

Innovate to Survive: The Effect of Technology Competition on Corporate Bankruptcy

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ABSTRACT

This paper establishes a strong relation between technology competition and corporate bankruptcy. Using a new dataset of firm-level patent applications and issues we show that (i) the competitiveness in technology-intensive industries predicts future bankruptcies better than the typical measures such as Z-score and credit rating; (ii) technology-driven bankruptcies are less related to the business cycle and industry success; and (iii) bankruptcies are significantly more costly if driven by patent competition.

Keywords: Bankruptcy, Technology, Patents

JEL Classifications: G33, O33

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I. Introduction

The finance literature has a long history of analyzing corporate bankruptcy. This includes development of bankruptcy prediction models, assessment of bankruptcy costs, and analysis of the association between bankruptcy and macroeconomic conditions. While many bankruptcy studies cover a large set of accounting- and finance-based data, no one has looked directly at the influence of technology competition on bankruptcy. In this paper we argue and find that the level of competitiveness of firms in technology-intensive industries provides important information with respect to the risk, costs, and pattern of bankruptcy.

Firms operating in highly technological industries have the opportunity to become market leaders if they develop the most recent, updated, and well-adopted technologies, but they are also subject to non-trivial operational risk if they lose in the technology race. Firms outperformed by their competitors in technology-intensive environments typically find it challenging to catch up. A recent article in *the Wall Street Journal* observes: “Wary of emerging from the recession with obsolete products, big U.S. companies spent nearly as much on research and development in the dismal last quarter of 2008 as they did a year earlier,... Big R&D spenders say they’ve learned from past downturns that they must invest through tough times if they hope to compete when the economy improves” (Scheck and Glader, April 6, 2009). And when firms in technology-driven competitive industries stop inventing or adopting new technologies, they can easily lose their market share to their competitors and suffer poor sales prospects and low profit margins, which ultimately result in bankruptcy.

The patent system makes the relation between technology competition and bankruptcy even more direct. A patent assignee firm can sue competitors for infringement of its patents. Litigation may prohibit the defendant from performing any activities potentially related to that infringement. Should a court grant the plaintiff firm's request of injunction, some operations of the defendant could be shut down. Such enforcement can result in severe financial distress for the defendant firm (see, e.g., Lanjouw and Lerner (2001)). Moreover, all other explicit and implicit costs that arise in a patent litigation process can seriously deteriorate the financial status of the defendant (see Lerner (1995) and Hall (2004)).

The association between technology competition and bankruptcy prompts three primary hypotheses. The first hypothesis posits that the level of a firm's technology competitiveness predicts its likelihood to go bankrupt in the short run. The common bankruptcy prediction models rely mostly on financial ratios that reflect the current financial status and operating performance of the firm. These ratios, however, do not necessarily capture the status of the firm in the technology competition, which could be a dominant factor in the survival likelihood of the firm, especially in industries characterized by intensive technological innovations.

The second hypothesis addresses the relation between bankruptcy and macroeconomic conditions. Economic intuition and the empirical evidence suggest that there are fewer bankruptcies in prosperous industries and when the economy is in good shape. We argue that this relation is weaker for bankruptcies that are driven by patent competition. The intuition is as follows. Technological innovations typically enhance the economy, and particularly the technology-intensive industries (e.g., Hsu, (2009)). Yet, at

the same time, these innovations put the firms that lose in the innovation competition at a serious disadvantage, which could propel them toward bankruptcy (e.g., Garleanu, Kogan, and Panageas (2009)).

The third hypothesis is that bankruptcies that are driven by technology competition are more costly. This is due to a rapid decline in demand for products of the “old technologies”, higher depreciation for obsolescent equipments and inventories, the poorer reputation of firms that do not move forward with the updated technologies, and costs of potential patent litigation. In other words, while bankrupt firms typically experience a gradual deterioration in performance, a firm that loses in the technology competition could find itself very quickly without any competitive strength.

We test these three hypotheses using data on firm-level patent applications and issues over 1976-2005.¹ The patent data have several advantages for assessing technological competitiveness. First, unlike research and development (R&D) expenditures, which involve uncertainty and often inefficiency (see, e.g., Jensen (1993)), patents are realized technologies of business value. Second, patents draw competition because they are proprietary and exclusive. Third, as patent competition and litigation have surged in a variety of industries, many firms have realized the necessity of defensive patent filings (see, e.g., Hall (2004) and Hall and Ziedonis (2007)). Fourth, patents are a powerful tool in hindering competitors or creating income from royalties (see, e.g., Lerner (1995)). In

¹ We recognize that the citations of patents could also serve as a measure of technological innovation, yet we believe that the counts of patent issues and applications are better fit for the purpose of this study. First, we mainly concern about the magnitude of competition but not the magnitude of innovation, and patent suits are based on the ownership of *individual* patents. And second, it takes five to ten years for a patent to be well cited (and such a citation lag varies in different industries; see, e.g., Hall, Jaffe, and Trajtenberg (2001)), which causes some difficulties in using patent citations to measure ongoing competition.

fact, many major patent-filing firms, such as Texas Instruments Inc. and Intel Corporation, have their own litigation teams to monitor their rivals' technology activities.

The empirical evidence supports our hypotheses. We first find that patent competition predicts future bankruptcies at three different levels. At the aggregate level, an increase in patent activity, especially in technology-intensive industries, leads to more bankruptcies. At the industry level, the number of patent issues in a technology-intensive industry is positively associated with bankruptcy among the firms in the industry that did not issue patents recently. This relation remains significant in the presence of well-used bankruptcy predictors, such as *Z*-score, credit rating, and the KMV measure. At the firm level, we propose a two-factor measure of a firm's technology competitiveness. Logit regressions show that both factors significantly predict firm bankruptcy. Furthermore, our two-factor model outperforms *Z*-score, credit rating, and the KMV measure in predicting bankruptcy. Technology competition hence explains a substantial and distinct part of corporate bankruptcy. These findings strongly support the first hypothesis.

Examination of the second hypothesis assesses the effect of technology competition on the relation between macroeconomic conditions and bankruptcy. At both industry and firm levels, the likelihood of bankruptcy as a result of patent competition is less sensitive to the business cycle and industry growth. Thus, technological innovations, which typically enhance market and industry conditions, also severely exacerbate the performance of firms that do not move forward with the technology waves.

Third, we examine whether firms that go bankrupt as a result of technology competition have higher indirect bankruptcy costs, as measured by the declines in accounting earnings and stock prices. Consistent with the hypothesis, indirect bankruptcy

costs are significantly higher for technology-driven bankruptcies than for ordinary bankruptcies, and these costs increase with the intensity of the patent competition.

The remainder of the paper is organized as follows. The next section motivates the economic association between technology competition and corporate bankruptcy. Section III states our set of hypotheses. Section IV describes the data and variable estimation. Section V tests the hypotheses, and Section VI concludes.

II. The Role of Technology Competition in Corporate Bankruptcy

Predicting corporate bankruptcy, or assessing the extent of financial distress, has been studied for over four decades. Models to measure the probability of bankruptcy are constructed using a variety of techniques. These include multiple discriminant analysis (e.g., Altman (1968) and Aziz, Emanuel, and Lawson (1988)); multiple choice analyses, such as logit (e.g., Ohlson (1980), Zavgren, (1985), Shumway (2001), and Campbell, Hilscher, and Szilagyi (2008)) and probit (e.g., Zmijewski (1984)); and contingent claim frameworks (e.g., Crosbie and Bohn (2002)).

The measures of bankruptcy risk are based mostly on financial ratios that indicate current financial status (e.g., book leverage), profitability (e.g., ROA, profit margin), liquidity (e.g., current ratio), efficiency (e.g., asset turnover), growth prospects (e.g., market-to-book ratio), and more. To the best of our knowledge, no measure directly incorporates the ongoing technology progress of the firms, and specifically the extent of its competence. A poor status of a firm in the technology race might not be reflected in its

current financial ratios, but could still have a great impact on performance in the upcoming years, which could mean quick and costly bankruptcy.

Technology competition has been recognized as a critical determinant of the industry dynamics. Griliches (1984) and Pakes (1985) both show that firms' R&D expenses and patent activities have positive effects on their stock prices. Cuneo and Mairesse (1984) and Griliches (1984) show a strong relation between productivity and R&D investment in both the U.S. and France. Dierickx and Cool (1989) argue that R&D capability is a valuable and sustainable asset in a competitive industry due to the lack of tradability. Greenwood and Jovanovic (1999) and Hobijn and Jovanovic (2001) show that new technologies are devastating for incapable old firms and obsolete industries in the long run. Moreover, the most recent work by Garleanu, Kogan, and Panageas (2009) suggests that innovation intensifies product competition and lowers the profits and values of existing firms.

All these studies indicate that the technological competence of a firm affects its financial conditions and likelihood of survival in the long run. Thus, firms with very limited technology competence or with none should be more financially distressed, especially in technology-driven industries.

It is not an overstatement to say that today's patent system is a major battlefield for corporations. According to Hall (2004), patent competition has become fierce since the establishment of a patent-specialized court (the Court of Appeals for the Federal Circuit, CAFC) in 1982 and a few highly publicized patent infringement cases in the mid-1980s. Bessen and Meurer (2005) find escalating patent litigations; the annual number of total patent lawsuits doubled from 1984 to 1999. Such a surge of patent competition should

not be surprising, as there is a self-reinforcing loop between more patent filings and more patent litigations. That is, escalating patent competition is an unavoidable consequence as technology advances and patent regulation becomes stronger.

For individual firms, patent competition can sometimes be devastating. A patent assignee firm can request a preliminary injunction to forestall infringement that would impose legal expenditures and operations costs on its competitors (see Lanjouw and Lerner (2001)). Moreover, announcement of patent infringement litigation has a negative impact on a defendant's reputation and stock price (see, e.g., Bhagat, Brickley, and Coles (1994) and Lerner (1995)), making it harder for a defendant firm to survive the court order. Finally, once a dispute is resolved by the court, litigation costs for the party that loses could be very high (see Lerner (1995) and Hall (2004)). As all these costs are driven by technology competition, bankruptcies are expected to be more costly in technology-intensive industries.

The work of Franzen, Rodgers, and Simin (2007) could be most related to our study as they also argue that the traditional measures of financial distress become less accurate in recent decades and require adjustments such as including information about technology development. Their research, however, is different from our study in many aspects. They aim to demonstrate the distortion in accounting-based distress measures due to the conservative treatment of R&D expenses, while we propose the causality between technology competition and bankruptcy. Their main suggestion is to modify Ohlson's (1980) bankruptcy prediction model by capitalizing R&D expenditures, while we present a new prediction model with patent-based factors.

Our study is also related to the work of Acharya and Subramanian (2007). While we analyze how technological innovations lead to bankruptcy, they investigate how different types of bankruptcy laws affect firms' innovation decisions. They find that when the bankruptcy code is creditor-friendly, excessive liquidations cause firms to shy away from innovations.

III. Hypotheses

We posit three sets of hypotheses concerning the importance of technology competition for corporate bankruptcies.

A. Technology competition and bankruptcy predication

Motivated by the aforementioned literature, we argue that technological innovations in general, and the status of a firm in the technology competition, can explain future bankruptcy. We form three sub-hypotheses at the aggregate, industry, and firm level.

H1a: *The increase in total patents reflects more severe technology competition overall, which leads to more bankruptcies.*

H1b: *The increase in industry patents reflects more severe technology competition within the industry, which leads to more bankruptcies among the firms incapable of generating patents.*

H1c: *Individual firms are more likely to go bankrupt if (i) they fall farther behind their competitors in patent competition, and (ii) the patent activity in the industry is more intense.*

B. Technology-driven bankruptcies and macroeconomic conditions

The conventional wisdom is that there should be more bankruptcies in fading industries or in recession years (see, e.g., Denis and Denis (1995) and Vassalou and Xing (2004)). We predict that bankruptcies that are driven by technology competition are less related to macroeconomic conditions. This is due to the dual effect of technology – on the one hand, technological innovations enhance the economy and typically lead to industry growth, and on the other hand, they significantly aggravate the standing and performance of firms that do not develop new technologies.

We thus propose two sub-hypotheses positing that the effect of technology competition is strong enough to offset the effect of business cycle and industry growth on bankruptcy:

H2a: *Technology-driven bankruptcies are less affected by the business cycle.*

H2b: *Technology-driven bankruptcies are less affected by the industry growth.*

C. Costs of technology-driven bankruptcies

The costs of bankruptcy are typically divided into direct costs that are associated with the bankruptcy process (e.g., legal, accounting, and other professional fees) and indirect costs that arise when a firm is approaching bankruptcy (e.g., loss of reputation, clients, suppliers, employees, potential business deals, partners). We focus on indirect bankruptcy costs, which appear to be more significant than direct costs (see, for example, Warner (1977), Altman (1984), and Opler and Titman (1994)) and more related to technology competition.

We argue that indirect bankruptcy costs should be higher in technology-driven cases for several reasons: (1) when a new technology is developed by competitors and becomes accepted in the market, the firms without the technology could experience a significant

decline in demand for their products, and could lose their market share in a relatively short time due to the short life cycle of hi-tech products; (2) in the presence of new technologies, all inventories and equipments associated with the old technologies depreciate very fast; (3) firms that fall behind in the technology-based competition could very quickly lose their reputation as strong players in the industry; (4) operations of the defendant in a patent litigation could be shut down by order of the court.

We thus propose two sub-hypotheses:

H3a: *Technology-driven bankruptcies incur higher indirect bankruptcy costs.*

H3b: *Indirect bankruptcy costs rise with the intensity of the patent competition.*

IV. Data and Variable Estimation

A. U.S. patent data

We first collect company names from the CRSP/Compustat database over the period 1976-2005, and then search for patents under these names in the assignee category of the Patent Full-Text and Image Database (PatFT) of the U.S. Patent and Trademark Office (USPTO) database. A total of 22,071 names appear in CRSP/Compustat. For firms that change names but remain the same permanent number, we combine the patents under the different names. We count the annual number of all patents (utility, design, plant, and reissue) assigned to each firm according to the application date (successful patent applications) or issue date (patent issues). The matching process generates 5,024 firms with 1,099,434 successful patent applications and 998,272 patent issues over the sample period.

Our dataset is different and in fact more updated than the NBER patent dataset of Hall, Jaffe, and Trajtenberg (2001) in several respects: (1) in the NBER dataset, the patents are assigned by Cusip identifiers using the 1989 ownership structure of the patent holder; (2) the NBER dataset ends in 1999; (3) the NBER dataset includes only utility patents; our dataset includes all types of patents.

B. Technology-intensive industries

To explore the effect of technology competition on bankruptcy, we need to measure its extent in each industry. For each 4-digit SIC code industry, we calculate the percentage of firms filing for at least one successful patent in every calendar year. The time series average of annual percentages of applications in an industry (denoted *Pct Ap*) serves as a measure of technology competition in that industry.

We then define patent-intensive industries as industries with a patent application rate higher than 25%. The threshold ratio approximates the percentage of firms owning patents in the whole CRSP/Compustat database. We obtain a total of 62 technology-intensive industries, listed in Table 1. This group of industries seems appropriate to represent an environment of technology-driven competition, as it includes most of the highly technological industries, such as computers, semiconductors, and biological and pharmaceutical industries.

C. Bankruptcy classification

We use the CRSP delisting file to classify bankrupt firms. Although CRSP has a specific code for bankruptcy, we include all the delisting categories associated with poor performance such as ‘liquidation’ and ‘dropping due to bad performances’ in the

bankruptcy group, because they relate to technology competition in the same way as bankruptcy does.

D. Bankruptcy prediction models

We use three measures of bankruptcy risk that represent different methodologies as control variables in our tests. The first one is Altman's (1968) Z-score, a widely used model of bankruptcy prediction.² The second is S&P bond credit rating, provided by Compustat, where a higher value indicates higher default risk. The third, known as the KMV approach, is built on Merton's (1974) default model (see Crosbie and Bohn (2002) and Leland (2004)).³ All the inputs required to calculate the three measures are taken from CRSP and Compustat.

E. Descriptive statistics

Table 2 reports descriptive statistics of the important variables for technology-intensive industries and other industries. The technology-intensive industries represent

² Altman's Z-score model for predicting bankruptcies is: $Z\text{-score} = 1.2(\text{Working capital}/\text{Total assets}) + 1.4(\text{Retained earnings}/\text{Total assets}) + 3.3(\text{Earnings before interest and taxes}/\text{Total assets}) + 0.6(\text{Market value of equity}/\text{Book value of total liabilities}) + 0.999(\text{Sales}/\text{Total assets})$.

³The KMV measure of default risk is estimated using a two-equation system. The first expresses the value of the firm's equity as the value of a call option on the firm's total asset using the Black and Scholes (1973) formula: $V_E = V_A N(d_1) - FV e^{-rT} N(d_2)$, where V_E is the firm's equity value, measured by the stock price multiplied by the number of shares outstanding; $N(\cdot)$ is the cumulative function of a standard normal distribution; $d_1 = [\ln(V_A/F) + (r + \sigma_A^2/2)T] / [\sigma_A \sqrt{T}]$, $d_2 = d_1 - \sigma_A \sqrt{T}$; F is the face value of debt, measured by the book value of total liabilities of the firm; r is the risk-free rate, measured by the one-year Treasury bill yield; T is the time to maturity of debt, measured by the weighted-average maturity of the short- and long-term debt; and V_A and σ_A are the unobservable market value and volatility of the firm's total assets. The second equation, a straightforward derivation of Ito's lemma, represents the relation between equity volatility, σ_E , measured by the realized monthly stock return volatility in the subsequent year, and asset volatility: $\sigma_E = [V_A N(d_1) \sigma_A] / V_E$. As there are no closed-form solutions to V_A and σ_A , we solve the two equations simultaneously using initial values of $V_E + FV$ and σ_E . The probability of bankruptcy is defined as the probability that the face value of debt exceeds the asset value at maturity, and is given by $1 - N(d_2)$, which is equivalent to the probability of not exercising a European call option.

30.4% of the entire market (i.e., all listed industrial companies), indicating that technology-based industries account for a substantial part of the overall economy. Firms in technology-intensive industries are usually larger, have lower leverage ratios and higher market-to-book ratios, and invest more in R&D.⁴ These differences are expected, as firms in technology-driven industries are usually capital-intensive with more growth opportunities. Another interesting result is that the average firms operating in technology-intensive industries appear to experience less financial distress than average firms in other industries, as indicated by all three measures of bankruptcy risk.

V. Empirical Tests

A. Hypotheses 1a, 1b, and 1c

Hypothesis 1a concerns the effect of total patents on bankruptcy frequency. Figure 1 provides a first indication for a positive effect of change in patent activity on the likelihood of bankruptcy in technology-intensive industries. We test this effect using the time series regression:

$$Bankruptcy\ freq_{t,t+3} = \beta_0 + \beta_1 \Delta \# Patents_t + \beta_2 Interest_t + \beta_3 Default_t + \beta_4 Recession_t + \varepsilon_t \quad (1)$$

where ‘bankruptcy freq’ denotes the percentage of firms that went bankrupt during the next three years; and ‘ Δ # patents’ is the change in total patent issues of all firms in the sample over the past one or three years.⁵ To eliminate marketwide effects on bankruptcy frequency, the regression also includes three variables that represent the state of the

⁴ Size is measured by the market value of equity, calculated by the stock price times the number of shares outstanding; market-to-book ratio is equity market value divided by equity book value; leverage is the book value of debt divided by the book value of total assets; and R&D investment is measured as a fraction of the book value of total assets.

⁵ We look at patent activity in both the past one year and the past three years for empirical simplicity.

economy: the interest rate, measured by the nominal return on 1-month Treasury bills; the default spread, which is the yield spread between long-term Baa- and Aaa-rated securities (taken from the Federal Reserve Bank of St. Louis's website); and the National Bureau of Economic Research (NBER) recession indicator.

Panel A of Table 3 shows regression results for patent issues in the past year. We find first that when the sample is confined to technology-intensive industries, an increase in patent activity significantly predicts bankruptcy frequency. The first regression indicates that, as a single explanatory factor, the change in the number of patents in the past year explains 18.7% of the variation in bankruptcy frequency with a p -value of 0.012. This effect remains significant when we control for marketwide variables (p -value of 0.015), indicating that the results are not driven by business cycle conditions.

Second, expanding the sample to all firms in all industries shows a similar effect. The p -values of the change in total patents are 0.015 and 0.037, with an explanatory power of 16.5% of future bankruptcy frequency. Panel B of Table 3 shows comparable and even somewhat stronger results when we use total patents in the past three years as the explanatory variable.

Overall, Table 3 prompts the observation that more intense patent activity leads to more bankruptcies. This finding strongly supports hypothesis 1a. It is also consistent with the argument of Greenwood and Jovanovic (1999) and Hobijn and Jovanovic (2001) that new technologies reshape industry organization by forcing incapable older firms and obsolete industries out of business.

Hypothesis 1b addresses the industry-specific relation between patents and bankruptcies in technology-intensive industries. To test it we run the pooled regression:

$$\begin{aligned}
\text{Bankruptcy freq}_{i,(t,t+3)} &= \beta_0 + \beta_1 \# \text{Patents}_{i,t} + \beta_2 \text{Mean } Z_{i,t} \\
&+ \beta_3 \text{Spec. Rating}_{i,t} + \beta_4 \text{Mean KMV}_{i,t} + \varepsilon_{i,t}
\end{aligned}
\tag{2}$$

where ‘bankruptcy freq’ is the number of firms in industry i that did not issue patents in the past one or three years and went bankrupt during the next three years, divided by the number of firms that did not issue patents in the past one or three years; and ‘# patents’ is the number of patents issued in the industry over the past one or three years.

To examine whether the patent activity incorporates information relevant for future bankruptcy that is not captured by common bankruptcy predictors, we include in the regression the following variables: the mean Z -score, the proportion of firms with speculative-grade bonds (ratings of BB+ or lower), and the mean KMV measure, all for the firms in the industry that did not issue patents in the past one or three years. As this regression (and others below) relies on time series cross-sectional data, we use the Newey-West (1987) procedure, modified for panel data, to correct for heteroskedasticity and serial correlation.⁶

Panel A of Table 4 shows regression results for patents issued in the past year. All regressions strongly indicate that patent activity increases the bankruptcy risk of the firms that do not issue patents. As a single explanatory variable, the coefficient of the industry number of patents has a p -value of 0.000, and it is barely affected when we add each of the three bankruptcy predictors. When we include all bankruptcy predictors in the regression, the industry number of patents remains significant (p -value of 0.048), and it increases the R -square from 7.5% to 8.6%.

Panel B of Table 4 shows very similar results for patent issues over the past three years, indicating a robust effect of industry patent activity on bankruptcies in technology-

⁶ The number of lags used in the Newey-West procedure is one less than the number of years for each firm.

intensive industries. Addition of the three common bankruptcy predictors to our regression analysis suggests that industry patent activity has a unique predictive ability for future bankruptcy that is not captured by current financial status or operating performance of the firm.

Table 4 therefore supports hypothesis 1b, implying that we should expect more incapable firms to be driven out of business in a rapidly evolving industry. For instance, the rise and fall of an internet company would occur faster than that of a lumber company because the technologies used in traditional industries usually develop more slowly.

We test hypothesis 1c concerning the association between a firm's place in the technology competition and its likelihood to go bankrupt using a logit regression:

$$\begin{aligned} \text{Bankruptcy indicator}_{i,(t,t+3)} = & \beta_0 + \beta_1 \# \text{Firm } PT_{i,t} + \beta_2 \text{Ind. } PI_{i,t} \\ & + \beta_3 Z \text{ score}_{i,t} + \beta_4 \text{Credit rating}_{i,t} + \beta_5 \text{KMV}_{i,t} + \varepsilon_{i,t} \end{aligned} \quad (3)$$

The dependent indicator variable equals one if firm i went bankrupt in the following three years, and zero otherwise. The independent variables include two patent-based factors. The first factor (*Firm PT*) measures the firm's relative strength in the industry patent competition; it is defined by the number of patents issued by the firm in the past one or three years, divided by the total number of patents issued in the industry. For example, if one firm owns most patents in its industry, it dominates the industry in technology and is thus less likely to experience financial distress. Note that we use patent issues, not patent applications, because only approved patents can be used to secure properties and attack competitors.

While this factor focuses on the ultimate result in terms of relative number of patents, it does not take into account the cost of innovation. A firm might not have generated many patents recently but still be able to compete successfully in its industry because its

R&D cost is relatively low (see, e.g., Dierickx and Cool (1989)). Similarly, a firm may strategically postpone its innovation efforts at certain times (e.g., for reorganization purposes), so both its R&D expenses and the number of patent issues are low, but its status in the competition remains strong. Therefore, we also run regression (3) using a modified measure, *Firm PT-RD*, defined by the difference between *Firm PT* and the ratio of the firm's average R&D expenditures in the past three years to its equity market value.

The second factor in regression (3), *Ind. PI*, measures the intensity of the technology competition in the industry. It is defined by the total number of patent applications in the industry in the year, divided by the industry size (the sum of equity market values of all firms in the industry). As discussed above, firms in fast-growing, highly technological industries confront harsher technology competition, and are more likely to go bankrupt because of fierce product competition and potentially fatal patent litigations. The regressions also include the three bankruptcy predictors: *Z-score*; a credit rating dummy variable that equals one if the rating is BB+ or lower (speculative-grade), and zero otherwise (investment-grade); and the *KMV* measure.

The results reported in Table 5 indicate that both the firm's technology competence and the industry technology intensity explain its likelihood to go bankrupt. The *p*-values are extremely low when only the two patent-based factors are included in the regression, and are lower than 5% (except for one case) in the presence of each bankruptcy predictor. That is, consistent with our earlier findings, patents provide additional information over common bankruptcy prediction measures.

Figure 2 visualizes the findings of Table 5 to provide an assessment of the economic significance of the proposed patent-based bankruptcy predictors. The first column

(sample frequency) denotes the unconditional probability of bankruptcy (6.78%). A one-standard deviation increase in *Firm PT-RD* and *Ind. PI* increases the bankruptcy probability to 9.25% and 7.94%, respectively. When both factors increase by one standard deviation, the conditional bankruptcy probability surges to 10.81%, which is higher than the effects produced by each of the three bankruptcy predictors. Note that the 4 percentage points increase in bankruptcy probability created by *Firm PT-RD* and *Ind. PI* is about the difference in the default rates of firms with Aaa-rated and B-rated bonds according to Moody's (see Hamilton (2004)), which provides another indication for the economic importance of the results.

The empirical evidence overall supports all three testable hypotheses, suggesting that intense patent competition increases a firm's possibility of bankruptcy. Moreover, technology competition explains a distinct part of firm bankruptcy that is not captured by traditional models such as *Z*-score, credit rating, and the KMV measure.

B. Hypotheses 2a and 2b

Table 6 reports the results for hypothesis 2a, which addresses the effect of technology competition on the relation between bankruptcy and business cycle. At the industry level (Panel A), we regress subsequent (one- and three-year) bankruptcy frequency in each industry on the NBER recession indicator (*RC*) and on an interactive term between *RC* and technology competition. We use two proxies defined earlier in Section IV to measure industry technology competition. The first one, *PDI*, is a dummy variable that equals one for technology-intensive industries (i.e., all 4-digit SIC industries in which at least 25% of the firms apply for patents, as listed in Table 1), and zero otherwise. The second one, *Pct Ap*, represents the intensity of the patent competition in the industry. It is measured as

the average percentage of firms in the industry that apply for valid patents during a calendar year.

First, as expected, the effect of business cycle on bankruptcies is statistically significant in all regressions in Panel A, validating the notion that more bankruptcies occur after recessions. Second, and more important, the coefficients of the interaction terms, $RC*PDI$ and $RC*Pct Ap$, are both significantly negative (p -values between 0.000 and 0.056), implying that bankruptcy frequency in technology-intensive industries is less sensitive to the business cycle.

We also examine the hypothesis at the firm level (Panel B) using a logit regression. The dependent dummy variable equals one if the firm went bankrupt in the following one or three years, and zero otherwise. The independent variables are the same as in Panel A: a business cycle dummy and an interaction term between the business cycle and the industry technology competition proxies. For the PDI proxy, the results are consistent with Panel A, as the coefficients of the business cycle dummy and the interaction term remain positive and negative, respectively. For the $Pct Ap$ measure is used, however, the coefficient of the interaction term is not significant.

We conduct a similar analysis to test hypothesis 2b on the effect of technology competition on the relation between bankruptcy and industry growth. Panel A of Table 7 shows an industry-level linear regression of subsequent bankruptcy frequency in an industry on the industry growth (IG , measured by the annual percentage change in the total revenues in the industry minus the annual percentage change in the total revenues in all industries) and on an interaction term between IG and the same proxies of industry technology competition as in Table 6 (PDI and $Pct Ap$).

As expected, the coefficients of industry growth are negative, indicating that bankruptcies are less likely to occur in prosperous industries. Consistent with the hypothesis, the coefficients of the interaction terms are all positive, although not significant for *Pct Ap*, suggesting that technology-driven bankruptcies are less related to the industry success.

The results are even stronger for the firm-level logit regression (Panel B), where we regress a bankruptcy dummy variable on the corresponding industry growth and the interaction term. As in Panel A, the coefficients of industry growth and the interaction term are significantly positive and negative, respectively.

The results in Tables 6 and 7 support our proposition that bankruptcies that are driven by technology competition are less affected by macroeconomic conditions, and, even in a promising industry, the possibility of failure of a firm could be high if technology competition is fierce in that particular industry.

C. Hypotheses 3a and 3b

Table 8 tests hypothesis 3a using a simple comparison of indirect bankruptcy costs of technology-driven bankruptcies and ordinary bankruptcies. We define technology-driven bankruptcies as all firms that went bankrupt without issuing any patent during the three years prior to bankruptcy in technology-intensive industries. The record shows a total of 279 technology-driven bankruptcies over 1976-2005.

We use two measures of indirect bankruptcy costs. The first is the sum of abnormal earnings in the three years prior to bankruptcy (scaled by asset book value), following

Altman's (1984) method.⁷ The second one is the cumulative stock return in the three years prior to bankruptcy. One advantage of using stock return is that it allows a much bigger sample than abnormal earnings does, because the latter requires data on the previous ten years. Both measures are used in both raw and industry-adjusted data (calculated by subtracting the industrywide medians of the measures from the firm's raw figures).

Table 8 presents the means and medians of the indirect bankruptcy cost measures for technology-intensive industries and other industries, as well as the p -value of the differences (T-test for means and Wilcoxon-Mann-Whitney test for medians). The first row in Table 8 shows that technology-driven bankruptcy firms suffer a greater decline in earnings when approaching bankruptcy. The mean drop in earnings for ordinary bankruptcies is 17.2%, compared to 28.1% for technology-driven bankruptcies (although the p -value of the difference is 0.178), and the median reductions is 16.2%, compared to 25.6% (p -value of 0.069). When we account for industry effects (second row in the table), the results remain significant, and are even somewhat stronger.

The stock return comparison is consistent with the earnings differences. The third row in the table shows that technology-driven bankruptcies lose 49.9% of stock price on average, while ordinary bankruptcies lose 43.1% (p -value of 0.089). In terms of median, technology-driven bankruptcies lose 76.4% of stock price, while ordinary bankruptcies lose 71.4% (p -value of 0.028). The industry-adjusted data show even stronger results, as

⁷ We first run a regression of the firm's annual sales on the aggregate sales in the industry in each of the past ten years. This regression's coefficients yield the firm's estimated sales for the current year. The firm's estimated profit (net income) for the current year is then given by multiplying the firm's estimated sales by its average profit margin in the past ten years. The firm's abnormal earning in each year is therefore the difference between the firm's actual and estimated profits. Finally, the firm's indirect costs are defined as the sum of its abnormal earnings in the three years prior to bankruptcy, scaled by the book value of total assets.

the p -values of all differences are very low. The comparisons in Table 8 thus unanimously indicate that technology-driven bankruptcy firms suffer higher costs.

To test whether indirect bankruptcy costs increase with the intensity of the technology competition (hypothesis 3b), we regress the cost measures in Table 8 (abnormal earnings and stock returns) on the patent application percentage in the industry (*Pct Ap*), the measure of industrywide technology competition used in Tables 6 and 7. The regression also includes firm size, book-to-market ratio, and leverage, as these may affect the magnitude of bankruptcy costs. The results are reported in Table 9.

The regressions in Panel A indicate that technology competition reduces earnings, and more significantly when raw data are used. The R -squares, however, are relatively low. The regressions in Panel B indicate a very strong negative effect of technology competition on stock return, with both raw and industry-adjusted data (all p -values are no higher than 0.001). The lower p -values in the stock return tests could be attributed to the larger sample size than the size for the abnormal earnings tests.

Table 9 corroborates the findings reported in Table 8, and further suggests that technology competition is a distinct factor in explaining indirect bankruptcy costs. The results in both tables therefore support our prediction that firms confront higher indirect bankruptcy costs when they operate in an environment characterized by intense technology competition.

VI. Conclusions

This paper analyzes the association between technology competition and corporate bankruptcy. Firms operating in technology-driven industries could find themselves very quickly in trouble in their industry, with a real risk of failure, if they do not match the

recent innovations. Moreover, the nature of highly technological industries could impose high costs on firms that lose in the competition, whether because of reduced or inefficient productivity, a rapid decline in demand, out-of-date equipment, shrinking market share, or various costs of potential patent litigations. Another distinctive characteristic of bankruptcies that are driven by technology competition is their relatively weak relation to macroeconomic conditions. This is because the technological innovations that cause some incapable firms to go bankrupt also enhance the economy.

Analysis of a dataset on firm-level patent applications and issues yields empirical evidence to support our hypotheses. Severe technology competition leads to higher frequency of bankruptcy, and firms that perform poorly in the technology competition are more likely to go bankrupt. Moreover, the ability of technology competition to predict future bankruptcy remains significant in the presence of common bankruptcy predictors, such as *Z*-score and credit rating, and even outperforms their predictive ability in technology-intensive industries. In addition, bankruptcies that are driven by technology competition are less sensitive to the business cycle and the industry growth, and result in greater declines in earnings and stock prices than ordinary bankruptcies. The results in this study therefore suggest an important role of technology competition in corporate bankruptcy.

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Table 1. Technology-intensive industries. The table presents the 62 4-digit SIC industries in which the average percentage of firms that apply for patents during a calendar year is at least 25% over 1976-2005.

Industry	% patent applications
Aircraft & Parts	93.75%
Electronic & Other Electrical Equipment (No Computer Equip)	76.74%
Computer & office Equipment	65.32%
Primary Production of Aluminum	59.70%
Motor Vehicles & Passenger Car Bodies	53.73%
Chemicals & Allied Products	52.51%
Papers & Allied Products	48.62%
Plastic Material, Synth Resin/Rubber, Cellulos (No Glass)	48.52%
Guided Missiles & Space Vehicles & Parts	45.70%
Electronic Connectors	45.67%
Semiconductors & Related Devices	45.16%
Heating Equip, Except Elec & Warm Air; & Plumbing Fixtures	44.57%
Aircraft	44.53%
Miscellaneous Chemical Products	43.77%
Office Machines, NEC	42.22%
Farm Machinery & Equipment	40.47%
Office Furniture	40.40%
Miscellaneous Products of Petroleum & Coal	39.33%
Lawn & Garden Tractors & Home Lawn & Gardens Equip	38.89%
Plastic Materials, Synth Resins & Nonvulcan Elastomers	36.95%
Auto Controls For Regulating Residential & Comm Environments	36.45%
Construction Machinery & Equip	35.93%
Rubber & Plastics Footwear	35.14%
Soap, Detergents, Cleaning Preparations, Perfumes, Cosmetics	34.78%
Surgical & Medical Instruments & Apparatus	34.05%
Paints, Varnishes, Lacquers, Enamels & Allied Prods	33.44%
Metalworkg Machinery & Equipment	33.41%
Aircraft Parts & Auxiliary Equipment, NEC	33.33%
Computer Storage Devices	33.20%
Motorcycles, Bicycles & Parts	32.81%
Special Industry Machinery, NEC	32.55%
Power, Distribution & Specialty Transformers	32.37%
Paper Mills	32.13%
Motor Vehicle Parts & Accessories	32.10%
Laboratory Analytical Instruments	32.08%
Search, Detection, Navigation, Guidance, Aeronautical Sys	31.98%
Beverages	31.87%
Household Audio & Video Equipment	31.84%
Greeting Cards	31.34%
Metal Cans	31.29%
Dolls & Stuffed Toys	30.77%
Food and Kindred Products	30.03%
Switchgear & Switchboard Apparatus	29.53%
Electronic Computers	29.33%
Engines & Turbines	28.90%
General Industrial Machinery & Equipment, NEC	28.65%
Household Appliances	28.07%
Industrial Process Furnaces & Ovens	28.04%
Public Bldg & Related Furniture	27.70%
Biological Products (No Diagnostic Substances)	27.65%
Grain Mill Products	27.44%
General Industrial Machinery & Equipment	27.43%
Pharmaceutical Preparations	26.90%
Computer Peripheral Equipment, NEC	26.84%
Electric Housewares & Fans	26.59%
Paperboard Mills	26.55%
Electromedical & Electrotherapeutic Apparatus	25.67%
Instruments For Meas & Testing of Electricity & Elec Signals	25.58%
Air-Cond & Warm Air Heatg Equip & Comm & Indl Refrig Equip	25.46%
Pumps & Pumping Equipment	25.35%
Oil & Gas Field Machinery & Equipment	25.28%
Electronic Components & Accessories	25.00%

Table 2. Descriptive statistics of technology-intensive industries and other industries. Patent-intensive industries include the 4-digit SIC industries in which the average percentage of firms that apply for patents during a calendar year is at least 25% (as listed in Table 1). Other industries include the remaining 4-digit SIC codes. For all variables, observations outside the top and the bottom percentiles are excluded. The firm-specific variables are: size (in millions of dollars) is measured by the market value of equity, calculated by the stock price times the number of shares outstanding; market-to-book ratio is equity market value divided by equity book value; book leverage is the book value of debt divided by the book value of total assets; R&D investment is measured as a fraction of the book value of total assets; Z-score is based on Altman's (1968) model for predicting bankruptcy; credit rating is the S&P senior debt rating, taken from Compustat; and the KMV measure follows the Merton-based approach developed by Crosbie and Bohn (2002) for measuring default risk. The results are calculated over 1976-2005.

	Patent-intensive industries (% market cap = 30.4)			Other industries (% market cap = 69.6)		
	Mean	Median	StdD	Mean	Median	StdD
# patent applications per firm in a year	15.25	0.00	59.65	1.87	0.00	21.24
# patent issues per firm in a year	14.23	0.00	57.33	1.75	0.00	20.82
% firms apply for patents in a year	32.95	0.00	47.00	7.17	0.00	25.79
% firms issue patents in a year	31.16	0.00	46.32	6.65	0.00	24.91
Size	1,731.67	101.02	9,503.16	974.13	63.16	7,585.40
Market-to-book	2.88	1.91	2.99	2.32	1.51	2.55
Book leverage	0.20	0.17	0.18	0.25	0.23	0.21
R&D investment	0.10	0.05	0.14	0.03	0.00	0.08
Z-score	4.33	3.46	3.64	3.70	3.07	3.19
Credit rating	10.88	11.00	4.09	12.26	12.00	4.02
KMV measure	0.11	0.02	0.19	0.13	0.03	0.21

Table 3. Time series regressions of future bankruptcy frequency on the change in number of patents in technology-intensive industries and in the entire market. In

Panel A the dependent is bankruptcy frequency, calculated by the number of firms that went bankrupt during the next three years, divided by the total number of firms. The primary independent variable is the change in the total number of patents (in thousands) issued in the past year. The results are presented for a sample of only technology-intensive industries, which are all 4-digit SIC industries in which at least 25% of the firms apply for patents (as listed in Table 1), and for a sample of all industries. The control variables are the interest rate, measured by the nominal return on 1-month Treasury bills; the default spread, estimated by the yield spread between long-term Baa- and Aaa-rated securities; and the NBER recession dummy variable. Panel B shows similar regressions where patents are considered in the past three years. The table shows regression coefficients and *p*-values, based on Newey-West standard errors, for a sample of 30 years over 1976-2005.

Panel A: Patent issues in the past year

Bankruptcy freq		Intercept	Δ # patents	Interest	Default	Recession	R-square
Tech. intensive industries	Coefficient	0.06312	0.01115				0.187
	P-value	(0.336)	(0.012)				
		0.09074	0.01045	-0.08354	-2.34366	0.02798	0.384
		(0.879)	(0.015)	(0.690)	(0.206)	(0.029)	
All industries	Coefficient	0.08654	0.00942				0.165
	P-value	(0.000)	(0.015)				
		0.11954	0.00836	0.09210	-3.72838	0.02333	0.285
		(0.000)	(0.037)	(0.781)	(0.213)	(0.229)	

Panel B: Patent issues in the past 3 years

Bankruptcy freq		Intercept	Δ # patents	Interest	Default	Recession	R-square
Tech. intensive industries	Coefficient	0.05576	0.00574				0.488
	P-value	(0.000)	(0.000)				
		0.07844	0.00496	0.27293	-3.56675	0.02017	0.647
		(0.000)	(0.007)	(0.183)	(0.003)	(0.052)	
All industries	Coefficient	0.07700	0.00533				0.462
	P-value	(0.000)	(0.000)				
		0.09591	0.00536	0.60705	-5.19626	0.01398	0.635
		(0.000)	(0.001)	(0.038)	(0.006)	(0.362)	

Table 4. Industrywide regressions of future bankruptcy frequency on recent number of patents in the industry. The sample contains all 4-digit SIC industries in which at least 25% of the firms apply for patents (as listed in Table 1). In Panel A the dependent variable is the number of firms in the industry that have not issued patents in the past year and went bankrupt during the next three years, divided by the number of firms that have not issued patents in the past year. The primary independent variable is the number of patents (in thousands) issued in the industry in the past year; as the number of patents has very large outliers, observations with more than 100 patents were set to 100. The control variables are the mean Z-score, the proportion of firms with speculative-grade bonds (rating of BB+ or lower), and the mean KMV measure, all among the firms in the industry that have not issued patents in the past year. Panel B shows similar results where patents are considered in the past three years. The table shows regression coefficients and *p*-values, based on Newey-West standard errors, for a sample of industry-years over 1976-2005.

Panel A: Patent issues in the past year							
Bankruptcy freq	Intercept	# patents	Mean Z	Spec. rating	Mean KMV	# Obs	R-square
Coefficient	0.05760	0.22350				1,812	0.018
P-value	(0.000)	(0.000)					
	0.06279	0.23202	-0.00306			1,822	0.026
	(0.000)	(0.000)	(0.002)				
	0.05920	0.14102		0.03262		747	0.024
	(0.000)	(0.012)		(0.007)			
	0.04228	0.23641			0.13518	1,344	0.045
	(0.000)	(0.000)			(0.000)		
	0.06683		-0.00351	0.01834	0.25039	474	0.075
	(0.000)		(0.007)	(0.197)	(0.000)		
	0.05341	0.15944	-0.00389	0.01684	0.22832	474	0.086
	(0.000)	(0.048)	(0.004)	(0.226)	(0.000)		

Panel B: Patent issues in the past 3 years							
Bankruptcy freq	Intercept	# patents	Mean Z	Spec. rating	Mean KMV	# Obs	R-square
Coefficient	0.04279	0.22625				1,722	0.014
P-value	(0.000)	(0.000)					
	0.04972	0.22940	-0.00359			1,722	0.028
	(0.000)	(0.000)	(0.000)				
	0.03869	0.17732		0.04454		657	0.034
	(0.002)	(0.034)		(0.001)			
	0.02659	0.24538			0.13991	1,233	0.041
	(0.005)	(0.000)			(0.000)		
	0.04969		-0.00250	0.03590	0.24949	422	0.083
	(0.000)		(0.018)	(0.023)	(0.000)		
	0.02243	0.20423	-0.00273	0.03303	0.23487	422	0.095
	(0.171)	(0.077)	(0.010)	(0.044)	(0.000)		

Table 5. Firm-specific logit regressions of the likelihood of bankruptcy on the relative number of patents issued by the firm and the industry patent activity. The

sample contains firms in technology-intensive industries (all 4-digit SIC industries in which at least 25% of the firms apply for patents, as listed in Table 1). In Panel A the dependent variable (bankruptcy indicator) equals one if the firm went bankrupt during the next three years, and zero otherwise. The primary independent variables are Firm PT, which is the ratio of the number of patents issued by the firm in the past year to the total number of patents issued in the industry in the past year; Firm PT-RD is the difference between Firm PT and the ratio of the firm's average R&D expenditures in the past three years to its equity market value; and Ind. PI is the total number of patent applications in the industry in the year divided by the industry size (the sum of equity market values of all firms in the industry). The control variables are the firm's Z-score; a credit rating dummy variable that equals one if the rating is BB+ or lower (speculative grade), and zero otherwise (investment grade); and the KMV measure (as described in Table 3). Panel B shows similar regressions where patents are considered in the past three years. The table shows logit regression coefficients and *p*-values for a sample of firm-years over the period 1976-2005.

