Journal of Financial Economics 101 (2011) 493–514

Contents lists available at ScienceDirect

Journal of Financial Economics

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

How did increased competition affect credit ratings? ☆

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ARTICLE INFO

Article history:
Received 5 April 2010
Received in revised form
15 September 2010
Accepted 22 October 2010
Available online 1 April 2011

JEL classification:
D43
G24
L14
L15

Keywords:
Credit ratings
Competition and reputation
Information quality

ABSTRACT

The credit rating industry has historically been dominated by just two agencies, Moody's and Standard & Poor's, leading to long-standing legislative and regulatory calls for increased competition. The material entry of a third rating agency (Fitch) to the competitive landscape offers a unique experiment to empirically examine how increased competition affects the credit ratings market. What we find is relatively troubling. Specifically, we discover that increased competition from Fitch coincides with lower quality ratings from the incumbents: Rating levels went up, the correlation between ratings and market-implied yields fell, and the ability of ratings to predict default deteriorated. We offer several possible explanations for these findings that are linked to existing theories.

1. Introduction

Credit ratings make information about default likelihoods and recovery rates of a security widely available, limiting duplication of effort in financial markets. They allow uninformed investors to quickly assess the broad risk properties of tens of thousands of individual securities using a single and well-known scale.[1] In addition, ratings are relied on extensively in regulation and private contracting, as a tool for measuring and limiting risk. For example, commercial banks, insurance companies and pension funds are among the institutions facing regulatory rules based on credit ratings. Many investors can hold securities only with investment-grade ratings (e.g., pension funds, money market funds) or are required to use different amounts of capital based on the ratings of securities they hold (e.g., insurance companies). For these reasons, ratings constitute a key channel of information

☆ We wish to thank Pierluigi Balduzzi, Robert Battalio, Doug Diamond, Serdar Dinc, Radhakrishnan Gopalan, Robin Greenwood, Burton Hollifield, Edith Hotchkiss, Dave Ikenberry, Darren Kisgen, Christian Leutz, Joe Mason, Atif Mian, Michael Meltz, Neil Pearson, Mitch Petersen, Joshua Pollet, Raghuram Rajan, Matthew Rhodes-Kopf, Sébastien Michenaud, Antoinette Schoar, and Gary Witt, as well as seminar participants at Helsinki, DePaul-Chicago Federal Reserve, the National Bureau of Economic Research (NBER) 2008 summer meeting, the NBER 2010 summer meeting on credit rating agencies, Massachusetts Institute of Technology, Harvard Business School, Boston College, Boston University, Temple University, the Philadelphia Federal Reserve, Standard & Poors' Academic Council, the Center for Economic Policy and Research/Einaudi conference on transparency, Disclosure and Market Discipline in Banking Regulation, and the University of Notre Dame for helpful comments. We also thank both Kangzhen Xie and Lan Xu for excellent research assistance. Any remaining errors are of our own. An earlier draft of this paper was circulated under the title "Reputation and Competition: Evidence from the Credit Rating Industry".
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[1] The majority of corporate security ratings relate to corporate bonds. Other corporate securities, such as preferred stock, are frequently rated as well, as are government bonds (at the municipal, state and federal levels) and structured financial products (such as residential mortgage-back securities, collateralized mortgage obligations, collateralized debt obligations, etc.). See Table 2 for an overview of ratings categories.

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doi:10.1016/j.jfineco.2011.03.012

dissemination in financial markets and are considered important by legislators, regulators, issuers, and investors alike.[2] The quality of ratings is, therefore, relevant for the proper functioning of the financial system.

While the importance of a viable ratings industry seems clear, the provision of accurate ratings is made more complicated by the peculiar market structure of the industry. First, the industry is dominated by only three players – Moody's, Standard & Poor's (S&P), and Fitch Ratings – with Fitch gaining prominence only in the past decade or so.[3] Second, ratings issued mainly by these agencies are paid for by the firms being rated. Once produced, ratings are made publicly available and investors that rely on them use them for free. Users of ratings, such as investors who consider buying a security, desire accurate ratings. However, firms whose securities are rated prefer favorable ratings as it directly lowers their cost of capital, and they do not necessarily prefer accurate ones. Because rating agencies' revenues come from issuers, a basic tension exists between the desire of raters to please individual paying customers and the raters' need to maintain the overall precision and informativeness of credit ratings.

