					0.146	
					(0.173)**	
Control variables						
# incumbents	1.003	1.004	1.010	1.009	1.010	1.003
	(0.002)	(0.002)*	(0.004)**	(0.004)**	(0.004)**	(0.001)**
# incumbents squared	0.999	0.999	0.999	0.999	0.999	0.999
	(0.000)**	(0.000)**	(0.000)**	(0.000)**	(0.000)**	(0.000)***
Growth of revenues	1.180	1.147	1.115	1.049	1.047	1.104
	(0.086)**	(0.087)*	(0.153)	(0.149)	(0.151)	(0.089)
Firm size range effects	Y	Y	Y	Y	Y	Y
Year effects	Y	Y	Y	Y	Y	Y
Market effects	Y	Y	Y	Y	Y	Y
Log likelihood						
Number of observations	5372	5372	3708		3708	5345

Marginal effects of selected patent variables

	(1)	(2)	(3)	(4)	(5)	(6)
ln Patents in market						
marginal effect of one std. dev. increase	-0.014	-0.010	-0.042	-0.043	-0.041	0.036
Firm's Patents pending						
marginal effect of one unit increase	0.007	0.007	0.007	0.007	0.007	0.009
D(Regime Change) X ln (Patents in Market)						
Average marginal effect of one log-unit increase in patents						-0.026
Average standard error of marginal effect						0.016

Coefficients expressed as hazard ratios. Marginal effect of the interaction term calculated using Stata's *predictnl* command.
* significant at 10%; ** significant at 5%; *** significant at 1%

Table 9: Competing Hazards Multinomial Logit Model of IPO/Acquisition

Dummies for year, market, stage of investment, and employment size range included.
Standard errors clustered by firm.

	(1)	(2)	(3)	(4)	(5)	(6)
Sample	All firms		All firms		Firms without patents	
Outcome	IPO	Acquisition	IPO	Acquisition	IPO	Acquisition
Patent variables						
Ln Patents in Market	1.480	1.113	1.925*	0.408	0.298**	1.109
	(0.673)	(0.277)	(0.735)	(0.716)	(0.165)	(0.320)
Firm's patents	1.254***	1.180**	1.264***	1.171**		
	(0.102)	(0.093)	(0.086)	(0.089)		
Investor's patents	1.000	1.000	1.000**	1.000	1.000	1.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
D(Regime Change)			0.669	111,842.655		
			(1.535)	(16504339.039)		
D(Regime Change) X ln (Patents in Market)			0.970	3.123		
			(0.374)	(5.866)		
Control variables						
ln Total amount invested	1.230	1.119*	1.192	1.108*	1.262	1.117
	(0.227)	(0.071)	(0.196)	(0.069)	(0.225)	(0.089)
Corporate investors	1.062	1.032	0.837	1.007	0.098*	1.156
	(0.427)	(0.379)	(0.313)	(0.376)	(0.124)	(0.426)
Investors' previous IPOs	1.001	0.992*	1.002	0.993*	0.997	0.994*
	(0.002)	(0.004)	(0.002)	(0.004)	(0.004)	(0.003)
Number of incumbents	0.996	0.947	1.782**	1.040	0.674	1.000
	(0.259)	(0.172)	(0.466)	(0.187)	(0.246)	(0.213)
Incumbents squared	1.009	0.998	1.013**	0.999	1.000	1.000
	(0.006)	(0.004)	(0.005)	(0.004)	(0.015)	(0.005)
growth of sales	1.000	1.000	1.000***	1.000	1.000	1.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	2434	2434	2434	2434	1893	1893

All regressions include market and year fixed effects, and dummy variables for the most recent stage of investment reached (round) and employment size range.
Robust standard errors clustered by firm in parentheses.
Coefficients expressed as hazard ratios.
* significant at 10%; ** significant at 5%; *** significant at 1%

Appendix

Table A.1
Timing of regime changes in software patentability for markets in the sample

Pre-1996	
ba_a	Automatic teller machine software
ma_c	Robotic software
ma_q	Quality control software
ut_h	Peripheral device drivers
After 1996	
ai_a	Voice technology software
ai_l	Natural language software
ai_n	Neural network software
cs_f	Fax software
cs_i	Internet tools
cs_l	Wide area network software
cs_w	Local area network software
dm_f	File management software
dm_mh	Hierarchical DBMS software
dm_mr	Relational DBMS software
dm_q	Database query language software
oa_gd	3D representation software
oa_me	Electronic message systems software
oa_p	Desktop publishing software
sv_ar	Artificial intelligence R&D
ts_er	Geographic information systems software
ts_er	Geographic information systems software
ut_r	Disaster recovery software
ut_x	Security/auditing software
ut_y	Performance measuring software
After 1998	
ac_b	Invoicing/Billing Software
ac_t	Tax preparation and reporting software
wd_i	Inventory management software
wd_o	Order entry/processing software