Journal of Corporate Finance 35 (2015) 329–344

Contents lists available at ScienceDirect

Journal of Corporate Finance

journal homepage: www.elsevier.com/locate/jcorpfin

Corporate innovation, default risk, and bond pricing☆

Po-Hsuan Hsu [a,]*, Hsiao-Hui Lee [a], Alfred Zhu Liu [b], Zhipeng Zhang [c]

[a] The University of Hong Kong, Hong Kong
[b] The University at Albany, SUNY, NY, USA
[c] BlackRock, Inc., CA, USA

ARTICLE INFO

Article history:
Received 16 August 2015
Received in revised form 11 September 2015
Accepted 19 September 2015
Available online 28 September 2015

JEL classification:
G12
O32

Keywords:
Innovation
Patent
Default risk
Bond premium
Bond return

ABSTRACT

We propose firm-level innovation performance to be an important determinant of corporate creditworthiness and examine this relation from the perspective of bond investors. We find that firms' default probabilities are negatively related to the quantity, impact, originality, and generality of their patent portfolios. Moreover, bonds issued by more innovative firms have lower issuance premiums and lower realized excess returns. Our findings are further supported by instrumental regressions that use monetary and time costs of innovation, and by difference-in-differences tests based on exogenous shocks from state-level R&D tax credits.

© 2015 Elsevier B.V. All rights reserved.

1. Introduction

Corporate bonds provide a significant source of external financing for U.S. companies, especially given historically low yields in recent years.[1] Whether and how bond investors price a firm's inventions and intangible assets is a timely, relevant issue that calls for empirical investigation, especially since a firm's long-term success and survival largely depend on its innovation competitiveness in the knowledge-based economy.[2] While credit rating agencies have suggested that a firm's innovation competitiveness determines its credit risk profile and thereby provides useful information beyond its financial characteristics (Standard and Poor's, 2006), the role

☆ The authors thank the Editor (Jeffry Netter), Heitor Almeida, Sreedhar Bharath, Dion Bongaerts, Sudheer Chava, Tarun Chordia, Ming Dong, Theodore Goodman, Vidhan Goyal, Gunnar Grass, Kewei Hou, Jennifer Huang, Neil Pearson, Guillaume Plantin, Stefano Rossi, Henri Servaes, Neal Stoughton, Marti G. Subrahmanyam, Dragon Tang, Sheridan Titman, Sergey Tsyplakov, Yuan Xie, Ju-Fang Yen, Motohiro Yogo, and Jerold Zimmerman, as well as participants at the 2011 AAA Annual Meeting, the 2011 EFM Symposium in Toronto, the 2011 FMA Annual Meeting in Denver, the 2011 SFM Conference in Kaohsiung, the 2012 EFA Annual Meeting in Boston, the 2014 FARS Mid-year Conference in Houston, and the 2015 TFA Conference in Taichung. We also thank colleagues from Clark University, National Chengchi University, National Taiwan University, and the University of Hong Kong for their valuable comments and suggestions. Po-Hsuan Hsu and Hsiao-Hui Lee acknowledge grants from the General Research Fund (GRF) sponsored by the Research Grants Council in Hong Kong (HKU 790913 and 791413B). A previous version of this paper was circulated under the title, "Corporate Innovation and Bond Pricing."

* Corresponding author at: Faculty of Business and Economics, The University of Hong Kong, Hong Kong. Tel.: +852 28591049.
E-mail address: paulhsu@hku.hk (P.-H. Hsu).

[1] In May 2013, the Barclays U.S. Corporate High Yield index fell below 5%, and the average yield of HQM 5-year corporate bonds fell below 2%.

[2] In the past 30 years, U.S. firms have invested significantly in innovation in order to thrive, and sometimes merely to survive, in competitive markets. For example, Skinner (2008) shows that, over the period from 1980 to 2005, U.S. public firms' overall capital expenditures increased by less than 50%, while their R&D investments increased by about 250%, and these investments were more than twice the amount of their capital expenditures in 2005.

http://dx.doi.org/10.1016/j.jcorpfin.2015.09.005
0929-1199/© 2015 Elsevier B.V. All rights reserved.

of corporate innovation in bond pricing remains underexplored in the extant literature. In addition, although innovation activities increase firm value in general (Griliches, 1984, 2000; Hall, 1993), the extent to which bond investors benefit from these activities remains a separate but important issue.

In this study, we use publicly available patent records—an alternative information source distinct from accounting R&D expenses—to measure firms' innovation performance and examine performance relevance for both corporate default risk and corporate bond pricing. Because patents represent exclusive rights to use certain knowledge in a technologically competitive economy and reflect firms' intangible intellectual assets and market prospects, patent records provide useful information about the outputs of corporate innovation. Accordingly, we use patent data to measure innovation performance by the level, impact, generality, and originality of a firm's innovation activities *relative* to its competitors in the same industry (Alcácer and Chung, 2007; Barker and Mueller, 2002; Ciftci et al., 2011). Our attempt to investigate patents' credit implications for bond investors is economically relevant, given the substantial overlap in bond-issuing and patenting activities: over the period from 1976 to 2006, 49.6% of new bonds were issued by firms with patent records in terms of issuance size.

For bond investors, patent information is more important than R&D information for two reasons. First, the territorial principle in U.S. patent laws requires all inventors who wish to protect their intellectual property to file patents to the U.S. Patent and Trademark Office (USPTO), and patent applicants are required to provide the public with reasonably detailed information (e.g., abstracts, claims, descriptions, technological classes) about their innovations. Such mandatory disclosure reduces information asymmetry due to innovation activities and helps investors weigh an innovation's cash flow consequence against its risk consequence, which is a major challenge for bondholders trying to assess an innovative firm's creditworthiness.[3] Second, patent information is not directly subject to accounting manipulation for short-term financial reporting purposes. In contrast, managers have incentives to manipulate R&D expenditures to achieve short-term performance goals (Bushee, 1998; Dechow and Sloan, 1991; Murphy and Zimmerman, 1993) or over-invest in R&D due to over-optimism and private benefits (Hall, 1993; Jensen, 1993). That said, the extant literature is yet to offer a unified understanding of the relation between R&D investment and creditworthiness (e.g., Eberhart et al., 2008; Gow et al., 2010; Shi, 2003).

We first propose that outsider investors, *ex ante*, consider a firm that is more competitive in innovation to have a lower default probability, as firms owning more and higher-quality patents are more likely to earn first-mover advantages and become market leaders because they are equipped with more recent and influential technologies. In addition, patents raise entry costs for newcomers and help prevent competitors from using similar technologies. Further, firms with more competitive patent portfolios are more likely to gain quasi-monopoly power in the market. Such competitive advantages in innovation thus improve firms' financial stability and decrease their default risk.[4] Accordingly, this line of argument leads to our first hypothesis:

Hypothesis 1. A firm's perceived default risk is negatively associated with its innovation performance.

Since bond investors are more concerned about a bond issuer's solvency, the bond issuer's probability of default should be a key determinant in corporate bond pricing. Investors would demand a lower risk premium if they consider firms with stronger patent performance to be less risky. To directly test if bond investors incorporate the expected association between the information content of patents and default risk into bond pricing, we examine if innovation performance, when measured using patents, is negatively associated with the costs of bond financing. We present our second hypothesis as follows:

Hypothesis 2. A firm's bond premiums are negatively associated with its innovation performance.

Our empirical analyses show that outsider investors consider a firm that is more competitive in innovation to have higher survival likelihood and price the firm accordingly in the bond market. We first find that innovatively competitive firms (i.e., firms owning more and higher-impact patents with higher generality and originality scores) are associated with lower default probability, after we control for R&D expenditures and other financial metrics. We then find that innovatively competitive firms have lower yields on newly-issued bonds (an *ex ante* proxy of risk premiums) in the primary market, as well as lower excess bond returns (an *ex post* proxy of risk premiums) in the secondary market.

To help support a causal interpretation of our findings, we implement the following tests. First, we conduct two-stage least squares (2SLS) regressions by using monetary and time costs of patenting activities as instrumental variables.[5] We find a consistently negative relation between perceived default risk and *predicted* innovation measures, suggesting that our baseline finding is unlikely driven by omitted variables at the firm level, since predicted innovation measures are purged of firm-level omitted variables. Second, we conduct a difference-in-differences test to examine the cross-sectional variation of the innovation-creditworthiness association based on the adoption of state-level R&D tax credits (Wilson, 2009), which is an exogenous shock to innovation activities. We find that default

[3] Since the mid-1980s, U.S. firms have become more active in patenting their inventions and defending their intellectual property rights (Hall, 2005; Hall and Ziedonis, 2001; Kortum and Lerner, 1998), which makes patents a good data source for constructing measures of firms' innovation performance. Recent studies show that patents may be more useful in predicting future earnings and cash flows than R&D expenses (Baily, 1972; Hirshleifer et al., 2013, 2014; Megna and Klock, 1993; Pandit et al., 2011). In addition, patents are valuable outputs of corporate innovation (e.g., tradable assets in intellectual property markets) (Lev, 2001), and can serve as either collaterals or valuable assets for sale when a borrower becomes financially distressed (Chava et al., 2013; Mann, 2014).

[4] Prior studies report that firms with more and better patents are associated with lower litigation risk (Lanjouw and Schankerman, 2004), generate less volatile earnings (Pandit et al., 2011), and are, therefore, less likely to go bankrupt (Eisdorfer and Hsu, 2011).

[5] We use industry-average R&D expenditures per patent and the industry-average duration for a patent's application to be approved to measure monetary and time costs of firms' patenting activities, respectively. These two instrumental variables satisfy the relevance and exclusiveness conditions based on both Kleibergen and Paap's (2006) identification test and Hansen's (1982) over-identification test; in addition, these variables are intuitively exogenous to credit risk, except when working through the potentially endogenous independent variable (i.e., firms' innovation performance).

probability decreases with the interaction term between innovation performance and an indicator variable for the adoption of state-level R&D tax credits.[6] This finding supports our causal interpretation because the innovation-creditworthiness association becomes stronger after the introduction of state-level R&D tax credits, which is unlikely to be associated with other financing and economic determinants of corporate creditworthiness. Specifically, our finding is less likely driven by reverse causality because we include lagged dependent variables in our regressions. In addition, we use industry-adjusted dependent and explanatory variables to mitigate issues (e.g., industry-wide distress, industry-specific technology changes) caused by time-varying omitted variables at the market and industry levels.

Our study contributes to the literature in two ways. First, our study proposes and empirically substantiates the important role of patent information in bond pricing for both the primary and secondary markets, which has not been documented in the extant literature. Further, we find that default probability, bond yields, and bond returns all decrease with firm-level innovation performance in terms of the quantity, impact, generality, and originality of patents. These findings complement the findings of a few recent studies that banks, who likely have access to *proprietary* information on corporate innovation, charge lower loan spreads for borrowers with better patent performance (Amore et al., 2013; Chava et al., 2013; Francis et al., 2012; Plumlee et al., 2015). Hence, our findings show that publicly available information disclosed in patent records benefits outsiders in the bond market who likely do not have access to such private information.