These industry features have raised questions about the quality of the ratings provided by these incumbent players. In particular, a broad consensus exists among policy makers and regulators around the potential benefits of increasing competition between ratings providers as a tool for improving ratings quality. For example, Paul Schott Stevens, president of the Investment Company Institute, stated: "I firmly believe that robust competition for the credit rating industry is the best way to promote the continued integrity and reliability of their ratings" in testimony before the US Senate Committee on Banking, Housing, and Urban Affairs.[4] The empirical merits of this push for competition are not at all well established, and because of the informationally opaque setting, the theoretical predictions are ambiguous as well.

In this paper, we wish to examine the effect of increased competition in the ratings industry and shed some light on the issue of whether or not it tends to improve the quality of ratings. The corporate debt ratings industry offers a clear instance of increased intertemporal competition as Fitch grew into a credible player perched to compete with the two incumbents in the corporate debt market, namely, Moody's and Standard & Poor's. Founded in 1913, Fitch's roots are as old as these main agencies, but it remained a markedly smaller player until 1989 when a new management team recapitalized Fitch. This was followed by a merger in 1997 with IBCA Limited, which specialized in coverage of financial institutions. "The merger of Fitch and IBCA represented the first step in our plan to respond to investors' needs for an alternative global, full-service ratings agency capable of successfully competing with Moody's and S&P across all products and market segments."[5] Fitch's continued growth from this year forward was both organic and inorganic, including the acquisitions of Duff & Phelps Credit Rating (American) and Thomson Bankwatch (Canadian) in 2000. Fig. 1 characterizes the evolution of Fitch Ratings over time (Fitch Ratings, 2002).

The emergence of Fitch as a larger player manifested itself in a significant increase in their market share. We measure the market presence of Fitch by the fraction of all bond ratings in a particular industry over a period of time (a month or a year) that are provided by Fitch. Fig. 2 shows that over the decade that we study, starting in the mid-1990s, Fitch's share of corporate bond ratings increased substantially. In the median industry, Fitch issued less than one in ten ratings in 1997, but approximately a third of ratings by 2007. Critical to the construction of our empirical tests is the fact that Fitch's growth in the corporate ratings market has varied considerably across industries. The range of market shares can be seen from the 25th and 75th percentile lines plotted in Fig. 2.[6] Table 1 lists Fitch's market share by industry, comparing the average for the earlier half of our sample (1995–2000) and the later half (2001–2006). By the end of the sample, Fitch was particularly prominent in finance, utilities, public administration, real estate, and retail. Fitch remained relatively less represented in agriculture, entertainment, other services, and transport. The largest gains during the sample occurred in accommodation and food services, real estate, construction, waste management, and retail.

Such increased market presence across a wide array of industries did not go unnoticed by the users of ratings, and institutional acceptance of Fitch's corporate ratings was cemented by the July 1, 2005 inclusion into the Lehman (now Barclays Capital) Index that differentiates between investment-grade and junk (high-yield) bonds (see Chen, Lookman, Schürhoff, and Seppi, 2010). Prior to this change, Lehman assigned the lower of Moody's or S&P rating to any corporate bond, and thus in situations in which one of these two incumbents placed a bond below investment grade (e.g., BB+) while the other placed it above (e.g., BBB−), the bond would necessarily be classified as part of the junkbond index. After this move to include Fitch's ratings as part of the classification, index classification was determined by the middle of the three

[2] See Graham and Harvey (2001) for a survey of financial executives' attitudes toward credit ratings, Campbell and Taksler (2003) for recent evidence on the effect of ratings on corporate bond prices, and Tang (2006) for the information transmission of ratings. Kisgen (2006) shows how firm capital structure decisions are affected by rating considerations.