Panel A: Patent issues in the past year							
Bankruptcy indicator	Intercept	Firm PT	Ind. PI	Z-score	Credit rating	KMV	# Obs
Coefficient	-2.56510	-4.53180	3.13350				29,203
P-value	(0.000)	(0.000)	(0.000)				
	-2.62280	-4.52000	3.13530	-0.01170			29,203
	(0.000)	(0.000)	(0.000)	(0.000)			
	-4.41810	-1.46620	2.91460		1.88750		4,554
	(0.000)	(0.0128)	(0.0363)		(0.000)		
	-3.15220	-10.64350	3.23780			2.19340	10,352
	(0.000)	(0.000)	(0.000)			(0.000)	
Panel B: Patent issues in the past 3 years							
Bankruptcy indicator	Intercept	Firm PT-RD	Ind. PI	Z-score	Credit rating	KMV	# Obs
Coefficient	-2.97950	-0.74740	3.17750				30,454
P-value	(0.000)	(0.000)	(0.000)				
	-3.00410	-0.68420	3.18080	-0.00912			30,454
	(0.000)	(0.000)	(0.000)	(0.000)			
	-4.84060	-1.00710	2.74880		1.92620		4,834
	(0.000)	(0.000)	(0.0370)		(0.000)		
	-3.64260	-0.93840	3.31390			2.34690	10,422
	(0.000)	(0.000)	(0.000)			(0.000)	
Panel B: Patent issues in the past 3 years							
Bankruptcy indicator	Intercept	Firm PT	Ind. PI	Z-score	Credit rating	KMV	# Obs
Coefficient	-2.67300	-3.62480	3.28870				27,827
P-value	(0.000)	(0.000)	(0.000)				
	-2.73660	-3.60350	3.31370	-0.01180			27,827
	(0.000)	(0.000)	(0.000)	(0.000)			
	-4.50910	-1.11540	3.16580		1.89370		4,716
	(0.000)	(0.0379)	(0.0201)		(0.000)		
	-3.27710	-9.27020	2.87080			2.41740	9,503
	(0.000)	(0.000)	(0.000)			(0.000)	
Panel B: Patent issues in the past 3 years							
Bankruptcy indicator	Intercept	Firm PT-RD	Ind. PI	Z-score	Credit rating	KMV	# Obs
Coefficient	-2.97830	-0.76570	2.98990				27,913
P-value	(0.000)	(0.000)	(0.000)				
	-3.01180	-0.69020	2.99990	-0.01010			27,913
	(0.000)	(0.000)	(0.000)	(0.000)			
	-4.91580	-1.47920	2.01100		2.00080		4,732
	(0.000)	(0.000)	(0.1523)		(0.000)		
	-3.65070	-0.67180	3.00240			2.60360	9,541
	(0.000)	(0.000)	(0.000)			(0.000)	

Table 6. Relation between bankruptcy and business cycle in technology-intensive industries. Panel A shows industry-year linear regressions. The dependent variable is the bankruptcy frequency in the industry (# of bankruptcies/# firms) in both the current year and the next three years. The independent variables are: RC is the NBER recession dummy variable; PDI is a dummy variable that equals one if the industry is technology-intensive (all 4-digit SIC industries in which at least 25% of the firms apply for patents, as listed in Table 1), and zero otherwise; and Pct Ap is the average percentage of firms in the industry that apply for patents during a calendar year. Panel B shows firm-year logit regressions. The dependent dummy variable equals one if the firm went bankrupt, in both the current year and the next three years, and the independent variables are as in Panel A. The table shows logit regression coefficients and *p*-values, based on Newey-West standard errors, for a sample of all industries over 1976-2005.

Panel A: Industry-level linear regression (# Obs=12,707)						
Bank_freq in the current year	Intercept	RC	RC*PDI	Intercept	RC	RC*Pct Ap
Coefficient	0.02522	0.00978	-0.01079	0.02522	0.01066	-0.02372
P-value	(0.000)	(0.000)	(0.023)	(0.000)	(0.000)	(0.056)
Bank_freq in the next 3 years						
Coefficient	0.09047	0.01038	-0.03215	0.09047	0.01372	-0.07780
P-value	(0.000)	(0.016)	(0.000)	(0.000)	(0.005)	(0.000)
Panel B: Firm-level logit regression (# Obs=190,507)						
Bankruptcy in the current year	Intercept	RC	RC*PDI	Intercept	RC	RC*Pct Ap
Coefficient	-3.77470	0.44660	-0.27010	-3.77470	0.40970	-0.00877
P-value	(0.000)	(0.000)	(0.011)	(0.000)	(0.000)	(0.975)
Bankruptcy in the next 3 years						
Coefficient	-2.38700	0.09260	-0.11830	-2.38700	0.07260	0.02500
P-value	(0.000)	(0.000)	(0.059)	(0.000)	(0.012)	(0.887)

Table 7. Relation between bankruptcy and industry growth in technology-intensive industries. Panel A shows industry-year linear regressions. The dependent variable is the bankruptcy frequency in the industry (# of bankruptcies/# firms) in both the current year and the next three years. The independent variables are: The industry growth (IG) is the annual percentage change in the total revenues in the industry minus the annual percentage change in the total revenues in all industries; PDI is a dummy variable that equals one if the industry is patent-intensive (all 4-digit SIC industries in which at least 25% of the firms apply for patents, as listed in Table 1), and zero otherwise; and Pct Ap is the average percentage of firms in the industry that apply for patents during a calendar year. Panel B shows firm-year logit regressions. The dependent dummy variable equals one if the firm went bankrupt, in both the current year and the next three years, and the independent variables are as in Panel A. The table shows logit regression coefficients and *p*-values, based on Newey-West standard errors, for a sample of all industries over 1976-2005.

Panel A: Industry-level linear regression (# Obs=12,295)						
Bank_freq in the current year	Intercept	IG	IG*PDI	Intercept	IG	IG*Pct Ap
Coefficient	0.02588	-0.02138	0.01874	0.02589	-0.02175	0.02715
P-value	(0.000)	(0.000)	(0.026)	(0.000)	(0.000)	(0.331)
Bank_freq in the next 3 years						
Coefficient	0.08811	-0.02893	0.03514	0.08807	-0.02690	0.01476
P-value	(0.000)	(0.000)	(0.045)	(0.000)	(0.003)	(0.776)
Panel B: Firm-level logit regression (# Obs=188,178)						
Bankruptcy in the current year	Intercept	IG	IG*PDI	Intercept	IG	IG*Pct Ap
Coefficient	-3.69680	-0.75120	0.75890	-3.69500	-0.81890	1.83120
P-value	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.004)
Bankruptcy in the next 3 years						
Coefficient	-2.39170	-0.24440	0.31520	-2.39090	-0.29780	1.11640
P-value	(0.000)	(0.000)	(0.017)	(0.000)	(0.000)	(0.002)

Table 8. Cost of bankruptcy in technology-intensive industries. The table compares indirect bankruptcy costs of technology-driven and ordinary bankruptcies. Patent-driven bankruptcies contain all bankrupt firms in the patent-intensive industries (the 4-digit SIC industries in which at least 25% of the firms apply for patents, as listed in Table 1) that did not issue patents in the three years prior to the bankruptcy, while during that period other firms in the industry issued patents. We use two measures of bankruptcy costs: the abnormal earnings during the three years prior to bankruptcy scaled by asset book value, based on Altman's (1984) method; and the cumulative stock return in the three years prior to bankruptcy. The table presents the means and medians of the two measures, at both raw data (the actual bankruptcy costs), and industry adjusted data, which is the difference between the actual cost and the industry median; and the two-sided *p*-values of the difference between the means (T-test) and the medians (Wilcoxon-Mann-Whitney test) over 1976-2005.

		Technology-driven bankruptcies			Ordinary bankruptcies			P-value of difference	
		# Obs	Mean	Median	# Obs	Mean	Median	Means	Medians
Abnormal earnings	Raw data	57	-0.281	-0.256	481	-0.172	-0.162	(0.178)	(0.069)
	Ind. adjusted	57	-0.236	-0.189	486	-0.124	-0.098	(0.141)	(0.067)
Stock return	Raw data	279	-0.499	-0.764	2,755	-0.431	-0.714	(0.089)	(0.028)
	Ind. adjusted	278	-0.572	-0.627	2,757	-0.444	-0.472	(0.003)	(0.000)

Table 9. Regressions of the cost of bankruptcy on the industry patent intensity. The sample contains all firms that went bankrupt and did not issue patents during the three years prior to bankruptcy. In panel A the independent variable is the abnormal earnings during the three years prior to bankruptcy scaled by asset book value, based on Altman's (1984) method; and in Panel B the dependent variable is the cumulative stock return in the three years prior to bankruptcy. Earnings and returns appear at both raw data (the actual bankruptcy costs) and industry adjusted data, which is the difference between the actual cost and the industry median. The main independent variable, Pct Ap, is the average percentage of firms in the industry that apply for patents during a calendar year. The control variable are: size is the log of the market value of equity, calculated by the stock price times the number of shares outstanding; market-to-book ratio is equity market value divided by equity book value; and leverage is the book value of debt divided by the book value of assets; all measured as of three years prior to bankruptcy. The table shows regression coefficients and *p*-values, computed over 1976-2005.

Panel A: Abnormal earnings							
Raw data	Intercept	Pct Ap	Size	Market-to-book	Leverage	# Obs	R-square
Coefficient	-0.14856	-0.27352				457	0.009
P-value	(0.000)	(0.048)					
	-0.08263	-0.26833	-0.01253	-0.00557	0.21112	457	0.043
	(0.268)	(0.051)	(0.075)	(0.503)	(0.001)		
Ind. adjusted							
Coefficient	-0.12003	-0.16927				465	0.004
P-value	(0.000)	(0.161)					
	-0.09636	-0.16553	-0.00722	0.00136	0.14529	465	0.023
	(0.143)	(0.172)	(0.243)	(0.848)	(0.008)		
Panel B: Stock return							
Raw data	Intercept	Pct Ap	Size	Market-to-book	Leverage	# Obs	R-square
Coefficient	-0.36126	-0.56782				2,879	0.006
P-value	(0.000)	(0.000)					
	0.44318	-0.44839	-0.06570	-0.05087	-0.11409	2,879	0.076
	(0.000)	(0.001)	(0.000)	(0.000)	(0.040)		
Ind. adjusted							
Coefficient	-0.37414	-0.46256				2,845	0.005
P-value	(0.000)	(0.000)					
	0.13473	-0.41425	-0.04068	-0.02559	-0.15984	2,845	0.040
	(0.097)	(0.001)	(0.000)	(0.000)	(0.003)		

Figure 1. Time series relation between the change in number of patents and future bankruptcy frequency in technology-intensive industries. The change in total number of patents is the difference between the number of patents issued in the current and previous years in technology-intensive industries (all 4-digit SIC industries in which at least 25% of the firms apply for patents, as listed in Table 1). Bankruptcy frequency is the number of firms in technology-intensive industries that went bankrupt during the next three years, divided by the total number of firms in these industries.

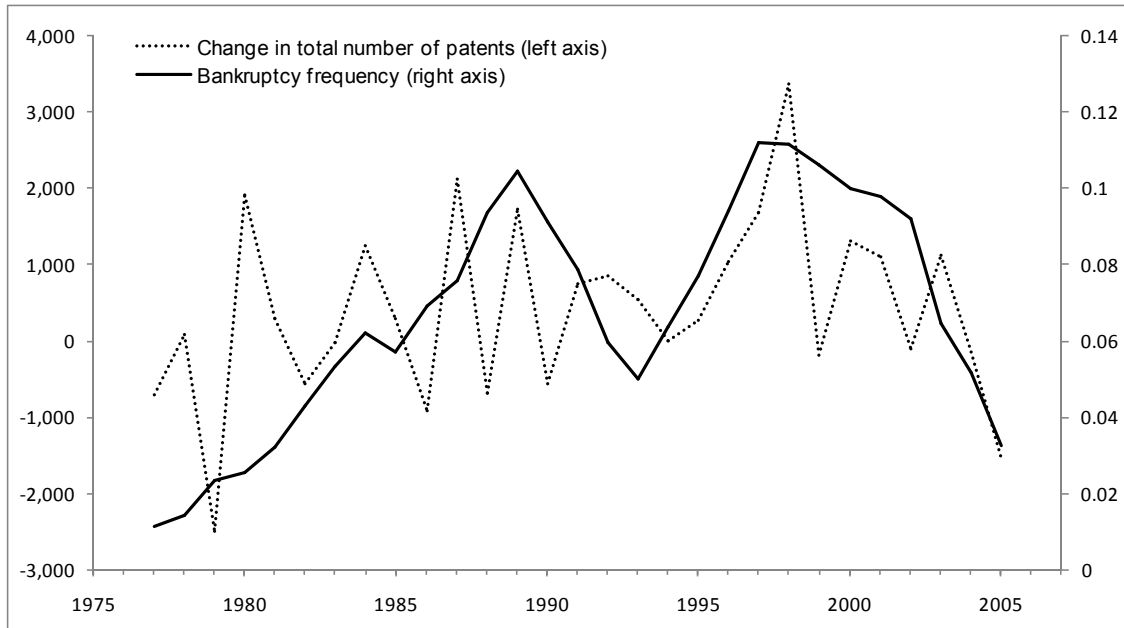


Figure 2. Predictive effect of patent-based and other measures on the probability of bankruptcy in technology-intensive industries. The sample contains firms in patent-intensive industries (all 4-digit SIC industries in which at least 25% of the firms apply for patents, as listed in Table 1) over the period 1976-2005. The results are based on the logit regressions appear in Table 5: *Bankruptcy indicator* = $\alpha + \beta' X + \varepsilon$, where X is a set of bankruptcy predictors. The model's probability of bankruptcy is $P(B) = e^{\hat{\alpha} + \hat{\beta}'x} / (1 + e^{\hat{\alpha} + \hat{\beta}'x})$, and the economic effect of each predictor is defined by the change in $P(B)$ as a result of one standard deviation change in the predictor value from its mean. The bankruptcy predictors (as described in Table 5) are: the patent-based measures, Firm PT-RD and Ind. PI (appear jointly in the regression), Z-score, credit rating, and KMV (appear separately in the regressions). The changes in $P(B)$ of all predictors are compared to the unconditional probability of bankruptcy, measured by the bankruptcy frequency in the sample.