Second, this paper responds to the debate in the extant literature with respect to how corporate innovation affects bondholders' welfare. Investments in innovation increase both the level and the variation of future cash flows and generate returns that are far more uncertain than returns from capital expenditures (Ciftci et al., 2011; Kothari et al., 2002; Pandit et al., 2011). Underscoring bondholders' challenges in weighing benefits and risks associated with innovation, Shi (2003) reports a negative impact of innovation on bondholders' welfare, whereas Eberhart et al. (2008) report a positive impact. In turn, our findings suggest that bond investors can benefit from incorporating both publicly available patent information and accounting R&D expenses into bond pricing.[7]

The rest of this paper is organized as follows. Section 2 describes the data, measures of innovation performance, and summary statistics. Section 3 reports our test results for the relation between innovation and default probability, and Section 4 reports our test results for the relation between innovation and bond pricing. Section 5 concludes this paper.

2. Data

2.1. Measures of innovation performance

To measure U.S. public firms' innovation activities, we retrieve the patent data of these firms from the updated National Bureau of Economic Research (NBER) patent database, originally constructed by Hall et al. (2005a); this database covers the period 1976–2006.[8] We then construct a panel of firm-year data that includes financial/accounting information of publicly listed firms from the CRSP/Compustat database and patent information from the updated NBER patent database in the period 1976–2006. Although we do not exclude financial and utility industries in our main sample, we obtain consistent empirical results if we exclude these industries.

We construct four patent-based measures of firm-level innovation performance. First, *quantity* is the number of total patents that the USPTO grants to a sample firm in year *t*. Second, *impact* is the total number of citations (until the end of 2006) received by all patents granted to a firm in year *t*.[9] For this measure, patents with greater impacts are cited more often than other patents. For firm-year observations in the CRSP/Compustat database that are not present in the NBER data, we follow the literature and set their patent counts (*quantity*) and citations (*impact*), respectively, to zero every year. Third, *generality* is the sum of generality scores of all patents granted to a firm in year *t*. The generality score of an individual patent is defined as one minus the Herfindahl index, based on the technology class distribution of all subsequent patents that cite this particular patent (Trajtenberg et al., 1997).[10] A general-purposed patent is cited by subsequent patents from a wide range of technology classes,

[6] R&D tax credits promote innovation by lowering the costs of innovative activities. Such a tax code change reasonably satisfies the exclusiveness condition because (i) R&D tax credits are arguably unrelated with other factors that may affect corporate financing choices and decisions except through innovation, and (ii) the adoption of R&D tax credits, which varies across states and years, is unlikely to coincide with any other economic or political forces. The interacted regression can be regarded as a difference-in-differences test as it compares the relation between innovation performance and default probability before and after exogenous policy shocks (e.g., Duchin et al., 2010).

[7] Note that our sample differs from the samples of Shi (2003) and Eberhart et al. (2008) in two important ways: (1) we consider all bond issues, while the other studies focus on only specific industries; and (2) for the sample period 1976–2006, our sample contains over 2000 bond issues, which is substantially larger and in a longer period than those data sets used in the other studies.

[8] The NBER patent data set records all patents assigned to each public firm by the US Patent and Trademark Office (USPTO) from 1976–2006; this data set is available at https://sites.google.com/site/patentdataproject/Home.

[9] The extant literature suggests that patent counts may not fully capture the economic value of a firm's patent portfolio, and that patent citations may better measure a firm's innovation performance from a *quality* perspective (e.g., Aghion et al., 2013; Deng et al., 2003; Hall et al., 2005b; Harhoff et al., 1999; Trajtenberg, 1990). We note that each patent's citations are related to its vintage, as the patents filed earlier usually receive more citations. To mitigate this vintage issue, the citations provided in the updated NBER patent data set have been adjusted with truncation weights (see Hall et al., 2005a).

[10] The USPTO adopts a three-digit class system that assigns each patent to a three-digit technology class; this class system is available at http://www.uspto.gov/web/offices/ac/ido/oeip/taf/cbcby.htm. For example, if Patent A is cited by Patent B (assigned to Class Y), by Patent C (assigned to Class Y), and by Patent D (assigned to Class Z), then Patent A's generality score is $0.444 = 1 - [(2/3)^2 + (1/3)^2]$.

resulting in a high generality score (between zero and one). Finally, *originality* is the sum of originality scores of all patents granted to the firm in year *t*. The originality score of a patent is defined as one minus the Herfindahl index of the technology class distribution of all patents that have been cited by this particular patent (Trajtenberg et al., 1997).[11] If a patent is more original, then it deviates from current technology trajectories to a greater extent by citing prior patents from a wider range, resulting in a higher originality score (between zero and one).

We scale each firm's patent-based innovation measures by its total assets to better capture that firm's innovation performance relative to its size (Eberhart et al., 2004, 2008; Hall et al., 2005a; Noel and Schankerman, 2013). We then adjust the scaled measures by the corresponding industry averages, defined by two-digit SIC codes in Compustat (Alcácer and Chung, 2007; Barker and Mueller, 2002; Ciftci et al., 2011). Such an adjustment for innovation performance measures is necessary and empirically important for three reasons. First, prior research shows that innovation activities vary widely across industries (e.g., Chan et al., 2001; Cohen et al., 2013; Hirshleifer et al., 2013, 2014; Lev and Sougiannis, 1996); therefore, this adjustment allows us to better measure how well a firm performs with respect to innovation when compared with its competitors.[12] Second, using comparative measures makes it unnecessary to limit our sample to patent-owning firms: a firm without patent records in a sample year will have negative values in innovation measures if its competitors have earned patents in the same year. Third, by removing all industry-related components, we help mitigate potential bias caused by omitted industry factors.

2.2. Summary statistics

Table 1 reports the summary statistics of all the variables used in our analyses (see Table 1 and subsequent sections for variable definitions). All variables in Table 1 are reported at raw values (i.e., we adjust all firm-level and issue-level variables by industry averages in regression analyses). Panel A reports the summary statistics of innovation-related measures. For example, a representative firm with total assets of one million dollars, on average, produces 0.011 patent counts, 0.216 patent citations, 0.021 generality scores, and 0.019 originality scores per year. Such a firm invests 0.037 millions of dollars in R&D per year.

Several issues regarding our patent-based measures are worth noting. First, we use grant years rather than application years to construct innovation measures for each firm in every year. This conservative approach ensures that all information has been fully disclosed to outside bond investors because the USPTO publishes granted patents and their details *weekly*. Second, two of our four measures—patent citations and generality—may suffer from forward-looking bias, as they are based on citations received after a patent is granted; nevertheless, bondholders should be able to understand and interpret the influence and generality of each patent by reading the USPTO's weekly reports on granted patents. Third, we include all self-citations in our calculations of citations, generality, and originality, as self-citations are associated with higher market values than citations by others (Hall et al., 2005b). Lastly, we use one-year data to construct innovation proxies, as Hall (1993) posits that a firm's patent flow is more informative to its economic value than its patent stock. For robustness, we also consider cumulative innovation proxies in three- and five-year windows (i.e., from year *t*–2 to year *t*, and from year *t*–4 to year *t*) in our empirical analysis, and we obtain qualitatively similar results (not tabulated).

Panels B–D of Table 1 report the descriptive statistics of the credit-related measures and other relevant control variables. The mean, median, and standard deviation of an average firm's perceived default probability are 0.246, 0.017, and 0.353, respectively. Premiums of newly-issued bonds, excess bond returns, and bond characteristics are computed/collected from the Thomson ONE Banker database and TRACE. The mean, median, and standard deviation of an average bond's risk premium at issuance (expressed in %) are 1.148, 0.808, and 2.192, respectively. The mean, median, and standard deviation of annual excess bond returns (expressed in %) are 5.828, 3.734, and 12.814, respectively. Other accounting and financial data are collected from the CRSP/Compustat database.

Panel E reports the descriptive statistics of two instrumental variables and an indicator variable for the adoption state-level R&D tax credits. Our two instrumental variables include industry average R&D expenses per patent (R&D per patent) and industry average duration (in years) from application to approval (i.e., application-grant lag). Meanwhile, the indicator variable for the adoption of state-level R&D tax credits follows Wilson (2009) and equals one if the state where a firm's headquarters reside offers R&D tax credits in that year, and zero otherwise. On average, a sample patent costs 13 million dollars, and it takes slightly over 2 years for a patent application to be approved. Of our firm-year observations, 11.2% have R&D tax credits.

Panels F–H of Table 1 report the pairwise Pearson correlation coefficients between innovation measures (Panel A) and other variables considered in Panels B–D. These correlation coefficients should be interpreted with caution because they are univariate in nature and may no longer hold once the effects of necessary control variables and cross-industry variation are considered.[13] Accordingly, we rely on multivariate regressions for our statistical inferences.

[11] For example, if Patent E cites Patent A (assigned to Class X), cites Patent B (assigned to Class Y), cites Patent C (assigned to Class Y), and cites Patent D (assigned to Class Z), then Patent E's originality score is $0.625 = 1 - [(1/4)^2 + (2/4)^2 + (1/4)^2]$.

[12] For example, a firm producing 0.02 patents with one million R&D dollars is regarded as an innovation leader in the Transportation Equipment Industry (SIC2 = 37), but is regarded as an innovation follower in the Chemicals and Allied Products Industry (SIC2 = 28).

[13] For instance, while the correlation coefficient between patent counts (citations) and R&D expenses is 0.646 (0.337), the correlation coefficient between industry-adjusted patent counts (citations) and industry-adjusted R&D expenses is 0.193 (0.106).

Table 1
Descriptive statistics for selected variables.
In Panel A, *Quantity* (*Patent count*/*Asset*) denotes the number of the focal firm's patents approved in year *t*, normalized by total assets in year *t*. *Impact* (*Patent citation*/*Asset*) denotes the total number of future patents citing the focal firm's patents approved in year *t*, normalized by total assets in year *t*. *Generality* (*Generality score*/*Asset*) denotes the sum of generality scores of the focal firm's patents approved in year *t*, normalized by total assets in year *t*. *Originality* (*Originality score*/*Asset*) denotes the sum of originality scores of the focal firm's patents approved in year *t*, normalized by total assets in year *t*. *R&D*/*Asset* denotes the focal firm's annual R&D expenses normalized by total assets in year *t*. In Panel B, *Default probability* is the 12-month default probability of firm *i* in year *t* (i.e., the 12-month average of firm *i*'s default probability). *Market*/*Book* denotes the ratio of the market equity to the book equity of firm *i* in year *t*. *Debt*/*Asset* denotes the ratio of total debts to total assets of firm *i* in year *t*. *Profit* denotes firm *i*'s profit margin. *Coverage* denotes the coverage ratio (i.e., income before interest expenses over interest expenses). *Asset* denotes the logarithmic value of total assets of firm *i*. *ROA* denotes the return on assets. *Loss* is a dummy variable that equals one if the firm reports a loss, and zero otherwise. *Beta* denotes market beta, and *IdioVol* denotes idiosyncratic return volatility, both estimated from the market model. In Panel C, *Premium* denotes the premium of the newly-issued bond *k* issued by firm *i* in year *t* (i.e., the bond's yield in excess of corresponding T-bill yields) in percentages. *Issue* denotes the size of bond *i* issuance in logarithm. *Moody* denotes the rating class (integer values 1 through 5 that represent the ratings of Aaa, Aa, A, Baa, and below Baa, respectively) of the newly-issued bond *k*. *Maturity* denotes the years to maturity of bond *k* in logarithm. *Call* denotes years to first call of bond *k*. *Convertible* is a dummy variable equal to one if bond *k* is convertible, and zero otherwise. In Panel D, *Return* denotes the excess return on traded bond *k* in year *t* (i.e., the bond's return in excess of one-year T-bill returns). In Panel E, we report the summary statistics of our instrumental variables and an indicator variable for the adoption of state-level R&D tax credits. Our two instrumental variables include industry average R&D expenses per patent and industry average duration (in years) from application to approval. In Panel F, we report the pairwise Pearson correlation coefficients between all innovation variables and the variables in Panel B. In Panel G, we report the pairwise Pearson correlation coefficients between all innovation variables and the variables in Panel C. In Panel H, we report the pairwise Pearson correlation coefficients between all innovation variables and the variables in Panel D. The sample in Panels A, B, and F includes all firm-year observations in 1976–2006. The sample in Panels C and G includes all new bond issues in 1976–2006. The sample in Panels D and H includes publicly traded, straight corporate bonds in 2002–2006. All values in Table 1 are reported without industry adjustment.

Variable	Mean	10%	Median	90%	St. deviation
A. Innovation-related variables for all firm-years					
Quantity (Patent count/Asset)	0.011	0.000	0.000	0.014	0.097
Impact (Patent citation/Asset)	0.216	0.000	0.000	0.136	3.809
Generality (Generality score/Asset)	0.021	0.000	0.005	0.043	0.082
Originality (Originality score/Asset)	0.019	0.000	0.004	0.039	0.065
R&D/Asset	0.037	0.000	0.000	0.098	0.143
B. Default probability and other characteristics for all firm-years					
Default probability	0.246	0.000	0.017	0.937	0.353
Market/Book	3.477	0.590	1.539	5.412	36.584
Debt/Asset	0.202	0.000	0.138	0.469	0.416
Profit	−0.111	−0.188	0.128	0.372	1.444
Coverage	11.509	0.000	4.264	27.210	21.253
Asset	5.631	2.688	5.568	8.647	2.324
ROA	0.029	−0.124	0.088	0.214	1.426
Loss	0.204	0.000	0.000	1.000	0.403
Beta	1.045	0.063	0.937	2.223	0.942
IdioVol	0.953	0.368	0.767	1.747	0.675
C. Premiums and other characteristics of newly-issued bonds					
Premium (%)	1.148	0.020	0.808	3.308	2.192
Market/Book	2.362	0.708	1.805	5.546	22.399
Debt/Asset	0.400	0.094	0.474	0.571	0.197
Profit	0.067	0.004	0.091	0.163	0.165
Coverage	1.056	0.625	1.320	7.308	303.591
Asset	10.312	6.330	10.822	13.671	2.853
Issue	4.576	3.047	4.615	6.220	1.342
Moody	3.498	1.000	3.000	5.000	1.160
Maturity	1.916	0.722	1.951	2.994	0.787
Call	3.307	0.000	1.750	10.802	7.174
Convertible	0.077	0.000	0.000	0.000	0.267
D. Excess returns and other characteristics of traded bonds					
Return (%)	5.828	−2.237	3.734	16.701	12.814
Market/Book	2.131	0.754	2.029	5.146	11.153
Debt/Asset	0.271	0.107	0.252	0.472	0.154
Profit	0.207	0.081	0.178	0.382	0.113
Coverage	9.215	2.649	6.271	17.842	9.899
Asset	9.852	7.794	9.874	14.449	1.734
Moody	3.785	1.000	4.000	5.000	1.022
E. Instrumental variables and R&D tax credits					
R&D per patent	13,502	0	860	42,516	28,124
Application-grant lag	2.141	1.464	2.062	3.000	0.801
State R&D tax credits	0.112	0.000	0.000	1.000	0.316

(*continued on next page*)

Table 1 (*continued*)

	Quantity (Patent count/Asset)	Impact (Patent citation/Asset)	Generality (Generality score/Asset)	Originality (Originality score/Asset)	R&D/Asset
F. Correlation between innovation and variables related to default probability					
Impact (Patent citation/Asset)	0.490	1.000			
Generality (Generality score/Asset)	0.901	0.496	1.000		
Originality (Originality score/Asset)	0.646	0.337	0.668	1.000	
R&D/Asset	0.227	0.124	0.313	0.398	1.000
Default probability	0.024	−0.016	0.007	−0.009	−0.077
Market/Book	−0.003	0.000	−0.024	−0.028	0.001
Debt/Asset	−0.001	−0.005	−0.078	−0.054	−0.017
Profit	−0.040	−0.012	−0.031	−0.069	−0.135
Coverage	−0.012	−0.008	−0.062	−0.059	−0.018
Asset	−0.114	−0.066	−0.318	−0.361	−0.234
ROA	−0.051	−0.027	−0.449	−0.491	−0.158
Loss	0.125	0.069	0.274	0.300	0.303
Beta	0.021	0.008	−0.073	−0.072	0.114
IdioVol	0.108	0.042	0.265	0.315	0.215
G. Correlation between innovation and variables related to newly−issued bonds					
Impact (Patent citation/Asset)	0.752	1.000			
Generality (Generality score/Asset)	0.921	0.871	1.000		
Originality (Originality score/Asset)	0.858	0.843	0.769	1.000	
R&D/Asset	0.534	0.563	0.405	0.468	1.000
Premium (%)	−0.011	−0.033	−0.086	−0.093	−0.068
Market/Book	0.034	0.037	0.013	0.026	0.075
Debt/Asset	−0.171	−0.178	−0.184	−0.118	−0.178
Profit	−0.103	−0.334	0.003	−0.051	−0.236
Coverage	0.004	0.014	−0.012	−0.014	−0.059
Asset	−0.155	−0.175	−0.125	−0.072	−0.258
Issue	0.017	0.038	0.050	0.122	0.068
Moody	−0.030	−0.032	0.006	0.064	−0.088
Maturity	0.026	0.027	0.012	−0.056	0.052
Call	−0.036	−0.039	−0.041	−0.046	−0.056
Convertible	0.125	0.143	0.096	0.211	0.281
H. Correlation between innovation and variables related to traded bonds					
Impact (Patent citation/Asset)	0.828	1.000			
Generality (Generality score/Asset)	0.711	0.959	1.000		
Originality (Originality score/Asset)	0.986	0.789	0.686	1.000	
R&D/Asset	0.614	0.493	0.337	0.486	1.000
Return (%)	0.008	0.067	0.125	−0.026	−0.025
Market/Book	−0.002	0.022	0.009	−0.026	0.040
Debt/Asset	−0.189	−0.153	−0.182	−0.271	−0.215
Profit	−0.219	−0.154	−0.136	−0.178	−0.119
Coverage	0.303	0.313	0.241	0.214	0.427
Asset	−0.040	−0.002	0.103	0.133	−0.050
Moody	−0.063	−0.054	−0.058	−0.117	−0.138

3. Innovation performance and default probability

3.1. Baseline results

We investigate whether investors consider firms that are more competitive in innovation relative to their peers to have lower default risk (Hypothesis 1). We specify the following model for the default probability of firm i in industry j in year t:

$$\begin{aligned} Default_{i,t} = \alpha + \beta_1 Innovation_{i,t} + \beta_2 R\&D_{i,t} + \beta_3 Default_{i,t-1} + \beta_4 Market/Book_{i,t} \\ + \beta_5 Debt/Asset_{i,t} + \beta_6 Profit_{i,t} + \beta_7 Coverage_{i,t} + \beta_8 Asset_{i,t} + \beta_9 ROA_{i,t} \\ + \beta_{10} Loss_{i,t} + \beta_{11} Beta_{i,t} + \beta_{12} IdioVol_{i,t} + Industry_j + Year_t + e_{i,t}. \end{aligned} \tag{1}$$

The dependent variable, $Default_{i,t}$, is the industry-adjusted default probability of firm i in year t (i.e., firm i's default probability in year t minus the simple average of all firms' default probabilities in industry j, defined by two-digit SIC codes in year t). Default probability is computed following the Merton (1974) model as implemented in Vassalou and Xing (2004) and

Bharath and Shumway (2008).[14] The estimated default likelihood represents the probability that the value of a firm's total assets will fall below the book value of that firm's total liabilities over the next 12 months.

The main explanatory variables of Eq. (1) are one of firm i's innovation measures (e.g., quantity, impact, generality, and originality of patents) and R&D expenditure ($R\&D_{i,t}$), both industry-adjusted. R&D expenditure ($R\&D_{i,t}$) is computed as firm i's annual R&D expenditures scaled by its total assets in year t, minus the corresponding industry average in the same year. We include both patent- and R&D-based innovation measures to measure both outputs and inputs of firms' innovation activities and to separate their effects on default risk, so we can examine if patent information is incrementally useful after controlling for R&D expenditures.

We include in Eq. (1) the lagged default probability, $Default_{i,t-1}$, as the default probability is persistent over time; also, including this lagged dependent variable helps preclude reverse causality in regressions.[15] We also include several control variables following the extant literature (e.g., Blume et al., 1998; Kaplan and Urwitz, 1979): firm i's market-to-book ratio ($Market/Book_{i,t}$), debt-to-asset ratio ($Debt/Asset_{i,t}$), profit margin ($Profit_{i,t}$), coverage ratio ($Coverage_{i,t}$), total assets in logarithm ($Asset_{i,t}$), return on assets ($ROA_{i,t}$), loss dummy ($Loss_{i,t}$), market beta ($Beta_{i,t}$), idiosyncratic return volatility ($IdioVol_{i,t}$), industry dummy variables ($Industry_j$), and year dummy variables ($Year_t$). The detailed definitions of these variables are provided in Table 1. Given that our dependent variables are industry-adjusted based on all firm-year observations rather than those observations with non-missing values in all variables used in Eq. (1), we still include industry dummies in regressions to further control for any industry-specific effect.

Table 2 reports our test results based on Eq. (1). We estimate panel regressions using the unbalanced panel data and compute the t-statistics using standard errors clustered by firms and years (Gow et al., 2010; Petersen, 2009).[16] Columns (1) and (2) show that patent quantity and impact are negatively correlated with a firm's perceived default probability. The coefficients on patent quantity and impact are −0.104 and −0.001 with t-statistics of −6.76 and −2.14, respectively. In terms of economic significance, a one-standard-deviation increase of a firm's patent quantity and patent impact is associated with a decrease in its default probability by 1.0% and 0.4% in magnitude, respectively.[17] This amounts to decreases in default probability at 4.1% and 1.6% (58.8% and 22.3%) of the sample mean (median), respectively. Collectively, these findings support the notion that firms owning more and higher impact patents relative to their competitors gain higher expected economic rents and have more secured future cash flows. In addition, such firms are better positioned in the race for technological advancement and are more likely to outperform their competitors, leading to a lower likelihood of default.

Columns (3) and (4) of Table 2 show that patent generality and originality, the other two dimensions of innovation activities, are also negatively related to firms' default risk.[18] The coefficients on patent generality and originality are −0.183 and −0.170 with t-statistics of −3.18 and −3.84, respectively. These estimates suggest that firms with patents that can be applied to broader areas or are based on broader knowledge domains have a significantly lower perceived default probability, likely due to fundamental merit and risk diversification. In terms of economic significance, we find that a one-standard-deviation increase in a firm's patent generality decreases its default probability by 1.2% in magnitude and 4.9% (70.0%) of the sample mean (median). In addition, we find that a one-standard-deviation increase in a firm's patent originality decreases its default probability by 2.9% in magnitude and 11.8% (168.6%) of the sample mean (median). These findings support the notion that firms owning either more general-purposed innovations or more original innovations generate more stable or higher cash flows to ensure their survival.

Estimated coefficients for the other control variables are largely consistent with those reflected in the literature. R&D intensity also reveals a significantly negative explanatory ability for firms' default probability. In addition, given that the standard deviation of industry-adjusted R&D expenditures scaled by total assets is 0.130, a one-standard-deviation increase in relative R&D input decreases a firm's default probability level by 1.6% to 1.8% across four different regressions. The coefficients on the lagged default probability are significantly positive and range between 0.533 and 0.560; these numbers support our model setting of Eq. (1), as default probability for firms is reasonably persistent, yet does not follow a unit root process. Among other control variables, the debt-to-asset ratio, profit margin, total assets, loss dummy, and idiosyncratic return volatility positively correlate with default probability, while coverage ratio, ROA, and market beta negatively correlate with default probability.[19]

We offer a range of findings in Table 2. First, we provide firm-level evidence for a significantly negative relation between a firm's perceived default probability and its innovation performance, as measured across four dimensions: quantity, impact, generality, and originality. This negative relation indicates that investors relate firms' innovation performance to their ability to fulfill their financial obligations, and also provides complementary evidence to support the positive relation between innovation and operating

[14] Using the pricing model of a European call option (Black and Scholes, 1973), the market value of a firm's equity (V_E) is determined by the following option: $V_E = V_A N(d_1) - Xe^{-rT} N(d_2)$, in which $d_1 = \frac{\ln e(V_A/X)+(r+0.5\sigma_A^2)T}{\sigma_A\sqrt{T}}$, $d_2 = d_1 - \sigma_A\sqrt{T}$. At the end of every calendar month in our sample period, we use the daily CRSP data from the previous 12 months as the initial value for the volatility of total assets which is not directly observable. Using the daily market value of equity, we derive the daily assets value (V_A) in the previous 12 months from these equations. We then compute from the daily V_A and use it as the value of for the next iteration. We repeat this process until converges at a level of 0.001. The estimated default likelihood for firm i at month k is computed using the final estimated V_A and σ_A, as follows:

$Default_{i,k} = N(-DD)$ and $Distant\text{-}to\text{-}Default\ (DD) = \frac{\ln(V_A/X)+(\mu-0.5\sigma_A^2)T}{\sigma_A\sqrt{T}}$, in which μ is the return to total assets computed using the daily implied log return on assets.

[15] For example, a situation in which a firm has fewer patents because it cuts intangible investment due to financial pressure from escalating credit risk will be reflected in the coefficient associated with lagged default probability.

[16] We also consider the Newey and West (1987) standard errors that correct for both autocorrelation and heteroskedasticity; in so doing, we obtain similar results in unreported tables.

[17] The standard deviation of industry-adjusted patent quantity, impact, generality, and originality are 0.096, 3.799, 0.065, and 0.169, respectively, in the sample 1976–2006.

[18] The numbers of observations in Columns (3) and (4) are much less than those in Columns (1) and (2) because, for firm-year observations without any patent record, we set their patent counts and citations to be zeros. On the other hand, we let these firms' generality and originality be missing because there is no appropriate interpretation for these two measures of firms without patents.

[19] The positive coefficients of total assets (marginally significant in Columns (1) and (2)) and the negative coefficients of market beta may be attributed to the correlation among the control variables and the inclusion of the lagged default risk in regressions.

Table 2
Default probability and innovation competitiveness.
We estimate the following model using pooled OLS regressions: $Default_{i,t} = \alpha + \beta_1 Innovation_{i,t} + \beta_2 R\&D_{i,t} + \beta_3 Default_{i,t-1} + \beta_4 Market/Book_{i,t} + \beta_5 Debt/Asset_{i,t} + \beta_6 Profit_{i,t} + \beta_7 Coverage_{i,t} + \beta_8 Asset_{i,t} + \beta_9 ROA_{i,t} + \beta_{10} Loss_{i,t} + \beta_{11} Beta_{i,t} + \beta_{12} IdioVol_{i,t} + Industry_j + Year_t + e_{i,t}$. $Default_{i,t}$ denotes the industry-adjusted default probability of firm *i* in industry *j* in year *t* (i.e., the firm's default probability minus the average of all firms' default probability in the same two-digit SIC industry). $Innovation_{i,t}$ denotes firm *i*'s innovation quantity (measured with patent counts), impact (measured with citations), generality scores, and originality scores, normalized by total assets in year *t*, minus the corresponding industry average in the same year. $R\&D_{i,t}$ denotes firm *i*'s annual R&D expenses, normalized by total assets in year *t*, minus the industry average in the same year. The following control variables are included in regressions: lagged default probability ($Default_{i,t-1}$), firm *i*'s market equity to book equity ratio ($Market/Book_{i,t}$), debt-to-asset ratio ($Debt/Asset_{i,t}$), profit margin ($Profit_{i,t}$), coverage ratio (i.e., income before interest expenses over interest expenses) ($Coverage_{i,t}$), total assets in logarithm ($Asset_{i,t}$), return on assets ($ROA_{i,t}$), loss dummy that equals one if the firm reports a loss (and zero otherwise) ($Loss_{i,t}$), market beta ($Beta_{i,t}$), idiosyncratic return volatility ($IdioVol_{i,t}$), industry dummy variables ($Industry_j$), and year dummy variables ($Year_t$). All control variables have been defined in Table 1 and are industry-adjusted measures (except industry and year dummies). *t*-Statistics reported in parentheses are based on two-way clustered standard errors by firms and years. The sample period is 1976–2006. *, **, and *** denote significance levels at 10%, 5%, and 1%, respectively.

	(1)	(2)	(3)	(4)
Innovation =	Quantity	Impact	Generality	Originality
Innovation	−0.104***	−0.001**	−0.183***	−0.170***
	(−6.76)	(−2.14)	(−3.18)	(−3.84)
R&D	−0.130***	−0.138***	−0.123***	−0.123***
	(−5.67)	(−5.77)	(−3.05)	(−3.24)
Default (lagged)	0.533***	0.533***	0.556***	0.560***
	(32.96)	(33.15)	(18.21)	(19.77)
Market/Book	−0.000***	−0.000**	0.000	0.000
	(−2.86)	(−2.24)	(0.10)	(0.00)
Debt/Asset	0.217***	0.217***	0.195***	0.184***
	(10.36)	(10.36)	(6.10)	(6.35)
Profit	0.000	0.000	0.000	0.000
	(1.32)	(1.30)	(1.07)	(0.98)
Coverage	−0.000***	−0.000***	−0.000	−0.000
	(−3.24)	(−3.25)	(−1.21)	(−1.21)
Asset	0.011*	0.012*	0.007	0.011
	(1.74)	(1.88)	(0.81)	(1.38)
ROA	−0.021***	−0.019***	−0.034*	−0.032*
	(−2.93)	(−2.76)	(−1.93)	(−1.73)
Loss	0.010	0.010	0.013**	0.008
	(1.52)	(1.42)	(2.09)	(1.64)
Beta	−0.013***	−0.013***	−0.012***	−0.012***
	(−3.87)	(−3.84)	(−3.10)	(−3.30)
IdioVol	0.103***	0.103***	0.096***	0.094***
	(9.37)	(9.34)	(4.68)	(5.11)
Constant	−0.051	−0.056	−0.174***	−0.380***
	(−0.00)	(−0.00)	(−3.31)	(−7.79)
R^2	0.548	0.547	0.531	0.531
Observation	42,552	42,552	11,363	12,070

performance (e.g., Baily, 1972; Eberhart et al., 2004, 2008; Hirshleifer et al., 2013, 2014; Megna and Klock, 1993; Pandit et al., 2011). Second, we show that patent-based measures are incrementally informative with respect to firms' perceived default probability, beyond that captured by R&D-based measures and private information. In addition, the economic significance of our patent-based measures is commensurate to that of R&D-based measures in our analyses, suggesting that patent output is at least as important as R&D input to outsider bond investors.

3.2. Endogeneity concerns and 2SLS regressions

We recognize that our Table 2 results could be subject to various endogeneity issues. Specifically, there may exist aggregate-, industry-, and firm-level omitted variables that influence both corporate creditworthiness and innovation activities, thereby leading to a positive innovation-creditworthiness relation. The potential effects of aggregate- and/or industry-level omitted variables—including business/economy cycles, industry life cycles, industrial structures, and time-variant innovation opportunities (e.g., innovation waves)—may affect our empirical tests. To mitigate this issue, we 1) include year dummy variables in all regressions and 2) remove the industry averages from credit risk measures (the dependent variable), patent-based measures (the key variables of interest), and other control variables before we conduct our regression analyses. As a result, our findings are less likely subject to economy/industry effects.

Firm-level omitted variables, on the other hand, have been discussed in prior empirical studies that examine the relation between R&D investments and operating performance.[20] For example, Lev and Sougiannis (1996) suggest that unknown or omitted firm-level

[20] While including firm dummy variables in regressions or using differenced regressions could offer complementary solutions, doing so may not be desirable because of consistency, panel size, and power reasons. Hall et al. (2005b) and Noel and Schankerman (2013) argue that, as firms' innovation policies change slowly across time, firm dummy variables will absorb innovation-related effects, and the differenced regression approach will then lead to downward-biased coefficient estimates, leading to underestimated effects of innovation performance on firm values. Moreover, because of the large cross-section used in our sample (over 1000), we reasonably assume that each firm is a random draw from the same population (e.g., Petersen, 2009).

factors that affect both firms' R&D expenditures and their operating incomes may result in inconsistent regression estimates and, in turn, bias the statistical inference regarding R&D investments' effect on profitability.[21] Although we include many firm-level variables in our regressions, we cannot rule out the possibility that a firm-level omitted variable may affect both innovation performance and default probability, leading to our baseline finding.

To address concerns over firm-level omitted variables, we use the 2SLS regressions with two instrumental variables (IVs): the industry average R&D expenditures per patent, and the industry average duration (in years) from application to approval.[22] Since these two IVs reflect monetary costs and time costs of firms' patenting activities, respectively, they should influence innovative firms' incentives to innovate to a great extent. On the other hand, we argue that these two IVs are exclusive by being uncorrelated with dependent variables of interest (i.e., default probabilities) except working through firm-level innovation activities. If a firm's relative patenting performance has no effect on dependent variables, then it is unlikely that the proposed two IVs would affect our dependent variables.[23] In addition to making these conceptual arguments, we also conduct relevant statistical tests to empirically justify the validity of these IVs in the following context.

To examine whether the negative effect of innovation on default probabilities is reasonably robust to endogeneity issues, we re-estimate Eq. (1) using 2SLS regressions and report our results in Table 3. In the first stage, we regress sample firms' industry-adjusted measures of patent quantity, quality, generality, and originality on two IVs and all control variables used in Eq. (1). In the second stage, we rerun tests specified in Eq. (1), using the predicted patent quantity, quality, generality, and originality (labeled as "Predicted Innovation") that are based on all coefficients estimated from the first-stage regression. Note that Predicted Innovation is purged of all firm-level omitted variables that are not contained by IVs and control variables.

Table 3 shows significantly negative coefficients on Predicted Innovation, which suggests that the negative relation between default probabilities and our patent-based innovation measures is not driven by firm-level omitted variables. Moreover, we use Kleibergen and Paap's (2006) identification test and Hansen's (1982) over-identification test to assess the proposed IVs' relevance and exclusiveness. First, we find that the identification test always reject the null hypothesis, which indicates that the proposed IVs are relevant because they significantly explain innovation measures. Second, we find that the over-identification test is not rejected in any column, which indicates that the proposed IVs are uncorrelated with the errors from the original regressions. Collectively, these results show that the proposed IVs are valid for our investigation of innovation's effect on default probabilities, since these IVs explain default probabilities only through innovation performance.

3.3. Difference-in-differences tests based on state-level R&D tax credits

To further examine if the innovation-default relation can be interpreted causally, we introduce state-level R&D tax credits as an exogenous shock that lowers firms' costs of innovation and thus affects the effect of innovation on default probability, if any; this shock is unrelated with firm- or industry-level omitted variables or unobservable conditions. The first R&D tax credit program was launched by the federal government in 1981, and Minnesota started to offer state-level R&D tax credits for the first time in 1982. By the end of 2006, 32 states provided tax credits to encourage corporate innovation, and such incentives effectively raised corporate R&D investments within these states (Wilson, 2009).

We propose using such a tax code change as an exogenous shock, if any, to examine innovation's influence on creditworthiness because doing so satisfies both relevance and exclusiveness conditions. First, state-level R&D tax credits only affect firms' innovation activities and are arguably unrelated with other variables or conditions that may affect corporate financing choices and decisions. Second, the adoption of R&D tax credits varies across states and thereby results in both cross-sectional and time-series variations that unlikely coincide with other economic or political forces.

We run the following regression to examine whether the existence of state-level R&D tax credits affects the influence of corporate patents and R&D on default probability:

$$\begin{aligned}Default_{i,t} = \alpha &+ \beta_0 Innovation_{i,t} \times I(StateR\&Dcredit)_{k,t} + \beta_1 R\&D_{i,t} \times I(StateR\&Dcredit)_{k,t} \\ &+ \beta_2 I(StateR\&Dcredit)_{k,t} + \beta_3 Innovation_{i,t} + \beta_4 R\&D_{i,t} + \beta_5 Default_{i,t-1} \\ &+ \beta_6 Market/Book_{i,t} + \beta_7 Debt/Asset_{i,t} + \beta_8 Profit_{i,t} + \beta_9 Coverage_{i,t} + \beta_{10} Asset_{i,t} \\ &+ \beta_{11} ROA_{i,t} + \beta_{12} Loss_{i,t} + \beta_{13} Beta_{i,t} + \beta_{14} IdioVol_{i,t} + Industry_j + Year_t + e_{i,t},\end{aligned} \tag{2}$$

[21] Prior research finds that managers may withhold investments in innovation activities when they face financial underperformance or increased uncertainty (Bushee, 1998; Czarnitzki and Toole, 2011; Dechow and Sloan, 1991; Murphy and Zimmerman, 1993).

[22] To construct the industry average R&D expenditures per patent for industry j in year t, we first scale each firm's granted patent by its R&D expenditures over the most recent five years (i.e., year t–4 to year t) and then compute the average across all firms in industry j in year t. To construct the industry average duration from applications to approval for industry j in year t, we first calculate each patent's duration from applications to approval (i.e., approval year minus application year) and then compute the average across all patents granted to the firms in industry j (as defined by SIC two-digit codes) in year t.

[23] We note that the potentially endogenous explanatory variable (i.e., firm-level innovation measures) is an industry-adjusted measure. Thus, even if a firm chooses not to file any patent, its innovation performance will change according to its competitors' choices.

Table 3
Default probability and innovation performance — 2SLS regressions.
To mitigate potential bias related to endogeneity issues, we use two instrumental variables (IVs) to conduct two-stage least square (2SLS) tests for the model specified in Table 4; these IVS include industry average R&D expenses per patent (i.e., monetary costs) and industry average duration (in years) from application to approval (i.e., time costs). We expect that these two IVs explain the potentially endogenous explanatory variable, *Innovation*, and are uncorrelated with default probability, except working through *Innovation* (see variable definitions in Table 4). All variables are industry-adjusted measures. *t*-Statistics reported in parentheses are based on two-way clustered standard errors by firms and years. The sample period is 1976–2006. The row "Identification test" reports the test statistics (and *p*-values in brackets) of the identification test with the null hypothesis that the IVs cannot explain endogenous explanatory variables (i.e., irrelevant). The rejection of the null hypothesis suggests that the IVs can significantly explain the endogenous variable *Innovation*. The row "Over-identification test" reports the test statistics (and *p*-values in brackets) of the over-identification test with the null hypothesis that the IVs are exclusive (i.e., uncorrelated with errors). The rejection of the null hypothesis suggests the IVs are not valid, as they are correlated with the errors from the main equation. *, **, and *** denote significance levels at 10%, 5%, and 1%, respectively.

	(1)	(2)	(3)	(4)
Innovation =	Quantity	Quality	Generality	Originality
Predicted Innovation	−9.091**	−0.193***	−4.152***	−3.647***
	(−2.12)	(−4.96)	(−2.60)	(−2.13)
R&D	1.037*	0.364**	0.098	0.027
	(1.66)	(2.43)	(0.76)	(0.28)
Default (lagged)	0.536***	0.533***	0.522***	0.515***
	(233.23)	(43.37)	(22.79)	(20.64)
Market/Book	0.000	0.000**	0.000	0.000
	(0.17)	(2.24)	(0.83)	(1.25)
Debt/Asset	0.131**	0.162***	0.189***	0.193***
	(2.16)	(2.90)	(5.79)	(5.23)
Profit	−0.000	0.000*	0.000	0.000
	(−0.25)	(1.77)	(1.42)	(1.48)
Coverage	−0.001***	−0.001***	0.000*	0.000
	(−3.00)	(−3.37)	(1.90)	(1.61)
Asset	−0.073***	−0.055***	−0.052**	−0.039
	(−6.98)	(−15.47)	(−2.18)	(−1.52)
ROA	−0.121*	−0.023	−0.332***	−0.345**
	(−1.81)	(−1.29)	(−2.66)	(−2.18)
Loss	0.062	0.045***	0.003	−0.022
	(1.57)	(2.64)	(0.10)	(−0.94)
Beta	−0.020**	−0.012*	−0.038***	−0.035***
	(−2.44)	(−1.92)	(−3.76)	(−3.15)
IdioVol	0.124***	0.101***	0.141***	0.147***
	(7.95)	(14.64)	(4.85)	(5.30)
Constant	0.227***	0.131***	0.025	−0.047
	(2.83)	(3.56)	(0.13)	(−0.21)
Identification test	5.530*	40.19***	12.703***	7.483**
(IV relevance)	[0.06]	[0.00]	[0.00]	[0.02]
Over-identification	1.913	1.002	0.796	0.049
Test (IV exclusiveness)	[0.17]	[0.32]	[0.37]	[0.83]

in which $I(StateR\&Dcredit)_{k,t}$ is an indicator variable that equals one if firm *i*'s headquarters' state *k* has started offering any R&D tax credit in year *t*, and zero otherwise. Eq. (2) can be regarded as a difference-in-differences test as it compares the relation between the explanatory variable and the dependent variable before and after exogenous policy shocks (e.g., Duchin et al., 2010).

We obtain the history of state-level R&D tax credits from Wilson (2009), and obtain the headquarters' state information from Compustat. All other variables are defined earlier in this paper. A negative (positive) coefficient β_0 of $Innovation_{i,t} \times I(StateR\&Dcredit)_{k,t}$ would suggest a more (less) pronounced effect of innovation performance on default probability. We also consider $R\&D_{i,t} \times I(StateR\&Dcredit)_{k,t}$ in the regression to account for the role of tax credits in the R&D-default risk relation.

In Table 4, we show that innovation performance lowers default probability to a greater extent in the presence of state-level R&D tax credits. The coefficient on $Innovation_{i,t} \times I(StateR\&Dcredit)_{k,t}$ is negative in all four columns for four innovation measures. In Columns (1) and (2), the estimates of β_0 are −0.052 and −0.001 with *t*-statistics of −2.03 and −1.65, respectively. For a firm with patent quantity that is one standard deviation higher, its default probability drops by an additional 0.50% if its headquarters' state offers tax credits. Similarly, for a firm with patent impact that is one standard deviation higher than its competitors, its default probability drops by an additional 0.38% if its headquarters' state offers tax credits. In terms of economic significance, if the state in which a firm's headquarters resides offers tax credits, then a one-standard-deviation increase in its patent quantity (impact) lowers default probability by an additional 2.03% (1.54%) of the sample mean or an additional 29.40% (22.35%) of the sample median.

Moreover, the sum of coefficient β_0 and β_3 is −0.134 in Column (1), which is lower than the coefficient of innovation (−0.104) in Column (1) in Table 2, confirming that innovative firms' default probabilities could become even lower if their headquarters' states provide R&D tax credits. These findings suggest that firms leading in technology competition significantly benefit from the introduction of state-level R&D tax credits because such firms enjoy lower R&D costs that, in turn, help firms create more patents.

On the other hand, the coefficient β_1 of $R\&D_{i,t} \times I(StateR\&Dcredit_{k,t})$ is statistically insignificant, and the coefficient β_2 of $I(StateR\&Dcredit_{k,t})$ is significantly positive. Our explanation for these seemingly counter-intuitive coefficients is that state-level R&D tax credits also intensify local technology competition; in other words, as more firms are encouraged to invest in

Table 4
Default probability and innovation performance — difference-in-differences tests based on exogenous R&D tax credits.
We estimate the following model using pooled OLS regressions: $Default_{i,t} = \alpha + \beta_0\, Innovation_{i,t} \times I(StateR\&Dcredit)_{k,t} + \beta_1\, R\&D_{i,t} \times I(StateR\&Dcredit)_{k,t} + \beta_2\, I(StateR\&Dcredit)_{k,t} + \beta_3\, Innovation_{i,t} + \beta_4\, R\&D_{i,t} + \beta_5\, Default_{i,t-1} + \beta_6\, Market/Book_{i,t} + \beta_7\, Debt/Asset_{i,t} + \beta_8\, Profit_{i,t} + \beta_9\, Coverage_{i,t} + \beta_{10}\, Asset_{i,t} + \beta_{11}\, ROA_{i,t} + \beta_{12}\, Loss_{i,t} + \beta_{13}\, Beta_{i,t} + \beta_{14}\, IdioVol_{i,t} + Industry_j + Year_t + e_{i,t}$. $Default_{i,t}$ denotes the industry-adjusted default probability of firm *i* in industry *j* in state *k* in year *t* (i.e., the firm's default probability minus the average of all firms' default probability in the same two-digit SIC industry). $I(StateR\&Dcredit)_{k,t}$ is an indicator variable that equals one if the sample firm's headquarters state has started offering any state-level R&D tax credit in year *t*, and zero otherwise. $Innovation_{i,t}$ denotes firm *i*'s innovation quantity (measured with patent counts), impact (measured with citations), generality scores, and originality scores, normalized by total assets in year *t*, minus the corresponding industry average in the same year. $R\&D_{i,t}$ denotes firm *i*'s annual R&D expenses, normalized by total assets in year *t*, minus the industry average in the same year. The following control variables are included in regressions: lagged default probability ($Default_{i,t-1}$), firm *i*'s market equity to book equity ratio ($Market/Book_{i,t}$), debt-to-asset ratio ($Debt/Asset_{i,t}$), profit margin ($Profit_{i,t}$), coverage ratio (i.e., income before interest expenses over interest expenses) ($Coverage_{i,t}$), total assets in logarithm ($Asset_{i,t}$), return on assets ($ROA_{i,t}$), loss dummy that equals one if the firm reports a loss (and zero otherwise) ($Loss_{i,t}$), market beta ($Beta_{i,t}$), idiosyncratic return volatility ($IdioVol_{i,t}$), industry dummy variables ($Industry_j$), and year dummy variables ($Year_t$). All control variables have been defined in Table 1 and are industry-adjusted measures (except industry and year dummies). *t*-Statistics reported in parentheses are based on two-way clustered standard errors by firms and years. The sample period is 1976–2006. *, **, and *** denote significance levels at 10%, 5%, and 1%, respectively.

	(1)	(2)	(3)	(4)
Innovation =	Quantity	Impact	Generality	Originality
Innovation	−0.052**	−0.001*	−0.121**	−0.072***
× I(State R&D credit)	(−2.03)	(−1.65)	(−2.07)	(−2.87)
R&D	0.001	0.001	−0.003	−0.003
× I(State R&D credit)	(0.30)	(0.06)	(−0.35)	(−0.36)
I(State R&D credit)	0.012***	0.012***	0.009*	0.010**
	(3.40)	(3.38)	(1.83)	(1.99)
Innovation	−0.082***	−0.001**	−0.129***	−0.119***
	(−5.55)	(−2.45)	(−2.69)	(−3.06)
R&D	−0.117***	−0.024**	−0.100**	−0.102***
	(−5.25)	(−2.14)	(−2.48)	(−2.62)
Default (lagged)	0.529***	0.532***	0.551***	0.554***
	(33.13)	(34.24)	(17.93)	(19.50)
Market/Book	−0.000***	−0.000	0.000	0.000
	(−3.38)	(−1.09)	(0.15)	(0.01)
Debt/Asset	0.206***	0.207***	0.191***	0.180***
	(10.24)	(10.33)	(5.95)	(6.18)
Profit	0.000	0.000	0.000	0.000
	(1.23)	(1.31)	(0.95)	(0.71)
Coverage	−0.000**	−0.000**	0.000	0.000
	(−2.23)	(−2.51)	(0.15)	(0.20)
Asset	0.015***	0.016***	0.015***	0.016***
	(6.96)	(7.17)	(4.68)	(5.02)
ROA	−0.027***	−0.010*	−0.036**	−0.034**
	(−3.49)	(−1.84)	(−2.27)	(−2.04)
Loss	0.026***	0.026***	0.030***	0.026***
	(3.83)	(3.89)	(4.93)	(5.26)
Beta	−0.022***	−0.023***	−0.021***	−0.021***
	(−6.01)	(−6.25)	(−4.35)	(−4.67)
IdioVol	0.124***	0.125***	0.125***	0.122***
	(9.02)	(9.28)	(4.57)	(4.98)
Constant	0.009	−0.138	−0.297***	−0.280***
	(0.00)	(0.00)	(−36.63)	(−24.67)
R^2	0.555	0.554	0.540	0.540
Observation	42,552	42,552	11,363	12,070

R&D, all firms experience greater pressure to innovate, which increases the uncertainty of an average firm's innovation inputs. We argue that state-level R&D tax credits benefit technology winners (i.e., significantly negative β_0), but cause severe competition that lowers an average firm's survival likelihood (i.e., significantly positive β_2). Following this argument, the insignificant coefficient β_1 of $R\&D_{i,t} \times I(StateR\&Dcredit_{k,t})$ confirms the limitation of using R&D expense to assess innovation in bond pricing.

Columns (3) and (4) of Table 4 show that the estimates of β_0 are −0.121 and −0.072 with *t*-statistics of −2.07 and −2.87, respectively. These estimates suggest that, with state-level R&D tax credits, firms with stronger patent portfolios—those patents that can be applied to broader areas and that are based on broader knowledge domains—are much less likely to default. If a firm is located in a state offering R&D tax credits, then a one-standard-deviation increase in its patent generality (originality) decreases its default probability by an additional 0.79% (1.21%), or an additional 3.21% (4.92%) of the sample mean and 46.26% (71.39%) of the sample median of default probability.

Overall, Table 4 suggests a more pronounced patent-creditworthiness relation in states that provide R&D tax credits. This finding further supports our interpretation of innovation's positive effect on corporate creditworthiness, as state-level R&D tax credits affect creditworthiness most likely only through corporate innovation activities.

4. Innovation performance and bond pricing

4.1. Innovation performance and bond pricing in the primary market

To examine how outside investors price innovation performance, we use two proxies: yields on newly-issued bonds in the primary market serve as an *ex ante* proxy of risk premiums, while excess returns on traded bonds in the secondary market serve as an *ex post* proxy of risk premiums.

To test Hypothesis 2 in the primary market, we specify the following model:

$$\begin{aligned} Premium_{k,t} = \alpha &+ \beta_1 Innovation_{i,t} + \beta_2 R\&D_{i,t} + \beta_3 Market/Book_{i,t} + \beta_4 Debt/Asset_{i,t} \\ &+ \beta_5 Profit_{i,t} + \beta_6 Coverage_{i,t} + \beta_7 Asset_{i,t} + \beta_8 Issue_{k,t} + \beta_9 Moody_{k,t} \\ &+ \beta_{10} Maturity_{k,t} + \beta_{11} Call_{k,t} + \beta_{12} Convertible_{k,t} + Industry_j + Year_t + e_{i,t}. \end{aligned} \tag{3}$$

The dependent variable, $Premium_{k,t}$, is the industry-adjusted premium of newly-issued bond k in year t and is expressed in percentage (i.e., bond k's premium in year t minus the average premium of all bonds issued by firms in industry j, defined by two-digit SIC codes in year t). The risk premium of a newly-issued bond is computed as each newly-issued bond's yield to maturity minus the Treasury bond's benchmark yield (based on a linear interpolation method that uses the yields of the two adjacent treasury bonds with maturities closest to the bond's maturity). We exclude all bonds with a time to maturity of less than one year.

The explanatory variable of interest in Eq. (3) is $Innovation_{i,t}$, which denotes firm i's innovation performance in patent quantity, impact, generality, or originality in year t. We also include in Eq. (3) R&D input ($R\&D_{i,t}$). Based on the extant literature, we also include

Table 5
Premiums on bond issues and innovation performance.
We estimate the following model using pooled OLS regressions: $Premium_{k,t} = \alpha + \beta_1 Innovation_{i,t} + \beta_2 R\&D_{i,t} + \beta_3 Market/Book_{i,t} + \beta_4 Debt/Asset_{i,t} + \beta_5 Profit_{i,t} + \beta_6 Coverage_{i,t} + \beta_7 Asset_{i,t} + \beta_8 Issue_{k,t} + \beta_9 Moody_{k,t} + \beta_{10} Maturity_{k,t} + \beta_{11} Call_{k,t} + \beta_{12} Convertible_{k,t} + Industry_j + Year_t + e_{i,t}$. $Premium_{k,t}$ denotes the industry-adjusted premium of new bond k issued by firm i in industry j in year t (i.e., the bond's yield in excess of corresponding T-bill yields minus the average of all bonds' yields in excess of corresponding T-bond yields in the same two-digit SIC industry) and is expressed in percentages. $Innovation_{i,t}$ denotes firm i's innovation quantity (measured with patent counts), impact (measured with citations), generality scores, and originality scores, normalized by total assets in year t, minus the corresponding industry average in the same year. $R\&D_{i,t}$ denotes issuing firm i's annual R&D expenses, normalized by total assets in year t, minus the industry average in the same year. The following control variables are included in regressions: firm i's market equity to book equity ratio ($Market/Book_{i,t}$), firm i's debt-to-asset ratio ($Debt/Asset_{i,t}$), firm i's profit margin ($Profit_{i,t}$), firm i's coverage ratio ($Coverage_{i,t}$), firm i's total assets in logarithm ($Asset_{i,t}$), bond i's size of the bond issuance ($Issue_{k,t}$), bond i's bond rating ($Moody_{k,t}$), bond i's years to maturity ($Maturity_{k,t}$), bond i's years to first call ($Call_{k,t}$), and bond i's convertible dummy ($Convertible_{k,t}$). $Industry_j$ denotes industry dummy variables, and $Year_t$ denotes year dummy variables. All control variables have been defined in Table 1 and are industry-adjusted measures (except industry and year dummies). t-Statistics reported in parentheses are based on two-way clustered standard errors by industries and years. The sample period is 1976–2006. *, **, and *** denote significance levels at 10%, 5%, and 1%, respectively.

	(1)	(2)	(3)	(4)
Innovation =	Quantity	Impact	Generality	Originality
Innovation	−9.616***	−0.477***	−29.124***	−29.490***
	(−2.92)	(−2.60)	(−3.23)	(−3.80)
R&D	−2.799*	−2.556*	1.144	1.191
	(−1.75)	(−1.66)	(0.48)	(0.52)
Market/Book	0.001	0.001	−0.002	−0.003
	(0.75)	(0.75)	(−0.17)	(−0.25)
Debt/Asset	0.370	0.368	0.188	0.247
	(0.39)	(0.39)	(0.77)	(1.04)
Profit	0.011	0.012	−0.037	−0.045***
	(0.44)	(0.49)	(−0.83)	(−3.33)
Coverage	−0.001***	−0.001***	−0.001***	−0.001***
	(−5.83)	(−5.71)	(−9.34)	(−14.76)
Asset	−0.288***	−0.287***	−0.168***	−0.176***
	(−5.25)	(−5.19)	(−2.67)	(−3.11)
Issue	0.131***	0.132***	0.064	0.075*
	(2.72)	(2.73)	(1.55)	(1.70)
Moody	0.843***	0.847***	0.807***	0.806***
	(9.01)	(9.05)	(7.12)	(7.19)
Maturity	−0.096	−0.100	−0.024	−0.037
	(−1.17)	(−1.23)	(−0.28)	(−0.44)
Call	0.002	0.002	0.009**	0.009**
	(0.29)	(0.47)	(2.06)	(2.32)
Convertible	−2.841***	−2.837***	−3.158***	−3.289***
	(−6.22)	(−6.25)	(−9.45)	(−10.40)
Constant	2.731***	2.681***	1.948	1.302***
	(6.20)	(6.24)	(1.43)	(3.69)
R^2	0.338	0.338	0.385	0.400
Observation	2548	2548	1382	1408

these control variables to explain bond premiums (the detailed definitions are provided in Table 1): issuing firm's market-to-book ratio ($Market/Book_{i,t}$); debt-to-asset ratio ($Debt/Asset_{i,t}$); profit margin ($Profit_{i,t}$); coverage ratio ($Coverage_{i,t}$); total assets in logarithm ($Asset_{i,t}$); the issued bond's size ($Issue_{k,t}$); Moody's bond ratings of Aaa, Aa, A, Baa, and Ba and below represented by integer values 1, 2, 3, 4, and 5, respectively ($Moody_{k,t}$); year-to-maturity in logarithm ($Maturity_{k,t}$); years to first call ($Call_{k,t}$); a dummy variable ($Convertible_{k,t}$) equal to one if the bond is convertible, and zero otherwise; industry dummy variables ($Industry_j$); and year dummy variables ($Year_t$) (Blume et al., 1998; Eberhart et al., 2008; Kaplan and Urwitz, 1979; Shi, 2003). We adjust all control variables (except dummy variables) for industry averages in the same year.

In Table 5, we estimate Eq. (3) using panel regressions for the unbalanced panel data, adjusted for standard errors clustered by industries and years.[24] In Columns (1) and (2), the coefficients on patent quantity and impact are −9.616, and −0.477 with t-statistics of −2.92 and −2.60, respectively. In terms of economic significance, the results suggest that a one-standard-deviation increase in a firm's patent quantity (impact) decreases its cost of debt by 92 (181) basis points, respectively.[25] In Columns (3) and (4), the coefficients on patent generality and originality are −29.124 and −29.490 with t-statistics of −3.23 and −3.80, respectively. Again, in terms of economic significance, the results suggest that a one-standard-deviation increase in a firm's patent generality (originality) decreases its bond premiums by 189 (497) basis points, respectively. These results suggest that innovation activities can have a significant economic impact on firms' debt financing costs. More specifically, these estimates suggest that firms with more and higher-quality patents than those of their competitors are less risky to bondholders because their market positions and cash flows are more secured. In addition, firms with patents that can be applied to broader areas and that are based on broader knowledge domains are also less risky to bondholders because their patent portfolios are associated with higher fundamental merit and better risk diversification.

The estimated coefficients for the control variables are largely consistent with those reported in the literature: the issuing firm's debt-to-asset ratio, the issued bond's size, Moody's bond ratings, and years to first call are all positively correlated with bond premiums, while the issuing firm's coverage ratio, total assets, time to maturity, and the issued bond's convertibility are negatively correlated with bond premiums. Also, the coefficients on R&D are negative and marginally significant in Columns (1) and (2), but are positive yet insignificant in Columns (3) and (4).[26]

In summary, Table 5 suggests that bond investors require significantly lower premiums for firms that outperform their rivals with respect to innovation; this finding supports Hypothesis 2 and the notion that better innovation performance reduces firms' costs of debt financing.

4.2. Innovation performance and bond pricing in the secondary market

To test Hypothesis 2 in the secondary market, we specify the following model:

$$\begin{aligned} Return_{k,t} = {} & \alpha + \beta_1 Innovation_{i,t} + \beta_2 R\&D_{i,t} + \beta_3 Return_{i,t-1} + \beta_4 Market/Book_{i,t-1} \\ & + \beta_5 Debt/Asset_{i,t} + \beta_6 Profit_{i,t} + \beta_7 Coverage_{i,t} + \beta_8 Asset_{i,t} + \beta_9 Moody_{k,t} \\ & + Industry_j + Year_t + e_{i,t}. \end{aligned} \tag{4}$$

The detailed definitions of all variables are provided in Table 1. The dependent variable, $Return_{k,t}$, is the industry-adjusted excess return on bond k in year t (i.e., bond k's excess return in year t minus the average excess return of all bonds issued by firms in industry j, defined by two-digit SIC codes in year t).[27] Excess bond returns reflect issuers' time-varying innovation performance, among other characteristics, from a dynamic perspective.

We note that excess returns on traded bonds can serve as an *ex post* proxy of risk premiums because the USPTO has disclosed patent application information since 2001, and firms often voluntarily disclose information on their pending patent applications after 18 months of application dates.[28] Fleming and Remolona (1999) and Balduzzi et al. (2001) show that bond markets are highly efficient in incorporating new information. Since a patent is usually granted about two to three years after its application date (Hall et al., 2005a), bond markets should have already impounded most of the information about a bond issuer's disclosed pending patent

[24] We refrain from clustering standard errors by firms because most firms do not issue bonds frequently.

[25] Our dependent variable, bond premiums, is expressed in percentage.

[26] This inconsistency may be attributed to several reasons. First, the sample size for the patent generality and originality tests is only half of that for the patent quantity and impact tests. Second, industry adjustment may weaken R&D's explanatory ability, for—given the same R&D input—some firms may be more efficient in generating intangible assets than others in the same industry. Third, including all industries in our sample may also weaken the R&D effect because costs for innovation significantly vary across industries. Lastly, patent-based generality and originality measures may simply overshadow R&D measures in explaining bond premiums.

[27] For each bond k, we calculate its return in year t as follows:

$$Return_{k,t} = \frac{P_{k,t} + C_k + AI_{k,t}}{P_{k,t-1} + AI_{k,t-1}} - 1,$$

in which $P_{k,t}$ is the clean price of bond k at the end of year t, is the annual coupon rate, and is the accrued interest accumulated in year t from the last coupon payment. We then calculate the excess bond return on bond k in year t by subtracting the market yield on treasury securities with a 1-year constant maturity from bond k's returns in year t.

[28] Patent application information is disclosed in the Application Full-text Database (AppFT) of the USPTO: http://patft.uspto.gov/.

applications in bond prices. For an innovative firm, outside bond investors use records disclosed by the USPTO to track that firm's patent application and, in turn, gradually raise its bond price until the price reaches a fair value based on intellectual properties. As a result, the release of patent application information results in *higher* bond prices when patents are finally granted as well as *lower* returns afterward. Therefore, realized bond excess returns corresponding to the grant years of patents used in our tests serve as an *ex post* proxy for expected premiums on innovation-related risk.

The main explanatory variables for Eq. (4) are one of firm *i*'s innovation measures (e.g., quantity, impact, generality, and originality) and firm i's R&D measures ($R\&D_{i,t}$), both industry-adjusted. Lagged excess return is included in the model as an explanatory variable to mitigate endogeneity issues, such as omitted firm-level variables or reverse causality. Other variables are defined earlier.[29] As with all tests, we adjust firm-level and issue-level variables by their industry averages to help us analyze the relation between innovation performance and bond returns.

In Table 6, we show how innovation is priced in the secondary bond market. We estimate Eq. (4) using pooled regressions and compute the *t*-statistics using standard errors clustered by bonds due to the short data panel (i.e., the corporate bond coverage on TRACE is from 2002 to 2006). Columns (1) and (2) show that patent quantity and impact are negatively correlated with excess returns on corporate bonds. The coefficients on patent counts and impact are −1.501 and −0.184 with *t*-statistics of −3.16 and −3.33, respectively. In terms of economic significance, a one-standard-deviation increase in a firm's patent counts and impact is associated with a decrease in excess bond returns by 14 and 70 basis points, respectively. These findings suggest that bondholders require lower returns on bonds issued by firms whose innovation activities are of larger scale and of greater impact when compared with those of their competitors.

In Columns (3) and (4) of Table 6, the coefficients on patent generality and originality are −13.257 and −2.853 with *t*-statistics of −3.58 and −2.91, respectively. In terms of economic significance, a one-standard-deviation increase in a firm's patent generality and originality decreases the excess returns on its bonds by 86 and 48 basis points, respectively. These relations are economically significant, given that the mean (median) excess bond return is 5.83% (3.73%). These findings suggest that bondholders understand that firms whose innovations can be applied to broader areas or are based on broader knowledge domains are more likely to generate stable cash flows and, thus, require lower returns on bonds issued by such firms.

We find that all coefficients of R&D expenses are insignificant, suggesting that R&D-related information does not provide incremental explanatory power for cross-sectional bond returns, after controlling for patent-based innovation measures and Moody's rating classes. Among other control variables, the debt-to-asset ratio is consistently and negatively correlated with excess returns on traded bonds. The insignificant coefficients of other control variables may be attributed to lower power, due to the small sample size limited by bond return data.

To conclude, Table 6 shows a negative association between firms' innovation performance and bond returns in the secondary market. When firms outperform their competitors in innovation quantity, impact, generality, and originality, they are better positioned in the technology race against their competitors, thereby lowering the expected returns of their bonds. We note that our patent-based measures outperform R&D-based measures in explaining excess returns on traded bonds. Hence, outside investors in the secondary bond market understand the incremental usefulness of patents and adjust their expected returns accordingly.

5. Concluding remarks

In this paper, we investigate whether publicly available patent information is incrementally useful for assessing the benefits and risks of corporate innovation in bond pricing. We propose that a firm's performance with respect to technological innovation relative to its peers positively affects its creditworthiness and, therefore, its bond pricing. Using patent data to measure a firm's innovation in terms of level, impact, generality, and originality, we show that outsiders consider firms that outperform their rivals in the technology race to have lower default risk; these outsiders, then, request lower risk premiums for new bonds issued in the primary market, and request lower returns for publicly traded bonds in the secondary market. Because our results hold after we include extensive control variables and use two identification strategies, we believe that our results are reasonably robust to endogeneity issues and support a causal effect of innovation performance on corporate creditworthiness.

In addition, these findings suggest that firms' patent filings provide multi-dimensional, useful information about their innovation performance beyond what can be inferred from accounting R&D expenses and other financial performance measures. Thus, our analyses highlight the importance of analyzing a firm's patenting activities for bond valuation; in short, outside bond investors benefit from using publicly available patent information to price corporate bonds. Moreover, our findings explain the economic motivation of many institutional investors who closely follow and analyze public companies' patenting activities. For example, *BusinessWeek* began its annual "Most Innovative Companies" ranking in 2005; meanwhile, *Thomson Reuters* announced its annual "Top 100 Global Innovators" starting in 2011, and *Forbes* publishes "The World's Most Innovative Companies" list annually. Finally, our findings have regulatory and public policy implications. Specifically, enhancing the disclosure of key innovation activities and patent portfolios in bond-issuing firms' prospectuses may further mitigate potential information asymmetry and innovation-related adverse selection in the corporate bond market, thereby reducing innovative firms' debt financing costs.

[29] We do not include issue size, years to maturity, years to first call, and convertible dummy in the regression because they are time-invariant characteristics and are known at the time of issuance.

Table 6
Excess returns on traded bonds and innovation performance.
We estimate the following model using pooled OLS regressions: $Return_{k,t} = \alpha + \beta_1\, Innovation_{i,t} + \beta_2\, R\&D_{i,t} + \beta_3\, Return_{i,t\text{-}1} + \beta_4\, Market/Book_{i,t} + \beta_5\, Debt/Asset_{i,t} + \beta_6\, Profit_{i,t} + \beta_7\, Coverage_{i,t} + \beta_8\, Asset_{i,t} + \beta_9\, Moody_{k,t} + Industry_j + Year_t + e_{i,t}$. $Return_{k,t}$ denotes the industry-adjusted premium of traded bond k issued by firm i in industry j in year t (i.e., the bond's return in excess of one-year T-bill returns minus the average of all bonds' returns in excess of one-year T-bond returns in the same two-digit SIC industry). $Innovation_{i,t}$ denotes firm i's innovation quantity (measured with patent counts), impact (measured with citations), generality scores, and originality scores, normalized by total assets in year t, minus the corresponding industry average in the same year. $R\&D_{i,t}$ denotes issuing firm i's annual R&D expenses, normalized by total assets in year t, minus the industry average in the same year. $Return_{i,t\text{-}1}$ denotes the lagged industry-adjusted premium, $Market/Book_{i,t}$ denotes the ratio of the market equity to the book equity of firm i that has traded bond k in year t, $Debt/Asset_{i,t\text{-}1}$ denotes issuing firm i's debt-to-asset ratio, $Profit_{i,t}$ denotes issuing firm i's profit margin, $Coverage_{i,t}$ denotes issuing firm i's coverage ratio (i.e., income before interest expenses over interest expenses), $Asset_{i,t}$ denotes issuing firm i's total assets in logarithm, $Moody_{k,t}$ denotes bond rating (Moody's bond ratings of Aaa, Aa, A, Baa, and Ba and below are presented with integer values 1, 2, 3, 4, and 5, respectively), $Industry_j$ denotes industry dummy variables, $Year_t$ denotes year dummy variables, and $e_{i,t}$ denotes the error term. All control variables have been defined in Table 1 and are industry-adjusted measures (except industry and year dummies). t-Statistics reported in parentheses are clustered by bonds. The sample period is 2002–2006. *, **, and *** denote significance levels at 10%, 5%, and 1%, respectively.