[3] The Securities and Exchange Commission now designates ten firms as Nationally Recognized Statistical Ratings Agencies, thereby granting their ratings regulatory status, but the other seven firms play a much smaller role in the corporate market (http://www.sec.gov/divisions/marketreg/ratingagency.htm#nrsroorders).

[4] See http://www.financial-planning.com/asset/article/527499/fund-industry-group-calls-more-credit.html.

[5] Drawn from the statement of Nancy Stroker (Managing Director) of Fitch Ratings, to the House Financial Services Subcommittee on Capital Markets, Insurance, and Government-Sponsored Enterprises, June 29, 2005.

[6] Fig. 2 plots the 24-month rolling average of Fitch's market share in the 25th percentile, median, and 75th percentile industries. Because our sample begins in 2005, the 24-month lag means that the graph starts in 1997. The industries are listed in Table 1 (the specific industries that constitute the 25th percentile, median, and 75th percentile lines vary over time).

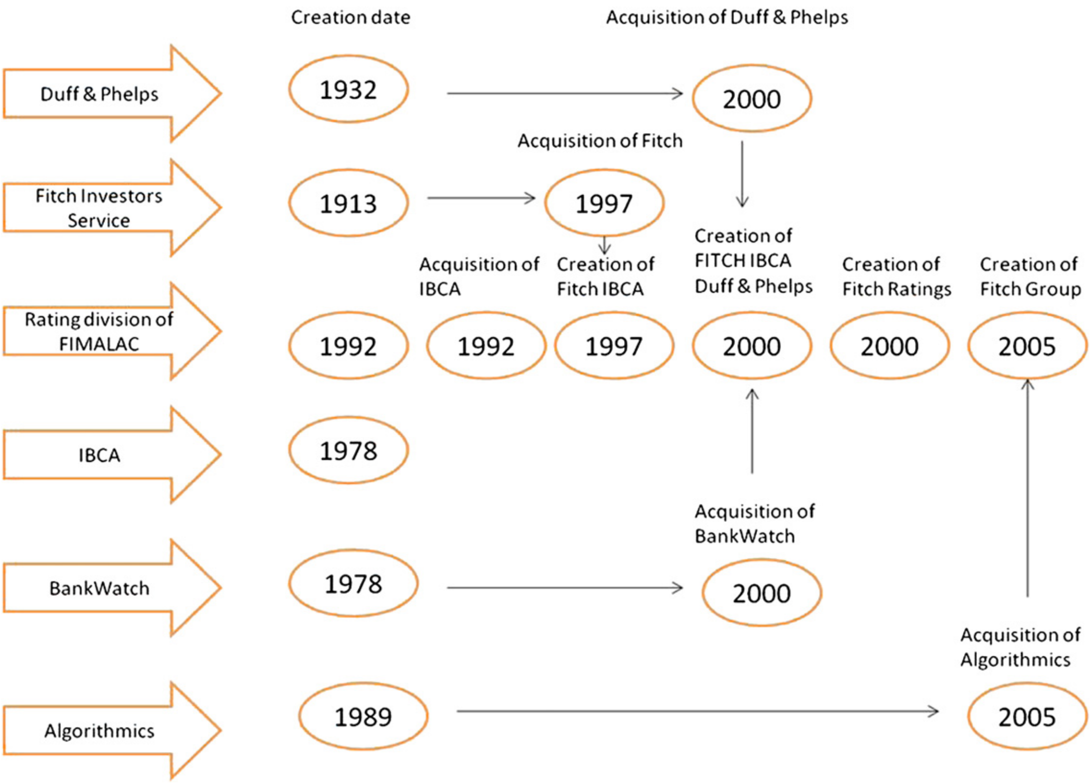

Fig. 1. The evolution of Fitch ratings: this figure is based on a figure found at: http://www.fitchratings.com/creditdesk/public/group_timeline.cfm.

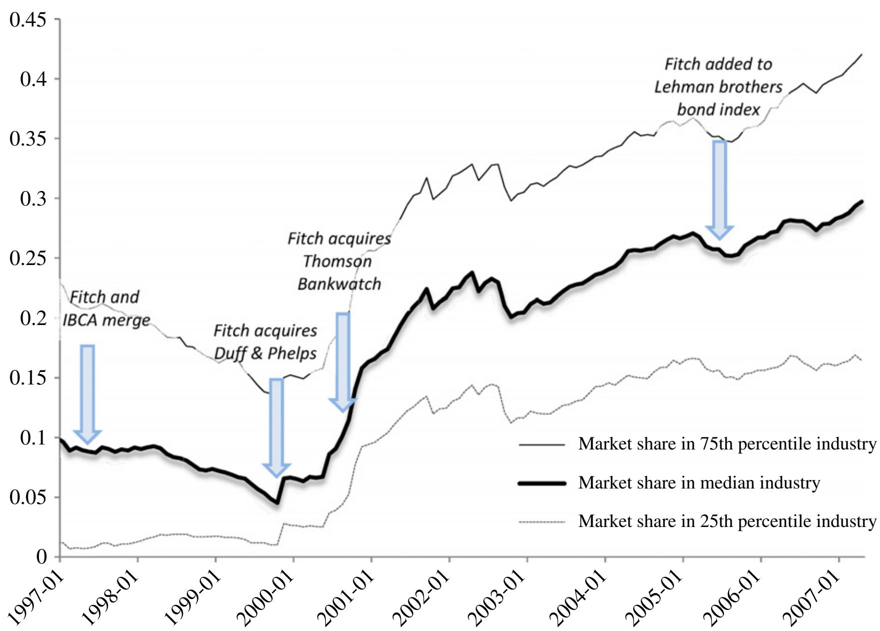

Fig. 2. Fitch market share (by industry and month): rolling 24-month averages of fraction of ratings issued by Fitch, in the 25th, 50th, and 75th percentile industries.

ratings, thereby affording Fitch a full seat at the corporate ratings table.

In this paper, we examine the impact of increased competition on ratings quality by exploiting the industry-level variation in Fitch's market share (see Table 1). Specifically, we examine how the quality of ratings issued by the incumbent agencies, S&P and Moody's, responds to the new competition presented by Fitch. Empirically,

Table 1
Fitch market share by two-digit North American Industry Classification System (NAICS) industry early and late in sample.

Each row presents the straight average of annual market shares for the earlier and later half of the sample period, respectively. Market share is the fraction of instrument ratings for corporate bonds issued by firms in a two-digit NAICS industry that have been issued by Fitch, as opposed to Moody's and Standard & Poor's.

NAICS	Industry name	Fitch market share	
		1995–2000	2001–2006
11	Agriculture, Forestry, Fishing and Hunting	0.09	0.23
21	Mining, Quarrying, and Oil and Gas Extraction	0.22	0.26
22	Utilities	0.29	0.34
23	Construction	0.08	0.28
31	Manufacturing: Food, Textile, Apparel	0.17	0.30
32	Manufacturing: Wood, Paper, Printing, Petroleum, Chemicals, plastics	0.16	0.26
33	Manufacturing: Metals, Machinery, Computers, Electrical, Furniture	0.18	0.28
42	Wholesale Trade	0.15	0.24
44	Retail Trade: Motor Vehicles, Furniture, Electronics, Food, Gas	0.09	0.28
45	Retail Trade: Sporting goods, Books, Florists, Office Supplies, Mail-Order, Vending	0.20	0.40
48	Transportation and Warehousing: Air Transport, Water Transport, Trucks, Pipelines	0.12	0.15
49	Transportation and Warehousing: Messengers, Storage	0.06	0.20
51	Information	0.18	0.28
52	Finance and Insurance	0.30	0.36
53	Real Estate and Rental and Leasing	0.17	0.42
54	Professional, Scientific, and Technical Services	0.18	0.27
55	Management of Companies and Enterprises	0.17	0.34
56	Administrative and Support and Waste Management and Remediation Services	0.12	0.29
61	Educational Services	0.11	0.28
62	Health Care and Social Assistance	0.16	0.27
71	Arts, Entertainment, and Recreation	0.16	0.21
72	Accommodation and Food Services	0.13	0.30
81	Other Services (except Public Administration)	0.12	0.22
92	Public Administration	0.28	0.36

we focus on two dimensions of ratings quality throughout the rest of the paper: the ability of ratings to transmit information to investors and their ability to classify risk. The basic intuition behind this interpretation of quality is as follows. Ratings that can predict future defaults and are correlated with current bond prices perform well in terms of information transmission. Ratings classifications that are stable (in how they map credit quality to ratings) perform well for classification purposes. If contracts specifying investment restrictions to securities only of certain ratings (e.g., investment-grade bonds) are to work effectively, ratings categories need to have a stable meaning. The same goes for regulation that relies on credit ratings (i.e., capital requirements that vary by ratings category). Thus, the use of ratings in contracts and regulation requires a stable interpretation of them. In other words, we treat ratings inflation (a general increase in ratings levels) as lessening the quality of ratings. Ratings inflation could hurt the information transmission of ratings if not all investors are sophisticated. That is, even if some investors are able to filter out ratings inflation when interpreting them, many other investors might not be, thereby reducing the value of ratings to precisely those investors who should be able to use them to assess risk and contract on risk-taking. Inflation also makes regulation and contracting with ratings more difficult because these rely on stable meanings of the categories.

The evidence we uncover appears unequivocally consistent with lower ratings quality as competition increased. First, ratings issued by S&P and Moody's rose (moved closer to the top rating of AAA) as competition increased. Second, the ability of S&P and Moody's ratings to explain bond yields decreased with competition. In other words, credit ratings are less informative about the value of bonds when raters face more competition. Third, the ability of firm-level ratings (i.e., issuer ratings) to predict default is lower when Fitch has a higher market share (for data reasons, we use only S&P ratings for these tests). In one specification, speculative grade firms are 7.7 times as likely to default within three years as investment grade firms when competition is low (Fitch market share is at the 25th percentile), but only 2.2 times as likely when competition is high (market share at the 75th percentile). These three sets of findings paint a rather pessimistic picture about the effect of competition on credit ratings quality.

Of course, interpreting these results as evidence of the causal effect of competition on incumbent behavior is valid only if competition can be treated as exogenous to the dependent variables we study. This raises the question of what drives the patterns of growth in this measure, i.e., what determined cross-industry variation in the growth of Fitch's market share. We tackle the endogeneity of Fitch's market share from a variety of angles. First, could the market share in a particular industry be driven either directly by future changes in ratings levels or indirectly by some omitted variable that also affects ratings? We address this concern in several ways. Apart from firm variables, we control for industry and year fixed effects in all our regressions, ruling out any overall time trends or purely cross-industry explanations. We also find that Fitch's growth does not appear related to the most obvious measures of credit growth. Fitch's market share is not statistically related to increases in demand for debt in an industry, the number of ratings issued in an industry, or several measures of industry profitability (for a range of leads and lags). Thus, it does not appear that Fitch found it easier to enter in good times (or bad). These results also suggest that the growth in the ratings market seen over the sample period is not the driver of any of our results.[7]

Furthermore, our results do not likely reflect selection on who is rated by Fitch (as suggested by, for instance, theories about ratings shopping). We find that individual bonds that are rated by Fitch tend to have lower ratings from S&P and Moody's, the opposite of the aggregate pattern we observe: industries for which Fitch issues a high share of ratings see higher ratings from S&P and Moody's. Therefore, the positive effect of competition on ratings cannot reflect the aggregation of firm-level selection.

Another possibility is that Fitch might find it easier to enter and grow in industries in which S&P and Moody's neglect firms and, therefore, produce uninformative ratings. This would generate an omitted variables bias producing a correlation between ratings informativeness and competition (the omitted variable being neglect by the incumbents). This story does not explain our results about ratings levels, and it leaves unexplained the basic issue of why S&P and Moody's would neglect certain industries at all. As discussed later with respect to the possibility of ratings shopping in this market, S&P and Moody's essentially provide full coverage ($>$ 99.95%) of any corporate bonds rated by Fitch. Yet another suggestion is that Fitch's ratings are more in demand when default is harder to predict, possibly owing to industry opacity or rates of industrial change. This could also generate the observed pattern of weaker predictive ability for ratings issued when competition is high. This story does not appear consistent with our findings for the level of ratings (i.e., why would ratings be higher when default is difficult to predict?). Furthermore, we can examine the information environment directly by testing the predictive ability of other variables, such as accounting ratios. It turns out that accounting variables are not worse predictors of firm default when competition is high, and thus it does not appear that Fitch gained a higher market share when predicting default was hard. Hence, the weaker predictability of rating likely does not reflect a particularly difficult information environment.

In a further attempt to compare alternative explanations for our findings, we use an instrumental variables regression. This should help address more generic endogeneity concerns regarding Fitch's market share. We use the predicted market share in each industry from 1996 and onward as an instrument by extrapolating from Fitch's 1995 market share. These tests rely on the fact that Fitch's growth was predictably slower in those industries in which initial market share was high (such as for finance and insurance firms) and faster in industries in which it was initially low (such as agriculture and utilities). Because predicted market shares are formed using only information from 1995, they cannot reflect events late in the sample, so any endogeneity must involve great foresight by industry participants or very long range reverse causality, which seems unlikely.

Granting our findings about how competition coincides with worse ratings quality, several potential explanations derive from a number of theories. First, this pattern could reflect a reputational mechanism at work, in which future economic rents motivate current (unobserved) quality. If increasing competition from Fitch reduced expected future rents for the incumbents, the incentives for quality provision were consequently reduced. Second, the empirical evidence could reveal ratings shopping. We discuss each of these in turn.

Our findings of reduced ratings quality are consistent with a reputation story. Because ratings predict future default events, which are infrequent and can be far off in the future, feedback about the accuracy of ratings is slow and imprecise. In this setting, raters' concern for their reputations as providers of honest and accurate ratings could help sustain ratings quality (see Cantor and Packer, 1994; Smith and Walter, 2002). By providing accurate ratings, they improve future business opportunities. Industry sources confirm this logic. According to a Bear Stearns & Co equity analyst in June 2007, S&P claimed that "reputation is more important than revenues" (Meltz, 2007, p. 2). Pittman (2008) cites Moody's chief executive officer Raymond McDaniel stating that "we are in a business where reputational capital is more important." Former executive vice president of Moody's Thomas McGuire stated in 1995 that "what's driving us is primarily the issue of preserving our track record. That's our bread and butter" (House, 1995).

A rich theoretical literature argues that the formation of reputations can help support quality provision in markets where information problems would otherwise preclude it. This literature has its origins in economics, but the role of reputation in financial market outcomes has been extensively explored as well.[8] For example, Diamond (1989) models the incentives of firms (borrowers) to develop a reputation for choosing the appropriate project. Meanwhile, Chemmanur and Fulghieri (1994) show how a bank's desire to acquire a reputation (in this case, for making efficient negotiation versus liquidation decisions) provides it with an incentive to devote a large amount of resources to information production. However, if the desire to have a positive

[7] Revenues and profits of raters grew quickly over the sample period. For example, from 1997 to 2007, roughly corresponding to our sample period, Moody's revenues rose from $457 million to $2,259 million, growing at 17% per year on average.

[8] See Klein and Leffler (1981), Benabou and Laroque (1992), Mailath and Samuelson (2001), Bar-Isaac (2005), and Bar-Isaac and Tadelis (2008) as examples. