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Corporate innovative efficiency: Evidence of effects on credit ratings

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ABSTRACT

This study shows that corporate innovation efficiency (IE) as measured by patents filed or cited divided by R&D expenditures improves credit ratings, but this occurs gradually. This gradual response implies that credit rating agencies (CRAs) impose in the near term a higher borrowing cost on innovative firms than their performance and risk characteristics would justify. We predict and confirm that the gradual improvement of credit ratings in response to IE is amplified for firms with more downside risk, with more financial constraints, and with increased sales or cash flows in the years following the IE. These results suggest a predictable response of CRAs to contemporaneous IE information based on economic factors relevant to credit analysis rather than a response based on CRAs' inefficient or biased use of innovation information.

1. Introduction

We examine the response of ratings by credit rating agencies (CRAs) to innovation efficiency (IE) information. This is an important topic for corporate finance for several reasons. First, the efficiency with which a firm manages its research and development (R&D) critically affects its performance in the long run. Most research, however, has focused on equity market relations (Deng et al., 1999; Gu, 2005; Cohen et al., 2013; Hirshleifer et al., 2013). Second, the few studies that examine how innovation relates to credit markets primarily use count measures of innovation (Czarnitzki and Kraft, 2004; Hall, 2010; Amore et al., 2013; Frey, 2013; Hsu et al., 2015). Higher patent or citation counts may not improve a firm's credit standing because they do not consider the resources used to generate the innovation. Third, potentially most important, the prior studies of credit ratings and innovation do not advance economic reasons or channels relevant to credit analysis to explain *why* and *when* CRA ratings might respond to information about corporate innovation.

We also focus on CRA ratings because the U.S. shift to a knowledge-based economy means that a firm's creditworthiness increasingly depends on the success of its R&D investments and intangible assets.[1] This shift represents a challenge to the credit rating process, however, because today's financial statements offer less information about firms' assets than before, as increasing amounts of R&D investments and intangible assets are written off as incurred (Kahle and Stulz, 2017), and because IE represents non-financial or

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[1] For instance, 21% of U.S.-originated secured syndicated loans were collateralized in part by intangibles over the 1996–2005 period, with intangible asset collateralization increasing significantly over this period (Loumioti, 2014; Mann, 2017).

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soft information, whose relation to credit ratings is not well understood. Compared to market-based measures of the cost of credit, CRA ratings are also a stable and more permanent measure (Cantor and Mann, 2003), having real effects on asset prices.[2]

We follow Hirshleifer et al. (2013) and use the ratio of the number of a firm's patent filings or patent citations divided by its R&D expenditures as our measures of IE.[3] These measures represent a firm's ability to translate corporate resource inputs (i.e., R&D expenditures) into innovative outputs (i.e., patents and patent citations). Following Hall et al. (2005) and others, we view patent filings as representing the *quantity* of innovative output and citations per patent as representing the *quality* of innovative output (by capturing the technical importance of a firm's patents). Patent filings and citations offer a comprehensive source of intelligence about protected corporate innovation, which is mainly introduced into the financial markets in the form of patent applications and approvals publicly filed with a patent and trademark office.

Why should CRAs care about innovative efficiency? As predicted in theory (Cochrane, 1991, 1996; Berk et al., 2004; Liu et al., 2009) and confirmed empirically (Kothari et al., 2002; Chambers et al., 2002; Ho et al., 2004), innovation invariably involves a greater degree of risk-taking. While IE reflects the outcomes of firms' innovation activities, there is still much uncertainty about whether and when IE translates into financial success (Cohen et al., 2013). Equity holders normally value this risk positively, which increases their call option value. But debt holders may not because of their asymmetric payoffs on a firm's net assets (Myers and Majluf, 1984). From debt holders' perspective, IE may also signify wealth transfer to shareholders. Supporting this view, Standard and Poor's (2013) indicates that it considers product innovation as an industry risk factor. Additionally, even though higher IE (i.e., a greater number of patents per R&D expenditure) may increase net asset value, the tradable value of IE investments, which are mostly intangible assets, in the event of bankruptcy could be less than the value of the firm's tangible assets such as property, plant, and equipment. Thus, higher IE, at least initially, could result in higher downside risk and lower credit ratings.

However, because innovation-efficient firms generate both upside and downside risk, it is the former that better protects credit investors from adverse events through increased future cash flow, thus improving the credit ratings of those firms. Higher levels of patents and citations can also be viewed as removing some of the uncertainty of R&D and, hence, providing a clearer picture of the potential future cash flows for creditors. Successful and efficient innovation, moreover, should eventually improve credit ratings through direct financial measures such as higher cash flow, higher interest coverage, and lower leverage. Thus, higher levels of IE could result in lower downside risk and improved credit ratings.[4]

Whether IE improves or lowers credit ratings does not, however, address the *timing* of CRAs' response to IE. On the one hand, CRAs are sophisticated information intermediaries with access to nonpublic information (Ederington and Yawitz, 1987; Standard and Poor's, 2013) and with extensive resources to access and analyze that information to isolate the more permanent changes in credit risk. CRAs may respond promptly to soft information such as "industry prospects for growth and vulnerability to technological change" (Standard & Poor's, www.spratings.com; Moody's, www.moodys.com). CRAs have also been shown to respond promptly to soft GAAP information and qualitative disclosures in financial statements (Kraft, 2015; Bozanic and Kraft, 2017). So, on balance, we might expect a prompt adjustment of credit ratings to IE information. On the other hand, CRAs have asymmetrical interests in firm-specific information (Fischer and Verrecchia, 1997; Plummer and Tse, 1999) and may focus more on downside risk information. With less certainty about the upside potential of high or increasing IE and, relatedly, less interest in the analysis of soft (non-GAAP) information, CRAs may respond gradually to that information. Consistent with this view but in the context of equity markets, Deng et al. (1999), Gu (2005), Cohen et al. (2013), and Hirshleifer et al. (2013) find positive future excess stock returns for firms with high innovation potential, suggesting that equity investors initially ignore firms' past records of innovation. Those studies, however, do not focus on how and why IE might relate to credit ratings in public debt markets.

Our contention is that credit ratings respond gradually to IE primarily through at least three channels. First, if CRAs initially view innovation activity as a sign of higher downside risk (Fischer and Verrecchia, 1997; Plummer and Tse, 1999), this means that it is less critical that they respond positively and promptly to IE information. With less focus on the upside of IE, CRAs' response to IE will be gradual.[5] Second, firms with more financial constraints may be viewed as subject to more managerial or outside discipline, which means they should spend their R&D dollars more wisely. CRAs will recognize that such firms can generate higher IE productivity. Third, CRAs will adjust gradually to IE to maintain their reputation by waiting for future sales or cash flows to confirm the innovation's longer-term financial success. By waiting, a rating agency avoids the loss of reputation that could have occurred if it had responded favorably to the IE information and been wrong. The prior literature supports this view by modeling rating agencies'

[2] CRAs recognized as NRSROs (nationally recognized statistical rating organizations) play a critical role in prudential securities regulation (Bullard, 2016).

[3] Jensen and Webster (2009, p. 262) show that innovative firms make extensive use of patents to protect their intellectual property, especially for product innovations that expose them to imitation by existing or future rivals.

[4] U.S. firms have become increasingly interested in the protection of knowledge through the use of patent legislation (e.g., the establishment of the Court of Appeals for the Federal Circuit 1982; the Hatch-Waxman Act 1984) and patent litigation (e.g., the Texas Instruments 1985 and Kodak–Polaroid 1986 litigation) (Hall and Ziedonis, 2001; and Hall, 2005). For example, legislation and the courts have allowed firms to patent items such as genetically modified organisms, software, and business methods. Patents and citations constitute a unique and comprehensive information source of corporate competitive intelligence. Governmental agencies collect and report the patent-related data using agreed-upon quality standards, and firms such as Thomson Data Analyzer and Derwent Innovations provide important add-on services for professionals and investors on patent and citation information. According to the European Patent Office (www.epo.org), about 80% of worldwide scientific and technical information comes from patents.

[5] For example, while most firms that default within one year of the original rating have speculative-grade ratings, by comparison, only eight firms with bonds initially rated as AAA defaulted over the 1981–2014 period (Standard and Poor's, 2015, p. 36).

timing choice as a trade-off between the loss of reputation from making a prompt rating adjustment that turns out to be incorrect and the loss of reputation from making a gradual adjustment that is costly to the rated firm and inconsistent with credit risk based on market pricing (Covitz and Harrison, 2003; Mathis et al., 2009; White, 2010).[6]

These channels are important in that they challenge the view that CRAs' gradual adjustment to IE information can be explained by their inefficient or biased use of that information. Supporting this view, Cohen et al. (2013) and Hirshleifer et al. (2013) conclude that the lagged relation between IE and equity returns is driven largely by equity investors' attention bias or inefficiency in pricing the implications of IE. We suggest otherwise, that the adjustment of CRAs to IE information is predictable and based on economic considerations. It is predictable that CRAs' gradual response to IE would relate to their initial concerns about downside risk; to firms' constraints on their use of excess cash; and to how IE is reflected in firms' future financial performance.

Using a maximum sample of 7965 firm-years with published patent applications and patent citations during 1985 to 2010, we first establish that firms with higher IE experience improved credit ratings, but this occurs with a lag. This lagged response suggests that in the short-term CRAs may impose lower ratings on innovative firms than their performance and risk characteristics would justify. Our tests show that if IE were reflected one year earlier in firms' future credit ratings, the average spread on the rated debt for our sample would drop by 34 basis points. Second, we find that the gradual improvement of credit ratings in response to IE can be explained by three key channels: the relation is more evident and positive (i) for firms closer to default, consistent with agencies' more immediate concern for downside risk, (ii) for more financially-constrained firms, consistent with the Jensen (1986) free cash flow argument, and (iii) for firms with a faster response of future sales or cash flows to IE, consistent with CRAs' focus on reputation. We further explain credit agencies' gradual response by showing that the relation between IE and future credit rating is amplified for firms with higher quality financial information.

We conduct several robustness tests. First, we adjust for truncation bias that can occur with patent and citation datasets (Lerner and Seru, 2017; Dass et al., 2015). One bias relates to the passage of time from patent filing to grant date (about two years on average), which means that some patent filings before a future credit rating may not have been granted in the filing year. To adjust for this bias, we adjust patent counts using the “weight factors” computed from the application-grant empirical distribution (Hall et al., 2001). Another bias relates to citation counts, in that while patents receive citations over long periods, we only observe citations received prior to a future credit rating. We correct for this bias by estimating the shape of the citation-lag distribution (Hall et al., 2001). We find qualitatively identical results based on these two adjustments. Second, we acknowledge the potential for endogeneity in the data relations by using a two-stage regression model with instrumental variables related to the endogenously chosen innovation-related policies. Our results hold under this test. Third, we employ a proportional hazard model to address a potential survivorship bias that could occur if credit ratings have a gradual reaction to IE because of firms that survived for *n* years into the future. The hazard model does not indicate that survivorship bias explains our main result of a gradual response of credit ratings to IE. Fourth, we test for a possible spurious correlation that can occur in regressions of future credit rating on IE from the persistency of IE over time. We find qualitatively identical results when we run the regressions in differences and when we follow the approach in Amihud and Hurvich (2004) and incorporate a model of IE persistency in the regressions. Our key findings hold under several other robustness tests as well.

Taken together, our results contribute to the literature on the relation between corporate innovation and credit quality in two ways. First, we show that firms with higher IE experience improved future credit ratings, but this occurs gradually. Second, we identify three key channels through which this response occurs. We show that CRAs' concern for downside risk, constraints on the ability to spend excess cash, and the extent to which future sales and cash flows respond to IE all help explain credit agencies' gradual response to IE. Understanding rating agencies' response to IE is important for corporate finance because it can influence price discovery in asset markets, in that investors trade on expectations and announcements of CRA rating changes (Holthausen and Leftwich, 1986; Hand et al., 1992) presumably conditional in part on IE.[7]

2. Literature and hypothesis development

Encouraged by access to datasets on patents and citations, considerable research has been conducted on the effects of innovation at the firm level. Much of this evaluates different measures of innovation and tests whether innovation associates with firm value, future growth, or other indicators of success (Pakes, 1985; Harhoff et al., 1999; Hall et al., 2001; Berk et al., 2004; Hall, 2005). As background, these studies establish the sufficiency of firm innovation measures based on patents and citations to proxy for firms' innovative output (Griliches, 1990; Jensen and Webster, 2009). Other work associates measures of innovation with the characteristics of the groups involved, such as inventors (Jaffe et al., 2000), firms (Bound et al., 1982), managers (Coles et al., 2006; Lerner and Wulf, 2007; Faurel et al., 2014), financiers (Hall, 2010), institutions (Aghion et al., 2013), financial analysts (He and Tian, 2013), and bank regulators (Amore et al., 2013).

Notwithstanding this literature and a small number of related studies (see note 11 below), researchers have paid little attention to

[6] In keeping with CRAs' concern for reputation, they also focus on permanent changes in credit risk, which add informational value, as CRA rating changes tend to be more stable and less disruptive to capital market decision making than assessed ratings based on market-based variables (Gredil et al., 2017).

[7] S&P, for example, offers advance public access to its rating announcements to subscribers through RatingsXpress and S&P Capital IQ. Advance public access is also available through Selerity, Inc., whose clients comprise hedge funds, large banks, and proprietary trading platforms (Bullard, 2016).

the effects of IE on credit ratings. One reason relates to firms' limited use of debt to finance innovation. Lenders may have less interest in financing innovation that mostly creates intangible assets, as such assets may offer little protection as collateral in the event of default (Hall, 2010; Brown et al., 2013). External financing may also be more expensive, because equity investors often have more information about (and may own the rights to) innovation as insiders. A third possible reason for lack of research attention is that credit agencies generally have more interest in downside risk. This means that non-financial measures relating to innovation and the potential payoff from successful innovative activity may have less immediate relevance. Successful and efficient innovation, however, should eventually improve credit ratings through direct measures such as increased future cash flow, higher interest coverage, and lower leverage. Accordingly, we predict that firms with higher levels of IE will experience improved credit ratings. These firms produce more innovation benefit in relation to innovation cost, as proxied by prior R&D expenditures. This leads to our first hypothesis, stated in the alternative form, as follows.

H1. Innovative efficiency varies positively with firms' credit ratings.[8]

This hypothesis does not, however, state the timing of the relation, that is, whether IE varies positively with past, present, or future credit ratings. If credit agencies were to fully anticipate IE from prior R&D expenditures and other firm characteristics, then one might expect that rating changes would lead IE. However, given the unpredictability of IE (i.e., the innovative output per dollar of prior R&D), questions about the quality of R&D information (discussed below), and the cost of accessing and analyzing contemporaneous IE information, this seems unlikely, despite the analytical resources available to credit agencies. If, by contrast, the rating agencies were to process IE information promptly, we might observe a rapid adjustment of credit ratings to the IE information.[9] Our specific hypothesis would then test whether IE measured at t varies positively with firms' credit rating measured at t. However, given uncertainty about whether and when IE translates into financial success and to capture a possible gradual reaction, we consider a more inclusive hypothesis, namely, that IE measured at t varies positively with credit rating measured at $t + \mathrm{k}$, where $\mathrm{k} > 0$ denotes a future time period. This leads to the following hypothesis, stated in the alternative form.

H1a. Innovative efficiency varies positively with firms' credit ratings in year $t + \mathrm{k}$.

While most models predicting firms' future credit ratings use current financial and stock market variables as predictors,[10] we are unaware of studies or statements by rating agencies that link IE metrics to future ratings.[11] It is possible, though, that rating agencies examine IE metrics but do not reveal how innovation affects the cost of debt due to the proprietary costs their clients face and that, similarly, firms do not divulge their own IE information to the rating agencies for the same reason (Wagenhofer, 1990). Since the rating process is mostly unobservable, we cannot know precisely the underlying reasons for a possible gradual adjustment.[12]

We can, however, at least determine whether the gradual adjustment is predictable and based on economic factors relevant to credit analysis. We contend that the mechanism of gradual adjustment of credit rating to IE occurs and intensifies through at least three channels. The first relates to downside risk. If the IE-future credit rating relation mainly reflects the risks of unsuccessful innovation (i.e., downside risk), then rating agencies will respond more promptly when firms are closer to default. That is, with more focus on downside risk, there is more need for the rating agencies to respond promptly, as the IE itself could suggest additional default risk. Additionally, we may observe a prompter response by agencies for firms closer to default because the threat of bankruptcy may induce these firms to emphasize innovation projects more likely to succeed. Firms closer to default may also suffer from asset substitution problems (Jensen and Meckling, 1976). This suggests that, to the extent that IE indicates firms' focus on intangible investments rather than tangible investments such as property, plant, and equipment, CRAs will, initially, be less tolerant of the longer-term potential of IE for firms with a higher probability of default. Accordingly, we state our second hypothesis in the alternative form as:

[8] We translate end-of-fiscal-year credit rating letters into numerical scores using the S&P Ratings Code, with the highest credit rating (AAA) set to 17 and the lowest credit rating (CCC+ or below) set to 1.

[9] For example, Kliger and Sarig (2000) show that stock prices and related equity instruments react efficiently to rating changes that convey unique information not reflected in prior fundamental information or news announcements. Also, Kraft (2015) and Bozanic and Kraft (2017) show that public credit markets react quickly to qualitative information in financial statements, which are also reflected in credit ratings.

[10] Early studies include Pogue and Soldofsky (1969), West (1970), and Pinches and Mingo (1973).

[11] Almost all prior studies use count measures. Czarnitzki and Kraft (2004), based on a sample of German firms rated by a national agency, find that a patent count measure associates positively with credit ratings one period ahead and negatively for patent counts above a threshold. Frey (2013) studies count measures and finds that increased citations worsen credit ratings for U.S. firms, which is a curious result in that higher citations should increase firm value. Hsu et al. (2015) show that patent count measures relate to corporate bond spread. Amore et al. (2013) and Cornaggia et al. (2015) document that patent counts relate to bank regulation and competition. Additionally, Plumlee et al. (2015) provide evidence on *private* information about counts of borrowers' upcoming patents as a source of lenders' ex-ante information advantage. Our study is also distinguished from Plumlee et al. (2015) in that we examine whether CRAs' incorporate *public* information on patents and citations into their ratings. Except for Hirshleifer et al. (2013), to our knowledge the equity market literature also focuses on count measures rather than efficiency measures of patents or citations. Our study is, thus, distinguished from these studies because we focus on *innovative efficiency* rather than *count* measures in credit analysis. Simply by generating patents without regard to the economic benefits of the expenditure is unlikely to improve a firm's credit standing. We also investigate and explain the timing and direction of a future credit rating response to efficiency measures.

[12] While uncertainty about the future financial success of IE suggests a gradual adjustment, as part of H1a, we also test for a contemporaneous adjustment of credit rating to IE, consistent with CRAs' potential prompt response to the anticipated effects of IE on future firm performance and credit risk.

H2. The positive relation between IE and firms' future credit rating is amplified for firms with a higher probability of default versus those with a lower probability of default.

A second channel to partially explain the gradual adjustment of credit rating to IE is through the presence of financial constraints, whose role should be beneficial for innovation because such constraints reduce the potential for firms to generate high agency costs (e.g., from excess cash flow) by investing in unproductive projects (Jensen, 1986; Kumar and Langberg, 2009; Hall and Lerner, 2010). Using different definitions of financial constraints, Almeida et al. (2013) confirm this prediction, showing that more financially-constrained firms reflect higher IE. They also find that this relation is most consistent with an agency-cost explanation. Almeida et al. (2013), however, do not consider whether and when CRAs might recognize this relation as a reduction in the risks of unsuccessful innovation (i.e., downside risk), which should also associate with a gradual improvement in financially-constrained firms' credit ratings, either as a way to mitigate downside risk or to protect CRA reputation. To shed light on this issue, we examine whether the unconditional relation between IE and future credit rating (our primary hypothesis), differs from the conditional relation, that is, when firms face financial constraints. Given the prior literature supporting the Jensen (1986) excess cash flow proposition, we predict that the positive relation should strengthen. Accordingly, we state a third hypothesis in the alternative form as:

H3. The positive relation between IE and firms' future credit rating is amplified for financially-constrained firms.

A third channel posits that subsequent financial performance helps explain the IE-future credit rating relation. Not all innovative outputs are created equal in terms of their financial success. While some innovative outputs translate quickly into superior financial performance in the near term, others take longer. The rationale is that if IE does not successfully translate into superior financial performance, the market may perceive the earlier rating upgrade as inaccurate or overstated, leading to a loss of CRA reputation. We select future sales revenues and cash flows as two relatively clean measures of financial performance. We then posit that when innovation investments have a greater impact on near-term future financial performance, the positive relation between IE and future credit rating is amplified in the near term; and when innovation impacts more distant financial performance, the positive relation is amplified in the longer term or not at all. Put differently, to protect their reputation, CRAs discount contemporaneous IE and wait until future cash flows or sales confirm that innovative success (Chang et al., 2013). We, thus, state our fourth hypothesis in the alternative form as:

H4. The positive relation between IE and firms' future credit rating is amplified when IE has a greater impact on near-term future sales or cash flows.

We also consider whether the IE-future credit rating relation might be predictable based on the quality of the firm's accounting information available to the CRA at the time of a future ratings adjustment. IE information at t may not contribute well to the assessment of credit rating at $t + \text{k}$ when the accounting information at t is of low quality if the low-quality information obscures perceptions of firms' innovative activity by investors including CRAs as their agents. Several prior studies suggest that accounting quality matters for understanding innovative input. For example, Lev and Sougiannis (1996), Chan et al. (2001), and Ciftci et al. (2011) conclude that investors misprice the implications of R&D expense for firm value; although Chambers et al. (2002) challenge that assumption concluding that the mispricing relates to the improper measurement of firm risk in the research design.[13] However, none of these studies examines the impact of accounting quality on IE.

In addition, high-quality accounting information can lower liquidity risk and facilitate long-term investments in higher-risk, higher return technologies, without requiring individual investors to commit their resources over the long term (Levine, 1997; Bushman and Smith, 2001). Innovatively-efficient firms may, thus, generate higher quality accounting information to reduce the cost of external financing, which further enhances credit ratings, for example, by reducing information asymmetry between innovative firms and the rating agencies (Sengupta, 1998; Ashbaugh-Skaife et al., 2006). Duffie and Lando (2001), moreover, show a direct relation between information quality and credit spread, predicting that firms with perfect financial reports have zero credit spreads as maturity approaches zero, while firms with noisy financial reports have positive credit spreads under the same condition. We apply this theory in the context of patents and patent citations as, initially, innovation information would have uncertain (noisy) implications for firm credit risk and firm value. However, with the official application for patents to the U.S. Patent and Trademark Office (USPTO), which requires a wide range of technical disclosure on patented assets, this uncertainty (noise) decreases, thus benefiting rating agencies' assessments of credit risk. Less noisy accounting information should also enable better access to capital markets, make future growth opportunities from patent-related assets more noticeable, and alleviate the adverse selection and moral hazard problems from debt financing. Accordingly, we state a fifth hypothesis in the alternative form as:

H5. Higher accounting information quality strengthens the positive relation between innovation efficiency and firms' future credit ratings.

[13] Hall (2010) reports that R&D expense accounts for about 50% of expenditure on innovation.

3. Sample and variable definitions

3.1. Sample

We obtain our sample of a maximum of 7965 firm-years by merging four datasets: (i) the most recent version of the patent and citation dataset from the National Bureau of Economic Research (NBER) patent database covering data to 2006,[14] (ii) the dataset in Kogan et al. (2017) covering patents and patent citations issued by the USPTO though November 2010, (iii) annual accounting and financial data from Compustat North America, and (iv) monthly corporate credit rating data from Mergent's Fixed Income Securities Database (FISD) for Academia, specifically, the S&P Domestic Long Term Issuer Credit Rating ("splticrm") (also available in Compustat). The patent datasets contain detailed information on all U.S. patents filed and granted by the USPTO from 1976 to 2010, namely, patent assignee names, firms' Compustat-matched identifiers, the number of citations received by each patent, the number of citations excluding self-citations received by each patent, application dates, grant dates, and the patent's category.[15] We exclude firms with four-digit standard industrial classification (SIC) codes between 6000 and 6999 (i.e., the finance, insurance, and real estate sectors).

Table 1, Panel A, reports the distribution of firms based on the 48 Fama and French (1997) industry categories, which is a classification based on four-digit SIC codes.[16] The table shows that our sample covers a wide range of industries, with high percentages in Electronic Equipment (9.88%), Machinery (9.60%), and Chemicals (9.20%). Panel B of Table 1 shows the distribution of firms by year based on the year of the patent grant date. While the patent and citation data extend to 2010, our data period runs from 1985 to 2015, as we require that the credit rating observations extend five years beyond the latest patent or citation. Panel B of Table 1 shows that we have measures of annual IE and lagged credit ratings for well over 200 firms per year over 1992–2015, with a dip in 2008–2011 arguably traceable to aftermath of the global financial crisis in 2007–2008. Thus, the sample covers a variety of economy-wide conditions and does not unduly cluster in time over the 31-year sample period.

3.2. Definitions of IE proxies

We employ two proxies for IE: the number of patents granted scaled by research and development (R&D) capital (*IEPA*) and the adjusted number of patent citations divided by historical R&D expenses (*IECIT*). Prior studies depreciate R&D expenses over the previous five years for all firms. However, if the innovation process differs across industries, then a one-size-fits-all formula ignores a significant portion of information on the innovation process. We, thus, use industry-level regressions to estimate the coefficients on how fast R&D expenses translate into patents and use these coefficients to construct industry-related R&D depreciation formulas. Specifically, we use empirically derived industry depreciation rates for historical R&D expenditure by regressing the number of patents (citations) in year t on R&D expenditures from year $t-2$ to $t-6$ (from year $t-3$ to $t-7$) in each of the 48 Fama and French (1997) industry categories. We then use these estimated coefficients as a depreciation rate for historical R&D expenditure in years $t-2$ to $t-6$ (in years $t-3$ to $t-7$) for a patent (citation). Our first proxy calculates the ratio of the number of a firm's patents granted in year t (Patents) scaled by its R&D capital based on the previous five-year cumulative R&D expenses starting in year $t-2$:

$$IEPA_t = \text{Patents}_t/(\omega_1\text{R\&D}_{t-2} + \omega_2\text{R\&D}_{t-3} + \omega_3\text{R\&D}_{t-4} + \omega_4\text{R\&D}_{t-5} + \omega_5\text{R\&D}_{t-6}), \quad (1)$$

where Patents_t denotes the number of patents granted to a firm in year t, $\text{R\&D}_{t-n}$ denotes firm R&D expenses (in millions) for the fiscal year ending $t-n$, and $\omega_1 \ldots \omega_5$ represent the industry-specific annual depreciation rates. The use of cumulative R&D expenses as the denominator assumes that R&D spending over the preceding five years starting at $t-6$ contributes increasingly to successful patent applications granted in year t.[17] Our second proxy calculates IE as the adjusted number of patent citations divided by R&D expenses (*IECIT*). The number of citations of a firm's patents may better reflect the technological or economic value of those patents. While, ideally, one might measure each patent's technological or economic value using *all* citations received before or after patent grant date through the end of the sample period, we focus on forward citations (from prior patents over prior years) aligned to year t.[18] Specifically, we define *IECIT* in year t at the firm level as the adjusted number of citations made in year t relating to all of firm i's

[14] Sites.google.com/site/patentdataproject/Home/downloads (data to 2006) and iu.app.box.com/v/patents/file/7307669062 (data from 2007 to 2010).

[15] The NBER and Kogan et al. (2017) data files contain information on patents granted during 1926–2010 and a match of patenting organizations to firms listed on Compustat. This match enables the assignment of patent ownership and citations to firms listed on Compustat, which are essentially all firms in the U.S. capital markets. Our complete matching begins in 1985, as we require at least 100 firm-years per year in all four datasets.

[16] mba.tuck.dartmouth.edu/pages/faculty/ken.french/Data_Library/det_48_ind_port.html.

[17] We also use the IE formula developed by Hirshleifer et al. (2013), where a 20% annual depreciation rate is presumed for the historical R&D expenditure in the denominator of *IEPA* and *IECIT*. We replicate the results of the regressions in Table 4 using this alternative measure. In supplementary analysis, we continue to find significantly positive IE coefficients at $p < 0.01$ for lags of $k = 3$ and 5 years for *IEPA* and *IECIT*, consistent with our primary hypothesis (H1) of a positive relation between IE and future credit rating.

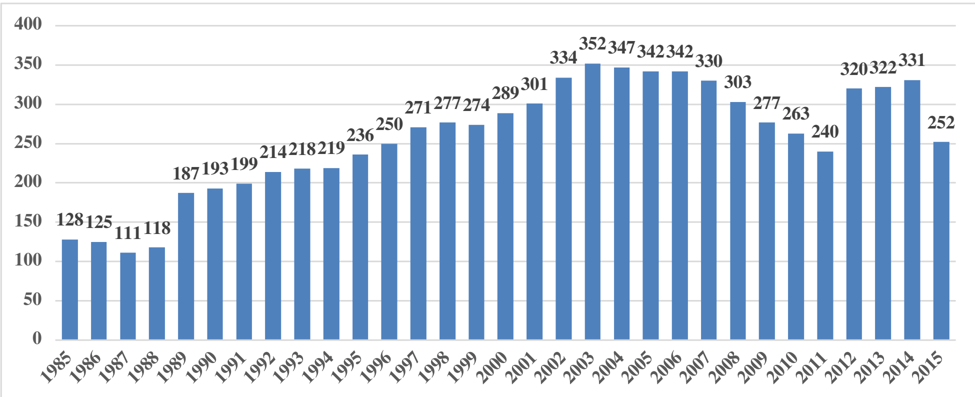
[18] Forward citations reflect the technological importance of patents as perceived by the inventors themselves (Jaffe et al., 2000) and knowledgeable peers in the technological field (Albert et al., 1991). Forward citations also reflect the economic importance of patents, as they represent a flow of knowledge from the firm to others (Hall et al., 2005). Because forward citations suffer from truncation problems, we weight the patent counts by truncation-adjusted cite counts from the patent and citation datasets (Hall et al., 2001, 2005) (Section 5.4).

Table 1
Sample distribution of firms with patent citations and credit ratings.

Panel A: Sample distribution by industry

Fama-French 48 Industry (industry number)	Frequency	Percent
Aircraft (24)	183	2.30
Alcoholic Beverages (4)	68	0.85
Apparel (10)	24	0.30
Automobiles and Trucks (23)	323	4.06
Business Services (34)	308	3.87
Business Supplies (38)	411	5.16
Chemicals (14)	733	9.20
Computers (35)	462	5.80
Construction (18)	16	0.20
Construction Materials (17)	259	3.25
Consumer Goods (9)	336	4.22
Defense (26)	88	1.10
Electrical Equipment (22)	226	2.84
Electronic Equipment (36)	787	9.88
Entertainment (7)	53	0.67
Fabricated Products (20)	7	0.09
Food Products (2)	305	3.83
Healthcare (11)	5	0.06
Machinery (21)	765	9.60
Measuring and Control Equipment (37)	246	3.09
Medical Equipment (12)	237	2.98
Nonmetallic Mining (28)	76	0.95
Petroleum and Natural Gas (30)	435	5.46
Pharmaceutical Products (13)	665	8.35
Printing and Publishing (8)	16	0.20
Recreational Products (6)	125	1.57
Restaraunts, Hotels, Motels (43)	4	0.05
Retail (42)	16	0.20
Rubber and Plastic Products (15)	74	0.93
Ship Building, Railroad Equipment (25)	6	0.08
Shipping Containers (39)	110	1.38
Steel Works, Etc. (19)	277	3.48
Telecommunications (32)	195	2.45
Textiles (16)	33	0.41
Tobacco Products (5)	30	0.38
Wholesale (41)	61	0.77
Total number of firm-year observations	7,965	100.00

Panel B: Sample distribution by year



patents granted over the previous five years scaled by the sum of the related R&D expenses:

$$IECIT_t = \sum_{j=1}^{5} \sum_{k=1}^{N_{t-j}} C_k^{t-j} / (\beta_1 \text{R\&D}_{t-3} + \beta_2 \text{R\&D}_{t-4} + \beta_3 \text{R\&D}_{t-5} + \beta_4 \text{R\&D}_{t-6} + \beta_5 \text{R\&D}_{t-7}), \quad (2)$$

where the adjusted number of citations, ${C_k}^{t-j}$, is the number of citations in year t by patent k, granted in year $t-j$ (j = 1–5) scaled by the average number of citations received in year t by all patents of the same patent subcategory granted in year $t-j$, and N_{t-j} is the total number of patents granted in year $t-j$ to the firm. Because citations in year t relate to patents granted in any of the previous five years, which result from earlier R&D, we scale by the sum of R&D expenses (in millions) in years $t-3$ to $t-7$, and $\nu_1 \dots \nu_5$ represents the industry-specific annual depreciation rate in years $t-3$ to $t-7$.[19]

[19] We scale the number of patents by cumulative amortized R&D spending from two years earlier ($t-2$) to acknowledge that recent R&D is more likely to affect current patents than older R&D. With citations, however, we scale by cumulative unamortized R&D from three years earlier ($t-3$). We do this because a citation can only occur once a patent has been granted, and a citation could relate to a patent granted in any of the earlier years. While we follow the earlier work on the measurement of IE (Hirshleifer et al., 2013), we acknowledge the possibility of alternative measures of innovative output. For example, a measure based on the ratio of citations to patents could be one alternative, although as the combination of two

Table 2
Descriptive statistics and variable definitions.
The sample consists of 7965 firm-year observations for a sample period between 1985 and 2015 satisfying the data requirements.

Variable	Year	Mean	Std. dev.	Q1	Median	Q3
Credit Rating	t	9.3161	3.7069	6.0000	9.0000	12.0000
IEPA	t	2.1397	4.7291	0.2824	1.0190	2.3790
IECIT	t	3.1625	7.6228	0.3220	1.2485	3.1944
OCF	t	0.0902	0.0945	0.0494	0.0944	0.1402
STDROA	$t-4$ to t	0.0396	0.0347	0.0169	0.0282	0.0492
TIMES	t	17.0307	30.6571	4.6509	8.6859	15.9773
RDEXP	t	0.0398	0.0427	0.0096	0.0241	0.0543
RETVOL	t	0.0232	0.0121	0.0151	0.0199	0.0276
BM	t	0.4696	0.4079	0.2453	0.4108	0.6334
SIZE	t	8.4725	1.5268	7.4511	8.3575	9.4830
LEV	t	0.2304	0.1509	0.1305	0.2065	0.2996
PPE	t	0.2792	0.1717	0.1440	0.2464	0.3767
CASHSIZE	t	0.1129	0.1168	0.0281	0.0736	0.1577

Variable definitions:

Credit Rating = Firm i's Standard & Poor's senior debt rating at end of year *t*. Standard & Poor's rates a firm's debt from AAA (indicating a strong capacity to pay interest and repay principal) to D (indicating actual default). We translate ratings letters into ratings numbers, with a higher number (e.g., AAA = 17, CCC+ and lower grades = 1) indicating a better rating.
IEPA = Patents granted to a firm in year *t* divided by R&D capital in year $t-2$. R&D capital is computed as the 5-year cumulative R&D expenses with industry-specific annual depreciation.
IECIT = Adjusted patent citations received in year *t* from all patents granted to a firm in years $t-1$ to $t-5$ divided by the weighted sum of R&D expenses in years $t-3$ to $t-7$ with industry-specific annual depreciation. The adjusted citations in year *t* to patent k are citations to patent k in year *t* divided by the mean citations to patents of the same subcategory and grant year group in year *t*.
OCF = Firm i's operating cash flows at year *t* divided by total assets at the beginning of year *t*.
STDROA = Firm i's standard deviation of ROA calculated using five years data from year $t-4$ to *t*. ROA is defined as net income before extraordinary items plus after-tax net interest expense divided by total assets at the beginning of year *t*.
TIMES = The natural log of (1+ times interest earned ratio), where times interests earned ratio is defined as firm i's operating income before depreciation and interest expense divided by interest expense, both for year *t*.
RDEXP = Firm i's R&D expense at year *t* divided by total assets at the end of year *t*.
RETVOL = Standard deviation of firm i's daily stock returns for year *t*.
BM = Natural log of firm i's book value of common equity divided by its market value of common equity, both measured at the end of year *t*.
SIZE = Natural log of firm i's total assets at the end of year *t*.
LEV = Firm i's long-term debt divided by total assets at the end of year *t*.
PPE = Firm i's net property, plant, and equipment divided by total assets at the end of year *t*.
CASHSIZE = Firm i's cash and short-term investments divided by total assets at the end of year *t*.

Table 2 reports descriptive statistics of our baseline regression variables winsorized at the top and bottom 1% for the continuous variables. Mean and median for *IEPA* (*IECIT*) are 2.14 and 1.11 (3.16 and 1.25), respectively. In broad terms, this means that $1 million dollars per year of R&D expense over five years ($t-6$ to $t-2$) generates an average of 2.14 patents per firm in year *t*.[20] Mean *IECIT* is more difficult to interpret intuitively, as this number represents all citations in year *t* relative to the average for the category (hence, mean ${C_{ik}}^{t-j}$ could be greater or less than one) scaled by five years of prior R&D spending. As the table suggests, these data skew to the right, with some firms exhibiting a high number of patent or citations per dollar of R&D expenditure. The other variables right skew as well except *OCF*, although not significantly so (except for *TIMES*), in that the means all fall within the range of the first to the third quartile.

Table 3 reports the Pearson correlations among the variables in the main regressions, with significant correlations shown in bold. The correlation between *IEPA* and *IECIT* is 0.55, suggesting that a firm with a higher value of the first IE measure also has a higher value of the second measure, despite the different concepts of IE. Most of the correlations among the explanatory variables are small in magnitude (below 10%), and most of the higher correlations reflect predictable relations, for example, corr (*OCF*, *TIMES*) = 0.26 (higher cash flow increases interest coverage), corr (*OCF*, *RETVOL*) = −0.31 (higher cash flow decreases stock return volatility), corr

(*footnote continued*)
measures of R&D output, this ratio could cancel out differences in efficiency. Such a ratio would be akin to representing the ratio of a professor's total citations in t to all his/her publications in $t-3$ to $t-7$ divided by his/her publications in t, which means that a professor with high publications in *t* but low citations in *t* to his/her works in earlier years would be considered inefficient. We also acknowledge that all patents are not equal, which means that our results could differ based on the type of patent (e.g., specialized versus general) and whether the patents might relate to core investments versus peripheral activities. Finally, Section 5.13 analyzes a measure of innovation productivity based on the relation of R&D to future sales, which is a broader measure of IE not constrained by patent availability.

[20] Almeida et al. (2013) show a similar innovation payoff from R&D spending. Based on their sample of patent data from 1980 to 2004, the average sample firm generates 1.63 patents by spending $1 million per year on R&D.

Table 3
Pearson correlations among selected variables.
The correlations in bold are significantly different from zero ($p < 0.05$). See Table 2 for the definitions of the variables.

Variable	IEPA	IECIT	OCF	STDROA	TIMES	RDEXP	RETVOL	BM	SIZE	LEV	PPE	CASHSIZE
Credit Rating	−0.002	0.008	**0.403**	**−0.323**	**0.280**	**−0.058**	**−0.546**	**−0.066**	**0.589**	**−0.501**	**0.194**	**−0.166**
IEPA	1	**0.549**	**−0.056**	−0.006	**−0.059**	**−0.030**	**−0.028**	**0.023**	**−0.089**	**0.050**	**0.078**	**0.001**
IECIT		1	**−0.033**	**0.030**	**−0.055**	**−0.020**	**−0.021**	**−0.014**	**−0.120**	**0.048**	**0.066**	**0.013**
OCF			1	**−0.122**	**0.256**	**−0.042**	**−0.311**	**−0.116**	**0.209**	**−0.269**	**0.160**	**−0.099**
STDROA				1	**0.040**	**0.316**	**0.374**	−0.012	**−0.213**	**0.079**	**−0.064**	**0.347**
TIMES					1	**0.172**	**−0.106**	**−0.082**	**0.223**	**−0.388**	**−0.084**	**0.261**
RDEXP						1	**0.181**	**−0.159**	**−0.066**	**−0.130**	**−0.271**	**0.495**
RETVOL							1	**0.045**	**−0.313**	**0.236**	**−0.082**	**0.202**
BM								1	0.019	**−0.124**	**0.160**	**−0.139**
SIZE									1	**−0.303**	**0.063**	**−0.052**
LEV										1	0.018	**−0.111**
PPE											1	**−0.368**
CASHSIZE												1

(*RDEXP*, *STDROA*) = 0.32 (higher R&D expense increases ROA volatility), and corr (*SIZE*, *RETVOL*) = −0.31 (larger firm size lowers stock return volatility). Note that the negative correlations for corr (*IEPA*, *RDEXP*) = −0.03 and corr (*IECIT*, *RDEXP*) = −0.02 include the predictable influence of *RDEXP* in the denominator.

4. Results

4.1. Baseline regressions

Table 4 summarizes the results of ordered logit regressions of *Credit Rating* at the end of fiscal year t, $t+1$, and $t+3$ on IE for year

Table 4
Innovative efficiency and future credit rating as the dependent variable.
This table summarizes the ordered logit regression coefficients and two-sided *t*-values for the maximum samples of 6649 firm-year observations for *IEPA* and 7965 firm-year observations for *IECIT*. We regress *Credit rating* for year $t + k$ on *IEPA* or *IECIT* and other control variables for year t. The regressions also control for year and industry fixed effects. We report *t*-statistics in parentheses with standard errors clustered by industry and year. *, **, *** denote significance at < 0.10, 0.05, and 0.01 level, respectively, all two-tailed. Table 2 states the definitions of the variables.

IE =	IEPA	IECIT	IEPA	IECIT	IEPA	IECIT
Dep. variable =	$Credit\ Rating_t$		$Credit\ Rating_{t+1}$		$Credit\ Rating_{t+3}$	
IE	−0.0111	0.0080	0.0097	0.0071	0.0047	0.0126
	(−0.74)	(0.61)	(22.75)***	(1.65)*	(12.13)***	(2.01)**
$Credit\ Rating_t$			2.8758	3.0717	1.3156	1.3572
			(24.95)***	(24.76)***	(19.55)***	(18.50)***
OCF	4.2404	3.2207	2.2031	2.2432	2.0423	2.1628
	(5.90)***	(4.03)***	(6.19)***	(5.73)***	(4.68)***	(4.27)***
STDROA	−9.6575	−6.0171	−0.9896	0.0118	0.0316	−0.3451
	(−6.61)***	(−4.18)***	(−1.44)	(0.02)	(0.03)	(−0.33)
TIMES	0.0042	0.0069	0.0004	0.0009	0.0015	0.0020
	(4.28)***	(8.71)***	(0.94)	(2.44)**	(3.01)***	(2.49)**
RDEXP	−2.4099	0.0296	−2.1211	−1.8105	−2.4872	−2.8373
	(−1.91)*	(0.02)	(−1.90)*	(−1.75)*	(−1.65)*	(−2.20)**
RETVOL	0.7339	−87.5391	−0.6073	−8.4554	−0.1913	5.4263
	(1.22)	(−10.88)***	(−1.23)	(−1.79)*	(−0.62)	(0.82)
BM	0.0008	−0.2429	−0.0164	0.0196	0.0018	0.0043
	(0.04)	(−5.32)***	(−0.71)	(0.42)	(0.06)	(0.09)
SIZE	0.8400	0.7677	0.0770	0.0737	0.1562	0.1648
	(12.62)***	(10.99)***	(2.66)***	(2.15)**	(3.91)***	(3.83)***
LEV	−4.3954	−3.8742	−0.5453	−0.5484	−0.1947	−0.2584
	(−8.28)***	(−7.77)***	(−2.70)***	(−2.49)**	(−0.69)	(−0.85)
PPE	−0.0941	0.0712	−0.4953	−0.5896	−0.3797	−0.4121
	(−0.21)	(0.18)	(−2.97)***	(−3.72)***	(−1.41)	(−1.49)
CASHSIZE	−0.9629	−0.1703	1.4864	1.3932	1.8303	1.6667
	(−2.54)**	(−0.42)	(4.84)***	(5.10)***	(3.26)***	(3.22)***
Num. of obs.	6649	7965	6587	7605	5897	6023
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE.	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R^2	0.1295	0.1496	0.6243	0.6441	0.385	0.3936

t and several other variables (at end of the fiscal year t or for fiscal year t) that would explain credit rating but for IE.[21] We first draw on the prior literature (Metz and Cantor, 2006; Blume et al., 1998; Alissa et al., 2013) to select the financial statement variables of profitability (*OCF*, *TIMES*), operating risk (*STDROA*), capital structure (*LEV*), asset specialization (*RDEXP*), and future growth options (*BM*), and a measure of cash holdings (*CASHSIZE*) to control for high levels of cash. We then add two market-based variables, $Credit\ Rating_t$ and *RETVOL*, to reflect additional contemporaneous expectations about firm risk not in the financial statements, which credit agencies would likely use to predict a future rating. This analysis shows that *Credit Rating* in t significantly explains *Credit Rating* in $t + 1$ and $t + 3$. In supplementary analysis, we also estimate equivalent regressions for *Credit Rating* in $t + 2$, $t + 4$, and $t + 5$ as the dependent variable. This analysis shows that the coefficients for $Credit\ Rating_t$ decline as the lead-time increases, consistent with $Credit\ Rating_t$ evolving as an autoregressive process (i.e., a fraction of the forecast error at t is passed into future expectations). The baseline model shows uniformly significant and positive coefficients for *OCF* and *SIZE*, suggesting that firms' economies of scale and profitability associate with better credit ratings. The baseline model also shows mostly uniformly significant and negative coefficients for *RDEXP* and *PPE*, indicating that asset specialization and corporate risk-taking adversely affect credit ratings. We then add IE to the baseline regression. If IE contributes significantly to the regression, then this offers evidence that such information at t can be used to explain future credit ratings.

Columns 4 and 6 of Table 4 summarize the regressions of $Credit\ Rating_{t+1}$ and $Credit\ Rating_{t+3}$ on IE defined as *IEPA*, and columns 5 and 7 summarize the regressions with IE defined as *IECIT*. The IE coefficients of interest are those for *IEPA* and *IECIT*. In all regressions, consistent with H1, we observe significantly positive coefficients for *IEPA* ($p < 0.01$) and *IECIT* ($p < 0.10$). That is, IE at t significantly explains *Credit Rating* at $t + 1$ and $t + 3$, and this is after controlling for $Credit\ Rating_t$, which our analysis shows is the best single predictor of $Credit\ Rating_{t+k}$. Supplementary analysis also shows similar results for *Credit Rating* at $t + 2$, $t + 4$, and $t + 5$. We also summarize in columns 2 and 3 of Table 4, regressions of $Credit\ Rating_t$ on IE after excluding $Credit\ Rating_t$ as a regressor variable. For these contemporaneous regressions, the IE coefficients are not significant. In other words, while contemporaneous IE significantly explains firms' future credit ratings (columns 4–7), it does not significantly explain credit ratings in the same year as the IE measure (columns 2 and 3).

These results are economically significant also. We use the IE coefficients in the Table 4 regressions to estimate the improvement in *Credit Rating* at $t + k$ (the dependent variable) for a one standard deviation increase in IE while holding the control variables at their sample means. We then convert the credit rating increase to a corresponding reduction in bond yield based on a smaller sample of firm-year bond ratings that match to actual yields on those bonds (yield data from Mergent). These reductions in yield range from 38.6 bps (t to $t + 1$) to 130.2 bps (t to $t + 5$) for IE = *IEPA* and from 33.7 bps (t to $t + 1$) to 105.6 bps (t to $t + 5$) for IE = *IECIT*. Stated conservatively, if the bond market at t were to price IE-intensive firms (one standard deviation higher than the average) consistent with the credit ratings at $t + 1$ that reflect IE at t, the average yields on the debt would be at least 34 bps lower. Given that the estimated aggregate face value of sample debt exposed to excess credit costs lies in the range of $434 million to several billion,[22] the overall dollar cost savings of a 34 bps accelerated yield reduction would be substantial.

4.2. Default risk as an explanation of the lagged relation between IE and credit rating

If CRAs' gradual response to IE relates to their focus on downside risk, then the lag between IE and firms' future credit rating should be amplified for firms with a higher default probability at t. These near-default IE firms have increased their risk-taking, which is reflected in a lower credit rating at t compared to IE firms with a lower default probability at t. However, IE firms on average are also those more likely to succeed and produce upside risk and a lower default probability in the future. Thus, the improvement in future credit rating from t to $t + k$ (and, thus, the positive relation between IE and future credit rating) should be amplified for firms with a higher probability of default at t. Firms with a higher default probability at t may also have stronger incentives to invest in IE, but only if the expected payout is sufficiently favorable so as not to compromise firms' solvency or threaten managers' jobs. Nonetheless, an opposite relation could also occur if some equity holders were to persuade managers to accept risky innovation projects as default risk increases, which would manifest itself in IE rather than building up corporate cash reserves (Jensen and Meckling, 1976). We might also observe a less prominent relation for firms closer to default if the CRA waits for confirmation of the success of IE before a rating adjustment, which could differ for firms with higher versus lower default risk.

We measure firm default risk in two ways; first, as a prediction at t based on the KMV-Merton (1974) distance-to-default forecasting model, and as an ex-post measure based on a firm's actual filing of default in the next five years. The first default risk measure (*D2D*) is from the default forecasting model designed by the KMV Corporation built on Merton's (1974) bond pricing model; hereafter, the KMV-Merton default forecasting model (Bharath and Shumway, 2008).[23] Second, we define a second default risk measure as one based on a firm's actual filing of default in the next five years. We extract the firms' actual filing of default from Securities Data

[21] We also estimate the ordered logit regressions using the partial proportional odds model of Peterson and Harrell (1990), where those parallel regressions not meeting the proportional odds assumption are constrained to meet that assumption (see Section 5).

[22] The estimated aggregate face value of debt exposed to the excess credit cost would be at least $434 million (each of the 394 separate firms in the sample is exposed once to the higher spread of at least 34 bps) (Exp 8.4725 (sample mean log of total assets) × 23.04% (sample mean leverage) × 394 (no. of firms)). If each firm-year observation were exposed to excess credit cost, the face value of the debt would be several billion. In a study of patent information at loan origination, Plumlee et al. (2015) also find significant economic effects of patent disclosure, documenting that borrowers with a forthcoming patent experience a 15.4 bps reduction in loan spread relative to borrowers without a forthcoming patent.

[23] The KMV-Merton default forecasting model yields a distance-to-default measure for each sample observation at time t. We follow the procedures in Bharath and Shumway (2008) to implement the Merton (1974) model.

Company Platinum database, which provides detailed information on > 3500 US bankruptcy filings since the 1980s. We then add *Default* (defined as a continuous variable for the first measure and a dummy variable for the second measure) and the interaction of *Default* and IE to the logistic regression in Table 4.[24] Panels A and B of Table 5 summarize the results for *Credit Rating* at $t + 1$ and $t + 3$.[25] We hypothesize that IE = *IEPA* and IE = *IECIT* both have a predictably different impact on firms' credit ratings at $t + 1$ and $t + 3$ conditional on default risk. The coefficients for the interaction of IE × *Default risk* are all significant and positive at significance levels of $p < 0.05$. Higher IE, thus, associates more positively with the future credit ratings of high default probability firms at t than the future ratings of low default probability firms at t. Overall, the findings in Table 5 support the view that the IE-future credit rating relation is amplified for firms with higher default probability (H2), which is the first channel that we contend explains the gradual response.[26]

4.3. Financial constraint as an explanation of the lagged relation between IE and credit rating

In this section, we examine whether CRAs' gradual response to IE information is likely to favor financially-constrained firms based on the premise that such firms reflect lower agency costs because the constraints motivate them to be more selective in their choice of innovation projects. To proxy for financial constraint, we use the index in Hadlock and Pierce (2010), which is a combination of firm size and firm age constructed to be higher for a financially-constrained firm. Almeida et al. (2013) show that this index relates positively and significantly with measures of IE similar to the *IEPA* and *IECIT* measures used here. Table 6 shows the results. Both IE *and* the interaction term (IE conditional on *Financial Constraint*) are significantly positive for *IEPA* and *IECIT* for ratings at $t + 1$ ($p < 0.01$), $t + 3$ ($p < 0.05$), and $t + 5$ ($p < 0.01$). Thus, not only does IE at t associate with improved future credit ratings (the unconditional relation) but, also, those future ratings are more improved for financially-constrained versus non-financially-constrained firms. Thus, the rating improvement from CRAs' gradual adjustment to IE information is not explained solely by firms with financial constraints. These results support H3, namely, that the gradual ratings improvement occurs in part because firms with financial constraints act more diligently in their choice of innovation projects. This alleviates CRAs' more pressing concern for credit assessment based on downsize risk.

4.4. Future financial performance as an explanation of the lagged relation between IE and credit rating

To test this explanation, we define two variables to reflect the speed with which IE relates to future financial performance, namely, future sales and future operating cash flows (CF). If contemporaneous IE generates higher future sales/CF in the near term, then IE coefficients in the near term should reflect this. To determine how fast IE translates into future sales/CF, we first estimate a three-year rolling time-series regression of IE at t on average sales/CF for years $t + 1$ and $t + 2$ (near future sales/CF) and a three-year rolling time-series regression of IE at t on average sales/CF for years $t + 4$ and $t + 5$ (far future sales/CF). For each regression, we then rank firms on the time-series coefficient in these rolling regressions for near and far future sales/CF. We define two subgroups—a *Fast Sales*/CF *response group* (firms with a high coefficient of near future sales/CF and a low coefficient of far future sales/CF) and a *Slow Sales*/CF *response group* (firms with a low coefficient of near future sales/CF and a high coefficient of far future sales/CF). The low and high coefficients are defined based on the sample median of these coefficients per year. We then specify the dummy variable *Fast response*, which equals one for the *Fast Sales*/CF *response group* and zero for the *Slow Sales*/CF *response group*. Lastly, we regress $\textit{Credit Rating}_{t+k}$ on IE_t, *Fast response*, the interaction of IE and *Fast response*, and the same firm-level controls as in Table 4.

Table 7 summarizes the results for *Fast sales* (Panel A) and *Fast cash flows* (Panel B). For IE = *IEPA*, Panel A shows a positive coefficient for IE × *Fast response* at $t + 1$ and negative coefficients at $t + 3$ and $t + 5$. For IE = *IECIT*, Panel A shows positive coefficients for IE × *Fast response* at $t + 1$ and $t + 3$ and an insignificant coefficient for $t + 5$. We then repeat the analysis for *Fast response* defined as future cash flow. Panel B shows significantly positive coefficients for IE × *Fast response* for $t + 1$ and $t + 3$ for *IEPA* and *IECIT*. Because we define *Fast response* as fast for $t + 1$ and $t + 2$ *relative to* $t + 4$ and $t + 5$, Table 7 documents the expected result of incrementally more positive IE coefficients in $t + 1$ (faster response) compared to $t + 5$ (slower response).

Thus, we observe a significantly different pattern of lagged response of credit ratings to IE depending on how promptly IE translates into future sales or cash flows. Consistent with our reasoning that the lagged adjustment of credit ratings to IE relates to future *financial* performance, we show the expected result for the *Fast sales* and the *Fast cash flow* groups, namely, that the positive coefficients for IE × *Fast response* at $t + 1$ decline monotonically in absolute value as the lag increases. This finding supports H4 – that the positive IE-future credit rating relation is amplified in the near term when IE has a greater impact on near-term future sales or cash flows.

[24] We follow the procedures in Norton et al. (2004) to test for the statistical significance of the interaction of IE x *Default risk* (and the interactions in the other tables). Norton et al. (2004) claim that a range of studies employs interaction terms in their nonlinear models such as logit models, yet those studies incorrectly interpret the coefficient on the interaction term. The marginal effect of a change in both interacted variables is not equivalent to the marginal effect of changing just the interaction term. Norton et al. (2004) show that to estimate the size of the interaction effect in nonlinear models, one should calculate the cross derivative of the expected value of the dependent variable.

[25] The results are similar for $\textit{Credit Rating}_{t+2}$ and $\textit{Credit Rating}_{t+4}$.

[26] This result could also occur if, regardless of credit rating, firms closer to default at t also have significantly higher mean IE at t than firms further from default. Supplementary analysis shows the opposite relation, however. In other words, despite the sample characteristic that lower default firms have higher IE on the average, the positive IE-future credit rating relation is still more prominent for firms closer to default. That is, these firms' ratings change more as the results of innovation efficiency become clearer in the future.

Table 5
Innovative efficiency and future credit rating conditional on firm default risk.

This table summarizes the regressions of future *Credit rating* on *IEPA* or *IECIT*, default risk, the interaction of these variables, and the same control variables as in Table 4. Panel A is based on levels of default risk (*D2D*) designed by Merton (1974) as reported in (Bharath and Shumway, 2008). Panel B is based on the indicator for a firm's default rating in the next five years. Firm-level control variables are included in each regression model. We report *t*-statistics with standard errors clustered by industry and year. *, **, *** denote significance at < 0.10, 0.05, and 0.01 level, respectively, all two-tailed. Regressions control for year and industry fixed effects. Table 2 states the definitions of the variables.

IE=	*IEPA*		*IECIT*	
Dep. variable=	$Credit\ Rating_{t+1}$	$Credit\ Rating_{t+3}$	$Credit\ Rating_{t+1}$	$Credit\ Rating_{t+3}$
Panel A: Default risk (*D2D*) (Merton, 1974)				
IE	−0.0030	0.0034	0.0029	0.0031
	(−0.47)	(0.45)	(0.83)	(0.79)
Default	7.8580	5.4404	5.7019	4.5116
	(5.55)***	(4.68)***	(6.80)***	(4.34)***
IE × *Default*	3.7339	2.9188	0.1447	0.1587
	(3.15)***	(2.31)**	(1.97)**	(2.58)***
Firm controls	Yes	Yes	Yes	Yes
Year and industry FE	Yes	Yes	Yes	Yes
Num. of obs.	6513	5841	6669	5750
Pseudo R^2	0.6273	0.3893	0.6366	0.394
Panel B: Default filing in the next five years				
IE	0.0055	−0.0021	0.0094	0.0128
	(5.01)***	(−1.35)	(1.91)*	(2.00)**
Default	−1.8823	−3.1789	−3.3495	−3.4251
	(−4.74)***	(−4.89)***	(−3.96)***	(−3.55)***
IE × *Default*	0.1021	0.1231	0.1799	0.2378
	(4.42)***	(2.15)**	(3.00)***	(2.63)***
Firm controls	Yes	Yes	Yes	Yes
Year and industry FE	Yes	Yes	Yes	Yes
Num. of obs.	6587	5897	7605	6023
Pseudo R^2	0.6267	0.3896	0.6458	0.3951

4.5. Accounting quality as an explanation of the lagged relation between IE and credit rating

To address the role of accounting quality (*AQ*) as a channel for understanding the IE-future credit rating relation, we re-estimate the predictive regressions in Table 4 after adding an *AQ* measure and the interaction of *AQ* with IE as additional explanatory variables. Each IE × *AQ* interaction is calculated for two high *AQ* quintile and two low *AQ* quintile combinations. The first reflects high or low *AQ* at $t = AQ_t$ (high $AQ_t = 1$, low $AQ_t = 0$) or short-term *AQ*. The second reflects high or low *AQ* at t *and* $t + 5 = AQ_t$ and AQ_{t+5} (high AQ_t and high $AQ_{t+5} = 1$, low AQ_t and low $AQ_{t+5} = 0$) or long-term *AQ*. We rank firms on short-term and long-term *AQ* based on the sum of the standardized measures of three versions of accounting accruals for firm *i* in year *t*, namely the measures in Wysocki (2009) (*AQW*), Rangan (1998) (*AQD*), and Kothari et al. (2005) (*AQK*).[27] We choose these measures as prior empirical studies show a significant association between credit rating quality and these or similar *AQ* measures.

We examine short-term and long-term measures of *AQ* because the effects of high *AQ* at *t* could strengthen the positive IE-future credit rating relation in the short-term. In contrast, *AQ* at *t* could matter less at t + k and, thus, potentially have less impact on the positive IE–future credit rating relation in future periods. Current accounting accruals tend to reverse over time, and the effects of period-specific financial statement error tend to diminish over time due to mean reversion, assuming the error in assessing high or low *AQ* at *t* does not correlate perfectly with the error at t + k. For firms with high *AQ* at *t and t* + 5, there could be more chance that accounting accruals would diminish or the error effects would attenuate due to mean reversion.[28]

Table 8 presents the results. Panel A shows the IE × *AQ* coefficients for short-term *AQ*. The coefficients are from regressions of

[27] Specifically, AQW equals accruals quality metric 3 (Wysocki, 2009, p. 21), calculated as the standard deviation of model A residuals divided by the standard deviation of model B residuals, where model A regresses $earnings_t$ on operating cash $flow_t$ and model B regresses $earnings_t$ on operating cash $flow_t$, operating cash $flow_{t-1}$, and operating cash $flow_{t+1}$. This ratio measure captures current accruals quality through the relative explanatory power of past, current, and future operating accruals compared to the explanatory power of current cash flows in isolation. A positive number represents greater current accruals quality. AQD equals minus one times the difference between actual and predicted current accruals scaled by beginning of year assets from Rangan (1998, p.110); and AQK equals minus one times a performance-matched version of Rangan (1998), where, following Kothari et al. (2005, pp. 174–175), for each year and for each two-digit SIC code industry, we create five portfolios by sorting the data into quintiles of *ROA* measured one year prior to the year of portfolio formation. The abnormal accrual for a given firm is the Rangan (1998) unexplained accrual for that firm minus the average (excluding the sample firm) unexplained accrual of the matched portfolio. We multiply the Rangan (1998) and Kothari et al. (2005) measures by minus one so that a positive number represents higher accruals quality.

[28] Our tests, which consider AQ measures as covariates to explain the lagged IE-future credit rating relation, could also be viewed as tests of information quality more generally.

Table 6
Innovative efficiency and future credit rating conditional on financial constraint.

This table summarizes the regressions of future *Credit rating* on *IEPA* or *IECIT*, financial constraint, the interaction of these variables, and the same control variables as in Table 4. Financial constraint is measured as the financial constraint index from Hadlock and Pierce (2010). Firm-level control variables are included in each regression model. We report *t*-statistics with standard errors clustered by industry and year. *, **, *** denote significance at < 0.10, 0.05, and 0.01 level, respectively, all two-tailed. Regressions control for year and industry fixed effects. Table 2 states the definitions of the variables.

IE=	*IEPA*	*IEPA*	*IEPA*	*IECIT*	*IECIT*	*IECIT*
Dep. variable=	*Credit Rating$_{t+1}$*	*Credit Rating$_{t+3}$*	*Credit Rating$_{t+5}$*	*Credit Rating$_{t+1}$*	*Credit Rating$_{t+3}$*	*Credit Rating$_{t+5}$*
IE	0.0718	0.1043	0.1349	0.0468	0.0720	0.1123
	(5.3719)***	(3.0431)***	(3.3147)***	(4.5997)***	(4.2225)**	(4.9257)***
Financial constraint	0.0135	0.0296	0.0397	−0.0110	−0.0119	0.0191
	(0.3797)	(0.5401)	(0.5256)	(−0.3230)	(−0.2538)	(0.2656)
IE × *Financial constraint*	0.0150	0.0223	0.0278	0.0094	0.0142	0.0228
	(3.7065)***	(2.6727)***	(2.7588)***	(3.8451)***	(3.5639)**	(4.3895)***
Credit Rating$_t$	2.9210	1.2963	0.9134	2.9809	1.3428	0.9409
	(23.5886)***	(17.4916)***	(16.0536)***	(24.2836)***	(17.7865)***	(16.2738)***
OCF	2.0767	2.1560	2.2120	2.1607	2.1968	2.2823
	(6.6275)***	(4.9197)***	(4.4612)***	(5.5492)***	(4.6133)***	(4.6983)***
STDROA	−1.1117	−0.6609	−0.6082	−0.1750	−0.2851	−0.7474
	(−2.2246)**	(−0.6823)	(−0.4454)	(−0.2582)	(−0.2739)	(−0.4810)
TIMES	0.0008	0.0027	0.0024	0.0005	0.0013	0.0010
	(0.8306)	(2.5431)**	(2.0597)**	(1.8061)*	(2.7670)***	(2.0685)**
RDEXP	−2.0525	−2.3693	−3.9785	−1.9271	−2.9821	−4.0033
	(−1.8549)*	(−1.3391)	(−2.2828)**	(−2.0165)**	(−2.3480)**	(−2.4396)**
RETVOL	−9.3175	4.4852	10.8964	−5.7108	7.1345	12.7893
	(−2.3149)**	(0.5992)	(1.1388)	(−1.0768)	(1.0402)	(1.3400)
BM	0.0045	0.0090	0.0076	0.0324	0.0105	−0.0143
	(2.7886)***	(2.8743)***	(4.7515)***	(1.2406)	(0.5391)	(−0.7232)
SIZE	0.0950	0.2045	0.2825	0.0759	0.1693	0.2576
	(2.5014)**	(3.9335)***	(4.6580)***	(1.9376)*	(3.4311)***	(4.4259)***
LEV	−0.2310	0.2017	0.2761	−0.3535	−0.2378	0.0034
	(−1.5230)	(1.0815)	(0.8942)	(−1.6398)	(−0.7775)	(0.0092)
PPE	−0.7747	−0.8610	−0.7429	−0.6865	−0.4881	−0.5453
	(−4.0974)***	(−2.8183)***	(−2.0751)**	(−3.6388)***	(−1.7468)*	(−1.5008)
CASHSIZE	1.5391	1.5754	1.4468	1.3672	1.6156	1.5702
	(4.0056)***	(2.7071)***	(2.3244)**	(4.0217)***	(2.8618)***	(2.6448)***
Num. of obs.	5128	4562	4128	6614	5698	4716
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R^2	0.6306	0.3803	0.2826	0.636	0.3917	0.2924

Credit Rating at $t + 1$ and $t + 3$ on IE, *AQ*, IE × *AQ*, and the controls as per Table 4. The main message from Panel A of Table 8 is that we observe IE × *AQ* coefficients that are positive and significant in $t + 3$. Apparently, with the passage of time, just as CRAs attach importance to future *financial* performance when assessing the benefits of IE (Table 7), those same rating agencies also apparently attach future importance to the benefits of *AQ* at *t* when assessing the effects of IE on firms' credit rating at $t + 3$.

As a check on the results in Panel A, Panel B of Table 8 defines high and low *AQ* more restrictively by assigning a firm into the high (low) quality *AQ* portfolio for observations in both the AQ_t and AQ_{t+5} high (low) quintiles (long-term *AQ*). These columns, thus, reflect the condition that low (high) *AQ* observations at *t* must also be low (high) *AQ* observations at $t + 5$. This restriction strengthens the results in Panel A. For the more restrictive definition of *AQ*, we observe positive coefficients for IE × *AQ* for $t + 1$ and $t + 3$, which are significant at $p < 0.01$ for *IEPA* and $p < 0.05$ for *IECIT* for both lags. In sum, these results support H5, namely, that higher accounting information quality strengthens the positive relation between innovation efficiency and firms' future credit ratings.

5. Sensitivity tests[29]

5.1. Endogeneity

Results based on regressions can produce unreliable results when the dependent and regressor variables interact in both directions. This can occur with IE, as certain unobservable factors might drive IE, which might then drive those same or other factors. Several studies, for example, show that credit market conditions can affect firm innovation (Ferreira et al., 2012; Amore et al., 2013; Chava et al., 2013, and Cornaggia et al., 2015). While we hypothesize that IE at *t* relates to credit ratings at $t + k$, endogeneity could occur in the present study if the expectation of credit ratings at $t + k$ were to induce a change in IE at *t*. One mechanism through

[29] Tables representing all supplementary analyses discussed in this section are available upon request from the authors.

Table 7
Innovative efficiency and future credit rating conditional on future sales and future cash flows.

This table summarizes the *IEPA* or *IECIT* coefficients from the ordered logit regressions of Credit Rating at end of year $t + 1$, $t + 3$, and $t + 5$ on IE = *IEPA* and IE = *IECIT* at t for two subgroups, based on how fast firms' contemporaneous IE translates into future sales. One subgroup is characterized as having a relatively fast translation of contemporaneous IE to future sales or cash flows (CF), while the other subgroup is characterized as having a relatively slow translation of contemporaneous IE to future sales/CF. To identify the speed with which IE translates into future sales/CF, we estimate a three-year rolling time series regression of IE at t on the average of near future sales/CF for years $t + 1$ and $t + 2$ and the average of far future sales/CF for years $t + 4$ and $t + 5$ at the firm level. For each year we then rank firms on the time series coefficient for near future sales/CF and far future sales/CF in these regressions and assign the firm-year observations into the Fast Sales/CF to IE response subgroup (high coefficient of near future sales/CF and low coefficient of far future sales/CF) and the Slow Sales/CF to IE response subgroup (low coefficient of near future sales/CF and high coefficient of far future sales/CF). Finally, we regress future *Credit Rating* on IE_t and interact IE_t with a dummy variable for the *Fast Response* partition. Firm-level control variables are included in each regression model. We report *t*-statistics with standard errors clustered by industry and year. *, **, *** denote significance at < 0.10, 0.05, and 0.01 level, respectively, all two-tailed. Regressions control for year and industry fixed effects. Table 2 states the definitions of the variables.

IE =	IEPA			IECIT		
Dep. variable =	*Credit Rating*$_{t+1}$	*Credit Rating*$_{t+3}$	*Credit Rating*$_{t+5}$	*Credit Rating*$_{t+1}$	*Credit Rating*$_{t+3}$	*Credit Rating*$_{t+5}$
Panel A: Future sales response						
IE	0.0040	0.0135	0.0127	0.0078	0.0140	0.0181
	(0.30)	(1.26)	(0.82)	(1.94)*	(2.01)**	(1.54)
Fast response	−0.0715	−0.0334	−0.0940	−0.1202	−0.1366	0.0312
	(−3.02)***	(−0.53)	(−1.56)	(−2.33)**	(−2.00)**	(0.47)
IE × *Fast response*	0.0083	−0.0732	−0.1028	0.2226	0.1396	−0.0081
	(0.39)	(−4.24)***	(−4.63)***	(5.08)***	(3.33)***	(−0.44)
Firm controls	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Num. of obs.	3004	2903	2719	3582	3174	2611
Pseudo R^2	0.6416	0.3966	0.2965	0.6534	0.4028	0.2988
Panel B: Future cash flow response						
IE	−0.0314	−0.0187	0.0089	−0.0099	0.0010	0.0141
	(−1.95)*	(−1.50)	(0.90)	(−1.60)	(0.09)	(0.84)
Fast response	0.1494	0.0578	0.1239	−0.3162	−0.2582	−0.0661
	(2.10)**	(0.93)	(1.45)	(−3.64)***	(−2.51)**	(−0.67)
IE × *Fast response*	0.0696	0.0464	−0.0863	0.0741	0.0345	0.0054
	(2.23)**	(3.13)***	(−6.88)***	(4.05)***	(1.66)*	(0.29)
Firm controls	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Num. of obs.	2526	2443	2285	3017	2685	2184
Pseudo R^2	0.6321	0.3973	0.3054	0.4907	0.4015	0.2977

which this could occur is if a firm with high IE at t anticipates a higher credit rating at $t + k$. Then, as a result of that expectation, it invests in less productive innovation projects, for example, because the higher rating removes some financial constraints. A related concern is whether common omitted variables might explain the relations observed. For example, the general health of the economy might promote conditions for increased innovation, which might also enable credit agencies to price debt at lower spreads independent of innovation. While the use of regressor variables lagging the dependent variable (future credit rating) by up to five years reduces substantially the likelihood of endogeneity (and reverse causation), we use a two-stage instrumental variables approach as a further check.

We choose two instrumental variables that should not relate to the *future* credit rating at the firm level yet correlate positively with contemporaneous IE for firm i at time t, namely, *Pendency* and *Intellect*. *Pendency* is the firm's patent pendency period, the natural logarithm of firm i's average pendency period between application year and grant year (Harhoff and Wagner, 2009). *Intellect* is the firm's intellectual property, the natural logarithm of a firm's number of employees.[30]

We first regress firm IE on *Pendency* and *Intellect* and the control variables in Table 4 and then use predicted firm IE from this first-stage regression as the predicted IE variable in the second-stage regression. To validate our choice of instruments, we implement weak instrument identification tests (Larcker and Rusticus, 2010). Table 9 summarizes the results. The partial F's are 4.80 ($p < 0.01$) and 4.05 (p-value < 0.05) for *IEPA* and *IECIT* for the first-stage regression models, respectively. These results suggest that the instruments pass the weak instrument test because they explain the variation in IE to a significant extent. The under-identification test yields a Chi-square value of 9.61 ($p < 0.01$) and 4.06 ($p = 0.13$) for *IEPA* and *IECIT*, respectively. This test, thus, indicates that the use of instrumental variables produces a marginally superior specification than OLS estimation. While the significantly positive IE

[30] To produce consistent estimators of the effects of IE on credit ratings, an instrumental variables approach requires that the industry component of the IE variable (e.g., patent pendency) relates to future credit ratings in ways unrelated to the firm component, for example, due to industry structure or regulation not affecting the innovative efforts of managers at the firm level (Gormley and Matsa, 2014).

Table 8

Innovative efficiency and future credit rating conditional on accounting quality.

This table summarizes the ordered logit regression coefficients for IE, *AQ*, and the interaction of IE × *AQ* and two-sided *t*-statistics for the maximum samples of 2822 firm-year observations for *IEPA* and 2906 firm-year observations for *IECIT* from 1985 to 2010. *AQ* is the composite measure of Accounting Quality from factor analysis of three different variables: Wysocki (2009) (AQW), Rangan (1998) (AQD), and Kothari et al. (2005) (AQK). High value of *AQ* indicates high accounting quality. Firm-level control variables are included in each regression model. The *t*-statistics are based on standard errors clustered by industry and year. *, **, *** denote significance at < 0.10, 0.05, and 0.01 level, respectively, all two-tailed. Regressions control for industry and year fixed effects.

IE =	*IEPA*		*IECIT*	
Dep. variable =	*Credit Rating*$_{t+1}$	*Credit Rating*$_{t+3}$	*Credit Rating*$_{t+1}$	*Credit Rating*$_{t+3}$
Panel A: *Accounting quality* = AQ_t				
IE	0.0008	−0.0169	−0.0065	−0.0007
	(0.10)	(−2.16)**	(−0.62)	(−0.04)
Accounting quality (*AQ*)	0.0759	−0.0098	0.1008	−0.0157
	(0.92)	(−0.12)	(1.30)	(−0.20)
IE × *AQ*	0.0078	0.0486	0.0033	0.0397
	(0.87)	(2.31)**	(0.41)	(1.65)*
Firm controls	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Num. of obs.	2822	2597	2906	2669
Pseudo R^2	0.6422	0.3939	0.6462	0.3997
Panel B: *Accounting quality* = AQ_t and AQ_{t+5}				
IE	0.0016	−0.0091	−0.0110	−0.0008
	(0.09)	(−0.49)	(−1.04)	(−0.07)
Accounting quality (*AQ*)	0.0763	0.0458	0.0749	0.0501
	(0.79)	(0.35)	(0.74)	(0.38)
IE × *AQ*	0.1097	0.1336	0.1340	0.0968
	(4.83)***	(2.90)***	(3.52)***	(2.04)**
Firm controls	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Num. of obs.	2067	1940	2113	1983
Pseudo R^2	0.6372	0.3906	0.6421	0.3938

coefficients in Table 9 are smaller compared to Table 4, overall, these tests do not offer strong evidence that any potential endogeneity regarding IE and future credit rating is likely to affect our results.[31]

5.2. Credit ratings that change subsequent to patent grant year

Because IE can be regarded as a regressor that is persistent over time, the positive relation between IE at t and *Credit Rating* at $t + k$ may also reflect a relation between *future* IE and *Credit Rating* at $t + k$ even though the ordered logit regressions include *Credit Rating*$_t$ as a regressor to control for rating agencies' current recognition of IE at t. Granger and Newbold (1974) show in this setting that *Credit Rating* at $t + k$ and IE can be statistically related even if there is no true relation between the two variables. We address the potential for spurious correlation in two ways. First, we use an augmented regression approach based on the theory in Amihud and Hurvich (2004). For the persistency model, we specify *IEPA* or *IECIT* as a first-order autoregressive (AR1) time series. We then use the estimated residuals from the persistency model (ν_t) as an additional explanatory variable in the baseline regressions in Table 4 that regress *Credit rating*$_{t+k}$ on *IEPA* or *IECIT* and other control variables for year t. Assuming a correct specification of the persistency model, Theorem 1 of Amihud and Hurvich (2004, p. 817) implies that the coefficients for *IEPA* or *IECIT* in the augmented regression will be reduced-biased estimators of the relation between IE and future credit rating.[32] In supplementary analysis, we find that the augmented regression coefficients for $IEPA_{t+1}$, $IEPA_{t+3}$, $IECIT_{t+1}$, and $IECIT_{t+3}$ are all positive and significant ($p < 0.05$) and of similar magnitude to those in Table 4.

A second way is to run the regressions in Table 4 in differences. Because of the persistency of credit ratings over time, rather than compute year-to-year differences, we select only those credit ratings that change from one year before the patent grant year to a

[31] Our research design also allays concerns about common omitted variables, as we use an adjusted measure of citations (by removing a common industry or economic effect), test for a non-contemporaneous association between IE and credit rating, and obtain similar results when we regress credit rating changes at t on changes in IE at t.

[32] Essentially, the augmented regression approach adds the unexpected (or non-persistent) amount of *IEPA* or *IECIT* (ν_t,) over the forecast interval to the regression, and then checks to see whether *IEPA* or *IECIT* helps predict future *Credit Rating* above and beyond the unexpected amount of *IEPA* or *IECIT* over the forecast interval. If ν_t does not relate to future *Credit Rating*, then according to Amihud and Hurvich (2004) the coefficients for *IEPA* or *IECIT* in the augmented regression will reflect a reduction in bias.

Table 9
Two-stage least squares tests of innovative efficiency and future credit rating.

This table summarizes the ordered logit regression coefficients and two-sided *t*-values for the maximum samples of 4805 firm-year observations for *IEPA* and 5015 firm-year observations for *IECIT*. We first regress IE on *Pendency* and *Intellect* and the control variables in Table 4 and then use predicted IE from this first-stage regression as the IE variable in the second-stage regression. The regressions also control for year and industry fixed effects. *Pendency* is the firm's patent pendency period defined as the natural log of firm i's average pendency period between application year and grant year. *Intellect* is the firm's intellectual property, measured as the natural log of firm i's number of employees. We report *t*-statistics in parentheses with standard errors clustered by industry and year. *, **, *** denote significance at < 0.10, 0.05, and 0.01 level, respectively, all two-tailed. Table 2 states the definitions of the variables.

Dep. variable =	*IEPA*	*Credit Rating*$_{t+3}$	*IECIT*	*Credit Rating*$_{t+3}$
	First stage	Second stage	First stage	Second stage
IE		0.0010		0.0018
		(2.8718)***		(22.2163)***
Pendency	−1.9436		−0.4351	
	(−1.95)*		(−0.52)	
Intellect	−0.8502		−0.5656	
	(−2.50)***		(−1.97)**	
Credit Rating$_t$	−0.0435	0.6548	−0.0981	0.0942
	(−0.80)	(12.0461)***	(−1.51)	(2.5114)**
OCF	−6.8014	1.9482	−6.8732	0.0203
	(−3.74)***	(4.2530)***	(−4.51)***	(21.3466)***
STDROA	−9.3448	0.3868	−9.7732	−0.0490
	(−1.89)*	(0.3869)	(−2.22)**	(−18.8100)***
TIMES	0.0008	0.0074	−0.0054	0.0124
	(0.20)	(4.6063)***	(−1.65)*	(12.7008)***
RDEXP	8.5024	−3.6269	−6.8282	−0.0557
	(1.72)*	(−4.3704)***	(−1.63)	(−14.1458)***
RETVOL	26.7302	0.7865	57.6369	95.3747
	(1.12)	(0.1223)	(2.77)***	(9.4869)***
BM	0.1532	−0.1242	0.1161	−1.5066
	(0.87)	(−0.9660)	(0.62)	(−10.1135)***
SIZE	0.8957	0.1441	−0.0259	3.7509
	(3.04)***	(3.1980)***	(−0.10)	(19.8563)***
LEV	−6.3842	0.5786	−0.3754	−8.6369
	(−4.87)***	(1.8773)*	(−0.33)	(−11.1971)***
PPE	−0.6673	−0.4310	1.4384	0.0544
	(−0.51)	(−1.2175)	(1.31)	(5.9494)***
CASHSIZE	−0.1475	0.8723	4.0189	0.0185
	(−0.08)	(1.8802)*	(2.65)**	(17.3702)***
Partial F-statistic	F = 4.80 (p-value < 0.01)		F = 4.05 (p-value < 0.05)	
Under-identification test	Chi-sq = 9.61 (p-value < 0.01)		Chi-sq = 4.06 (p-value = 0.13)	
Endogeneity test	Chi-sq = 51.76 (p-value < 0.0001)		Chi-sq = 2.90 (p-value < 0.10)	
Durbin-Wu Hausman test (p-value)	T = −0.53 (p-value = 0.60)		T = −1.12 (p-value = 0.26)	
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Num. of obs.	4805	4296	5015	4468
Pseudo R^2	0.0137	0.1864	0.0249	0.3278

future year, that is, when the firm has a different credit rating. We then use generalized ordered logit regression (same as Table 4) to regress those rating changes on equivalent changes (over the same interval) in the regressor variables, including Δ*IEPA* and Δ*IECIT*. In supplementary analysis, we find that after controlling for changes in the other regressor variables in Table 4, we continue to observe significantly positive coefficients for Δ*IEPA* ($p < 0.05$) and Δ*IECIT* ($p < 0.10$). These positive coefficients for Δ*IEPA* and Δ*IECIT* are also of the same approximate magnitude as the *IEPA* and *IECIT* coefficients in Table 4. Overall, the results of these two sets of tests do not support the view that the significant results in Table 4 of a positive relation between IE and future credit rating reflect a spurious relation due to persistent regressors.

5.3. R&D expenses

We address two potential concerns related to our IE denominator, R&D expenses. First, we acknowledge that R&D expenses do not always capture innovative investment. Hall (2010) reports that only 50% of innovation expenses are in R&D. In addition, Koh and Reeb (2015) show that firms with no reported R&D do eventually patent. If the underreporting were constant among firms, this would not create a design issue. But R&D is also a choice variable, and firms adopt many ways to disclose (and protect) their innovative activities and output (Hall et al., 2014). To address the issue of R&D as a measure of input that also potentially correlates with R&D as a measure of disclosure, we test whether our results differ when we use a measure of disclosure unrelated to R&D. We use that portion of SG&A representing intangible investment expenditure to support or maintain current operations not classified as R&D or advertising as the measure. Because these SG&A investments can exceed R&D spending by three times on average (Enache and Srivastava, 2017), they offer an alternative, reported accounting measure of a firm's resources devoted to intangibles. However, because firms do not report these expenditures as R&D, we do not expect them to relate to R&D output in the same way. To implement this test, for each firm-year, we calculate the intangible investment component of SG&A (called *MainSG&A*) as per the procedures in Enache and Srivastava (2017) and substitute that amounts for R&D in the calculations of *IEPA* and *IECIT*. In supplementary analysis of the regressions in Table 4 using this alternative measure of innovative efficiency, we find that none of the IE coefficients is significant, supporting our view of the appropriateness of reported R&D as a measure of innovative input versus an SG&A alternative.[33]

Second, as noted by Koh and Reeb (2015), we address the issue of missing R&D, which could introduce a sample selection bias, as some missing R&D firms file and receive patents. In the main tables, we use R&D over years $t-2$ to $t-6$ to compute R&D capital in Eq. (1) (for patents) and R&D over years $t-3$ to $t-7$ to compute cumulative R&D in Eq. (2) (for citations). However, as a low threshold for sample inclusion, we require only at least one non-missing R&D observation over the prior five-year period to include the IE observation in the sample. For R&D capital and cumulative R&D in the main tables, we denote a missing R&D observation as zero. Following Koh and Reeb (2015, p. 76), as an alternative, we replace each missing R&D observation with the industry average R&D (based on the Fama-French 48 classifications). Supplementary analysis shows no qualitative difference in the IE coefficients in Table 4 under both treatments of missing R&D. We also re-estimate Table 4 amortizing R&D over three or eight years versus five years with no substantive change in the Table 4 results. Lastly, we re-estimate Table 4 where instead of adjusting patents and patent citations by R&D expenses as per Eqs. (1) and (2), these variables are deflated by the sum of R&D expenses as per Eqs. (1) and (2) plus SG&A expenses (Compustat item #189) with no substantive change in the Table 4 results. In short, the Table 4 results are unchanged by the R&D inclusion criteria (which are minimally restrictive) and are robust to different treatments of missing R&D and different definitions of innovative input.

5.4. *Patent data truncation*

We adjust our innovation output measures to address two key truncation issues associated with the original (data to 2006) NBER dataset. The first arises because patents appear in the dataset only after the grant date. This truncation occurs because the lag between a patent's application year and its grant year is significant (about two years on average), and many patent applications filed during these years were still under review and had not been granted by 2006. Following Hall et al. (2001), we adjust the patent count data using "weight factors" computed from the application-grant empirical distribution. The second type of truncation problem relates to citation counts, as patents receive citations over long periods, but we observe only citations received up to 2006. We correct for this second truncation by deleting the citations from the last two sample years, 2005 and 2006. Supplementary analysis shows that the results based on these two truncation adjustments to the IE variables are qualitatively the same as those in Table 4.

5.5. *Survivorship*

Our result that credit ratings adjust gradually to contemporaneous IE may have occurred to the extent that our research design reflects a survivorship bias, as a decreasing number of sample firms all survived from t to k years into the future. We check for possible effects of survivorship in two ways, using (i) firm-year samples with constant observations and (ii) a hazard function model.

5.5.1. *Constant observation samples*

In supplementary analysis, we show that the results in Table 4 are qualitatively the same as when the number of observations in each credit rating year $t+1$ to $t+5$ remains constant each year, namely, those firm-year observations that "survived" all years.

5.5.2. *Proportional hazard model*

To conduct this test, we first divide the firm-year observations into two sub-samples, i.e., firms that experienced a rating upgrade or rating downgrade. We then estimate a Cox proportional hazard model (Cox, 1972) to check whether our main result holds for the instantaneous credit rating upgrade/downgrade likelihood after controlling for the impact of past credit rating changes. Specifically, we specify the following proportional hazard model:

$$\ln h_{jk}(t) = \mu(t - t_{j(k-1)}) + \beta_1 IE_{jk} + \sum_{i=2}^{n} \beta_i (i^{th} Control\ Variable_{jk}) + \varepsilon_{jk}, \tag{3}$$

where $h_{jk}(t)$ is the hazard, or instantaneous likelihood of credit rating upgrade (downgrade) for firm j at time t, conditional on the fact that k upgrades (downgrades) have happened for firm j by time t, the time of the $(k-1)$th event; and where the same control variables as in Table 4 represent the baseline hazard function covariates except for IE. We then predict that $\beta_1 > 0$ in the credit rating upgrade subgroup, indicating that the hazard of a credit rating upgrade occurrence increases with IE and $\beta_1 < 0$ in the credit

[33] Some firms could combine patenting with other forms of protection of innovation such as trade secret protection. As previously argued, patents and citations play the role of a publicly-available disclosure regarding firms' innovative projects. Should patent and citation counts in year t coincide with counts of other forms of protection in the same year, our results would then potentially show a more gradual adjustment of credit ratings to IE, as the denominator of our IE variable would not capture the other forms of protection.

rating downgrade sub-group, indicating that the hazard of a credit rating downgrade occurrence decreases with IE. Supplementary results show that the hazard ratio for IE in the credit rating upgrade subgroup is 1.225 (not significant at $p < 0.10$), suggesting that greater IE does not associate with the instantaneous likelihood of a credit rating upgrade. In contrast, the empirical estimates based on the credit rating downgrade subgroup show a significant IE hazard ratio of 0.382 ($p < 0.05$). Given the coefficient estimates, this implies that a one standard deviation increase in IE decreases the subsequent downgrade hazard rate by 19.71% ($\exp^{(0.9675*0.1860)} - 1$) after controlling for other covariates affecting the credit rating upgrade in Eq. (3). In other words, these findings indicate that the instantaneous credit rating downgrade likelihood of firms with high IE at *t* is lower than that of firms with low IE at *t*, conditional on *k* downgrades having occurred at different times by time t. These hazard model results confirm the ordered logistic regression results in Table 4.

5.6. Partial proportional odds model

The results thus far derive from estimations based on generalized ordered logit regression. This procedure does not constrain the regression to meet the proportional odds or parallel regression assumption of generalized logit regression for ordered dependent variables. As an alternative, we re-estimate Table 4 based on the partial, proportional odds model of Peterson and Harrell Jr (1990). This approach tests for possible violations of the proportional odds or parallel regression assumption and uses an iterative process to impose a constraint only in those cases where we can reject the hypothesis that the assumption is not violated (based on a chi-square test). Supplementary analysis shows that we obtain qualitatively similar results to those shown in Table 4 under this alterative procedure.

5.7. Managerial ability

To test whether managerial ability rather than IE might drive our results, we calculate average managerial ability over the prior three years using the Demerjian et al. (2012) measure and assign firms to managerial ability terciles, where tercile one (three) represents less able (abler) managerial ability.[34] We then test whether the IE coefficient increases positively and significantly for high versus low ability managers. In supplementary analysis, we find only weak support for this prediction in that while the coefficients for IE × Managerial Ability are consistently positive, only one is significantly positive at $p < 0.10$. Thus, overall, while we observe mostly significantly positive IE coefficients (similar to Table 4), these coefficients are not significantly more positive for firms with high ability versus low ability managers.

5.8. Mergers and acquisitions

If firms leaving the sample due to mergers and acquisitions have higher or lower IE than firms not leaving the sample, then this could bias our results. We, therefore, identify *why* firms leave the sample, finding that of a total of 155 departures over the study period, 115 relate to merger and acquisition (M&A), 11 to bankruptcy, 16 to closure, and 13 to reasons not identifiable. Because 115 departures relate to M&A, as a bias check, we code merger versus non-merger as a binary variable and use nominal logit analysis to assess whether the probability of M&A varies with IE, with controls for the other variables in Table 4. Supplementary analysis shows positive coefficients for IE ($p < 0.01$). This implies that those not leaving the sample (i.e., not taken over due to M&A) will reflect more conservative estimates of the lagged credit rating adjustment to current IE because those that leave on average have a positive IE coefficient.

5.9. Non-linearity

Czarnitzki and Kraft (2004) and Frey (2013) posit that an excessive amount of innovation may reflect moral hazard and generate litigation and, thereby, generate higher firm risk. This means that the IE-future credit rating relation could be negative for firms above an IE threshold, such that the overall relation between IE and the future credit rating is hump-shaped. We examine this possibility by replicating the regressions in Table 4 with the inclusion of IE^2 as an additional regressor variable. If the positive IE-future credit rating relation should differ for high IE, then the coefficient for IE squared should be negative. Supplementary results indicate that the coefficient for IE^2 is mostly insignificant for $t + 1$ to $t + 5$ and for both definitions of IE.

5.10. Regulation FD

CRAs' continuous access to clients' private information, including an exemption from Regulation FD (Fair Disclosure), may have allowed them to incorporate the implications of IE into ratings efficiently rather than with a lag. However, on September 29, 2010, the SEC issued rule release, "Removal from Regulation FD of the Exemption for Credit Rating Agencies," under the Dodd-Frank Wall Street Reform and Consumer Protection Act of 2010. While previously exempted from receiving material nonpublic information under Regulation FD (e.g., about innovation investments), this release removed that exemption. As such, it may have significantly increased credit raters' liability for issuing inaccurate ratings and made it easier for the SEC to sue them for receiving privileged

[34] Based on data at https://community.bus.emory.edu/personal/PDEMERJ/Pages/Download-Data.aspx.

information. Dimitrov et al. (2015) provide evidence that CRAs responded to the greater threat of legal and regulatory action by issuing lower and less informative ratings than those based on fundamentals. Legally, however, the threat of SEC action was considered weak. Moreover, the FD exemption may have been unnecessary if Regulation FD had never applied to CRAs in the first place (because CRAs after 2006 were excluded from the definition of investment advisor) (Bullard, 2016). In supplementary results, we find results more consistent this second view, that is, in most of the regressions, we find no qualitative difference in the IE coefficients in Table 4 during the period of CRAs' exemption from the Regulation FD (from the time of passage of Dodd-Frank in 2000 to its elimination in 2010) versus the other years in the sample.

5.11. Moody's and Fitch ratings

Our study uses Standard & Poor's ratings to document a gradual response of CRAs to IE information. As a further test, we examine whether our results are robust to the two other major agencies in the United States, namely, Moody's and Fitch IBCA ratings services. While prior research shows a high consistency between Moody's and S&P ratings and rating changes, our results may not hold for Fitch because it (i) issues ratings only when requested and paid and (ii) may restrict public disclosure if the rated firm is not satisfied with the rating. This means that Fitch ratings could be biased due to self-selection (Cantor and Packer, 1997; Jewell and Livingston, 1999; Livingston et al., 2010). As predicted, given the high consistency, in supplementary analysis we generate findings virtually identical to the *IEPA* and *IECIT* coefficients in Table 4 based on S&P ratings, even though we use a reduced sample of Moody's ratings of a maximum of 2971 firm-observations for *IEPA* and 4092 observations for *IECIT*. In other words, the response to IE by Moody's follows the same pattern of gradual response to IE as Standard & Poor's. By contrast, the results are less clear-cut for a smaller sample of Fitch ratings. On the one hand, we generate results that are very similar to those in Table 4 for the *IECIT* coefficients based on a sample of Fitch's ratings, of a maximum of 1183 firm-observations for *IECIT*. On the other hand, the Fitch results for *IEPA* are insignificant for all future years. This latter result is consistent with the view that Fitch's ratings reflect IE information differently from other rating agencies such as Moody's and S&P. However, it is also possible that our results lack statistical power due to a much smaller sample size.

5.12. Firms transitioning from speculative to investment grade status

Building on the idea in Almeida et al. (2013) that the collapse of the junk bond market in 1989 meant that a junk-bond issuing firm would have been forced to tighten financial constraints, we consider a subset of firm-years in our sample in which the firm transitions from speculative grade to investment grade after 1989. These firms, arguably, would not only be less financially constrained following their prior junk status but, also, the CRA has indicated through its rating change that it now has less concern for downside risk. Given the Jensen (1986) free cash flow argument, firms transitioning from speculative grade to investment grade may exploit the increased free cash flow to engage in empire building or pet projects. Thus, we might expect the positive IE-future credit rating relation to weaken or disappear for these firms (argument 1). Contrariwise, we might also expect a positive IE-future credit rating relation if the success of the earlier innovation were to help IE firms reduce financial frictions for their innovative investment projects (argument 2). Thus, the overall effect is theoretically an open question. Our supplementary analysis shows evidence partially supporting both arguments. Based on the same regressions as in Table 4 but for only the subset of firms that transitions from speculative status to investment grade after 1989, we find significantly positive coefficients on *IEPA* for future credit ratings at $t+2$ and $t+3$ (with p-values ranging from < 0.00001 to 0.0007) (supports argument 2) and insignificant coefficients on *IEPA* for $t+1$ and *IECIT* for $t+1$, $t+2$, and $t+3$ (supports argument 1). Thus, the idea that the firms in our sample transitioning from speculative to investment grade status become less efficient innovators is only partially supported by our evidence.[35] However, we caution that our insignificant results may be driven by the reduced sample size, since we consider only firms transitioning from speculative grade to investment grade after 1989.

5.13. Research productivity

An alternative way to view innovative efficiency is from the perspective of innovative productivity. We use the research quotient (RQ) measure as defined by Knott (2008) to test this prediction. RQ represents the percentage increase in firm revenue from a 1% increase in R&D, which is a measure of the output elasticity of R&D. Since RQ is a similar construct compared to IE, we predict that our results based on a measure of innovative productivity should be similar. We obtain the RQ measure for each firm-year from the Research Quotient (RQ) database hosted by WRDS. In supplementary analysis, we show the same positive relation between RQ and future credit rating as in Table 4 when we replace IE with RQ.

6. Conclusion

This study sought answers to open questions on the relation between innovative efficiency (IE) and firms' credit ratings. Using two measures of IE – the number of patents or citations divided by R&D expenditures – we show that the CRAs' ratings of firms with higher

[35] This analysis also suggests that the potential endogeneity concern of the impact of an improved credit rating at $t+\mathrm{k}$ on IE at t is unlikely to affect our results. See also our discussion in Section 5.1.

IE eventually improve, but this takes place gradually, over multiple years in many situations. Tests of economic significance suggest that the average credit spread would drop by at least 34 basis points if we assume that the gradual improvement occurs one year earlier. We also identify and confirm the presence of three key channels to explain why CRAs respond gradually to IE information. The gradual response is amplified for firms closer to default, underscoring credit agencies' emphasis on downside risk, for firms subject to financial constraints, potentially making them more productive, and for firms with a faster response of future sales or cash flows to IE, reflecting CRAs' concern for reputation. We further explain credit agencies' gradual response by showing that accounting quality also plays an amplifying role, finding that the positive relation between IE at t and future credit rating is stronger for firms with higher quality accounting. These results survive the challenge of multiple robustness tests. Taken together, we conclude that the gradual response of CRAs to innovation information is predictable based on economic considerations relevant to credit analysis. A caveat is that our sample does not include firms without patents. These firms may innovate, disclose, and protect their intellectual property in other ways.

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Appendix A. The KMV-Merton default probability forecasting model

The KMV-Merton default forecasting model yields an expected default probability for each firm in the sample at a given point in time. To compute the probability, the face value of the firm's debt is subtracted from an estimate of the market value of the firm (e.g., the sum of the market values of the firm's debt and the value of its equity) scaled by a measure of the volatility of the firm. The market value of debt is estimated with the Merton (1974) bond-pricing model. The Merton bond-pricing model derives from the assumption that the total value of a firm follows the geometric Brownian motion, stated as:

$$dV = \mu V dt + \sigma_v V dW, \tag{1a}$$

where V is the total value of the firm, μ is the expected continuously compounded return on V, σV is the volatility of firm value, and dW is a standard Weiner process. The Merton model also assumes that the firm has issued just one discount bond maturing in T periods. Under these assumptions, the equity of the firm is a call option on the underlying value of the firm with a strike price equal to the face value of the firm's debt and time-to-maturity of T. In addition, the value of equity derives from the Black-Scholes-Merton formula. By put-call parity, the value of the firm's debt equals the value of a risk-free discount bond minus the value of a put option written on the firm, again with a strike price equal to the face value of debt and a time-to-maturity of T. Symbolically, the Merton model stipulates that the equity value of a firm satisfies the following:

$$E = VN(d_1) - e^{-rT} FN(d_2), \tag{2a}$$

where E is the market value of the firm's equity, F is the face value of the firm's debt, r is the instantaneous risk-free rate, $N(\cdot)$ is the cumulative standard normal distribution function, d_1 is:

$$d_1 = \frac{\ln\left(\frac{V}{F}\right) + \left(r + 0.\ 5\sigma_V^2\right)T}{\sigma_V \sqrt{T}}, \tag{3a}$$

and $d_2 = d_1 - \sigma V\sqrt{T}$. This formula is referred to as the Black-Scholes-Merton option valuation equation. The KMV-Merton model also relates to the volatility of the firm's equity relative to the volatility of firm value. Under Merton's assumptions, the value of equity is a function of the value of the firm and time, so it follows directly from Ito's lemma that:

$$\sigma_E = \left(\frac{V}{E}\right)\frac{\partial E}{\partial V}\sigma_V \tag{4a}$$

In the Black-Scholes-Merton model, it can be shown that $\partial E/\partial V = N(d_1)$, so that under the Merton model's assumptions, the volatilities of the firm and its equity are related by:

$$\sigma_E = \left(\frac{V}{E}\right)N(d_1)\sigma_V \tag{5a}$$

The KMV-Merton model derives from nonlinear Eqs. (2a) and (5a), which translate the value and volatility of a firm's equity into an implied probability of default. We implement the KMV-Merton default forecasting model in three steps. First, we measure σE from either historical stock returns data or from option implied volatility data. Second, we use historical returns data to estimate σE using a forecasting horizon of one year (T = 1) and use the book value of the firm's total liabilities as the face value of the firm's debt. Third, we collect values of the risk-free rate and market equity of the firm. These three steps determine values for each of the variables in

Eqs. (2a) and (5a) except for V and σV, the total value of the firm, and the volatility of firm value, respectively. Finally, we simultaneously solve Eqs. (2a) and (5a) numerically for values of V and σV to calculate the distance to default as where d_1 is defined in Eq. (3a). Our measure is:

$$DD = \frac{\ln\left(\frac{V}{F}\right) + (\mu - 0.5\sigma_V^2)T}{\sigma_V\sqrt{T}}, \tag{6a}$$

where μ is an estimate of the expected annual return of the firm's assets. The corresponding expected default probability (*D2D*), which we use to calculate relative *DTD* is:

$$D2D = N\left(-\left(\frac{ln\left(\frac{V}{F}\right) + (\mu - 0.\ 5\sigma_V^2)T}{\sigma_v\sqrt{T}}\right)\right) = N(-DD). \tag{7a}$$

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