	(1)	(2)	(3)	(4)
Innovation =	Quantity	Impact	Generality	Originality
Innovation	−1.501***	−0.184***	−13.257***	−2.853***
	(−3.16)	(−3.33)	(−3.58)	(−2.91)
R&D	−0.123	−0.116	−0.092	−0.119
	(−1.01)	(−1.04)	(−0.70)	(−0.96)
Return (lagged)	−0.196***	−0.198***	0.072	0.020
	(−4.59)	(−4.68)	(1.46)	(0.46)
Market/Book	0.000	0.000	−0.000	−0.000
	(0.25)	(0.25)	(−0.17)	(−0.66)
Debt/Asset	0.299***	0.300***	0.190***	0.177***
	(5.56)	(5.58)	(3.28)	(3.55)
Profit	−0.000	−0.000	0.000	0.000
	(−0.61)	(−0.97)	(1.25)	(0.81)
Coverage	0.000	0.000	0.000	0.000
	(0.36)	(0.61)	(0.76)	(0.69)
Asset	0.009**	0.009**	−0.001	−0.001
	(2.50)	(2.56)	(−0.32)	(−0.34)
Moody	−0.028**	−0.027**	−0.000	−0.016
	(−2.28)	(−2.15)	(−0.00)	(−1.28)
Constant	0.100	0.093	−0.034	0.158**
	(1.64)	(1.52)	(−0.75)	(2.42)
R^2	0.160	0.164	0.176	0.151
Observation	1433	1433	730	929

References

Aghion, P., Van Reenen, J.V., Zingales, L., 2013. Innovation and institutional ownership. Am. Econ. Rev. 103, 277–304.
Alcácer, J., Chung, W., 2007. Location strategies and knowledge spillovers. Manag. Sci. 53, 760–776.
Amore, M.D., Schneider, C., Zaldokas, A., 2013. Credit supply and corporate innovation. J. Financ. Econ. 109, 835–855.
Baily, M.N., 1972. Research and development costs and returns: the U.S. pharmaceutical industry. J. Polit. Econ. 80, 70–85.
Balduzzi, P., Elton, E.J., Green, T.C., 2001. Economic news and bond prices: evidence from the U.S. treasury market. J. Financ. Quant. Anal. 36, 523–543.
Barker, V.L., Mueller, G.C., 2002. CEO characteristics and firm R&D spending. Manag. Sci. 48, 782–801.
Bharath, S.T., Shumway, T., 2008. Forecasting default with the Merton distance to default model. Rev. Financ. Stud. 21, 1339–1369.
Black, F., Scholes, M., 1973. The pricing of options and corporate liabilities. J. Polit. Econ. 81, 637–654.
Blume, M.E., Lim, F., Mackinlay, A.C., 1998. The declining credit quality of U.S. corporate debt: Myth or reality? J. Financ. 53, 1389–1413.
Bushee, B., 1998. The influence of institutional investors on myopic R&D investment behavior. Account. Rev. 73, 305–333.
Chan, L.K.C., Lakonishok, J., Sougiannis, T., 2001. The stock market valuation of research and development expenditures. J. Financ. 56, 2431–2456.
Chava, S., Oettl, A., Subramanian, A., Subramanian, K., 2013. Banking deregulation and innovation. J. Financ. Econ. 109, 759–774.
Ciftci, M., Lev, B., Radhakrishnan, S., 2011. Is research and development mispriced or properly risk adjusted? J. Account. Audit. Financ. 26, 81–116.
Cohen, L., Diether, K., Malloy, C., 2013. Misvaluing innovation. Rev. Financ. Stud. 26, 635–666.
Czarnitzki, D., Toole, A.A., 2011. Patent protection, market uncertainty, and R&D investment. Rev. Econ. Stat. 93, 147–159.
Dechow, P.M., Sloan, R.G., 1991. Executive incentives and the horizon problem: an empirical investigation. J. Account. Econ. 14, 51–89.
Deng, Z., Lev, B., Narin, F., 2003. Science and technology as predictors of stock performance. In: Hand, John, Lev, Baruch (Eds.), Intangible Assets: Values, Measures, and Risks. Oxford University Press, New York.
Duchin, R., Ozbas, O., Sensoy, B., 2010. Costly external finance, corporate investment, and the subprime mortgage credit crisis. J. Financ. Econ. 97, 418–435.
Eberhart, A.C., Maxwell, W.F., Siddique, A.R., 2004. An examination of long-term abnormal stock returns and operating performance following R&D increases. J. Financ. 59, 623–650.
Eberhart, A.C., Maxwell, W.F., Siddique, A.R., 2008. A reexamination of the tradeoff between the future benefit and riskiness of R&D increases. J. Account. Res. 46, 27–52.
Eisdorfer, A., Hsu, P.-H., 2011. Innovate to survive: the effect of technology competition on corporate bankruptcy. Financ. Manag. 40, 1087–1117.
Fleming, M.J., Remolona, E.M., 1999. Price formation and liquidity in the U.S. treasury market: the response to public information. J. Financ. 54, 1901–1915.
Francis, B., Hasan, I., Huang, Y., Sharma, Z., 2012. Do banks value innovation? Evidence from U.S. firms. Financ. Manag. 41, 159–185.
Gow, Ian D., Ormazabal, G., Taylor, D.J., 2010. Correcting for cross-sectional and time-series dependence in accounting research. Account. Rev. 85, 483–512.
Griliches, Z., 1984. R&D, Patents, and Productivity. The University of Chicago Press, Chicago, IL.
Griliches, Z., 2000. R&D, Education, and Productivity — a Retrospective. Harvard University Press, Cambridge, MA.
Hall, B.H., 1993. The stock market's valuation of R&D investment in the 1980's. Am. Econ. Rev. 83, 259–264.
Hall, B.H., 2005. Exploring the patent explosion. J. Technol. Transfer. 30, 35–48.
Hall, B.H., Ziedonis, R.H., 2001. The determinants of patenting in the U.S. semiconductor industry, 1980–1994. RAND J. Econ. 32, 101–128.

Hall, B.H., Jaffe, A., Trajtenberg, M., 2005a. The NBER patent citation data file: lessons, insights and methodological tools. In: Jaffe, A., Trajtenberg, M. (Eds.), Patents, Citations and Innovations: A Window on the Knowledge Economy. The MIT Press, Cambridge, MA.
Hall, B.H., Jaffe, A., Trajtenberg, M., 2005b. Market value and patent citations. RAND J. Econ. 36, 16–38.
Hansen, L.P., 1982. Large sample properties of generalized method of moments estimators. Econometrica 50, 1029–1054.
Harhoff, D., Narin, F., Scherer, F.M., Vopel, K., 1999. Citation frequency and the value of patented inventions. Rev. Econ. Stat. 81, 511–515.
Hirshleifer, D., Hsu, P.-H., Li, D., 2013. Innovative efficiency and stock returns. J. Financ. Econ. 107, 632–654.
Hirshleifer, D., Hsu, P.-H., Li, D., 2014. Don't hide your light under a bushel: Innovative originality and stock returns SSRN: http://ssrn.com/abstract=2117516.
Jensen, M.C., 1993. The modern industrial revolution, exit, and the failure of internal control systems. J. Financ. 48, 831–880.
Kaplan, R.S., Urwitz, G., 1979. Statistical models of bond ratings: a methodological inquiry. J. Bus. 52, 231–261.
Kleibergen, F., Paap, R., 2006. Generalized reduced rank tests using the singular value decomposition. J. Econ. 133, 97–126.
Kortum, S., Lerner, J., 1998. Stronger protection or technological revolution: what is behind the recent surge in patenting? Carn.-Roch. Conf. Ser. Public Policy 48, 247–304.
Kothari, S.P., Laguerre, T.E., Leone, A.J., 2002. Capitalization versus expensing: evidence on the uncertainty of future earnings from capital expenditures versus R&D outlays. Rev. Acc. Stud. 7, 355–382.
Lanjouw, J.O., Schankerman, M., 2004. Protecting intellectual property rights: are small firms handicapped? J. Law Econ. 47, 45–74.
Lev, B., 2001. Intangibles: Management, Measurement and Reporting. Brookings Institution Press, Washington, D.C.
Lev, B., Sougiannis, T., 1996. The capitalization, amortization, and value-relevance of R&D. J. Account. Econ. 21, 107–138.
Mann, W., 2014. Creditor rights and innovation: Evidence from patent collateral. Working paper. University of Pennsylvania.
Megna, P., Klock, M., 1993. The impact of intangible capital on Tobin's q in the semiconductor industry. Am. Econ. Rev. Pap. Proc. 83, 265–269.
Merton, R.C., 1974. On the pricing of corporate debt: the risk structure of interest rates. J. Financ. 29, 449–470.
Murphy, K.J., Zimmerman, J.L., 1993. Financial performance surrounding CEO turnover. J. Account. Econ. 16, 273–315.
Newey, W.K., West, K.D., 1987. A simple, positive semi-positive, heteroskedasticity and autocorrelation consistent covariance matrix. Econometrica 55, 703–708.
Noel, M., Schankerman, M., 2013. Strategic patenting and software innovation. J. Ind. Econ. 61, 481–520.
Pandit, S., Wasley, C.E., Zach, T., 2011. The effect of R&D inputs and outputs on the relation between the uncertainty of future operating performance and R&D expenditures. J. Account. Audit. Financ. 26, 121–144.
Petersen, M.A., 2009. Estimating standard errors in finance panel data sets: comparing approaches. Rev. Financ. Stud. 22, 435–480.
Plumlee, M., Xie, Y., Yan, M., Yu, J.J., 2015. Bank loan spread and private information: pending approval patents. Rev. Acc. Stud. 20, 593–638.
Shi, C., 2003. On the trade-off between the future benefits and riskiness of R&D: a bondholders' perspective. J. Account. Econ. 35, 227–254.
Skinner, D.J., 2008. Accounting for intangibles — a critical review of policy recommendations. Account. Bus. Res. 38 (3), 191–204.
Standard and Poor's, 2006. Corporate Rating Criteria 2006.
Trajtenberg, M., 1990. A penny for your quotes: patent citations and the value of innovations. RAND J. Econ. 21, 172–187.
Trajtenberg, M., Henderson, R., Jaffe, A., 1997. University versus corporate patents: a window on the basicness of invention. Econ. Innov. New Technol. 5, 19–50.
Vassalou, M., Xing, Y., 2004. Default risk in equity returns. J. Financ. 59, 831–868.
Wilson, D.J., 2009. Beggar thy neighbor? The in-state, out-of-state, and aggregate effects of R&D tax credits. Rev. Econ. Stat. 91, 431–436.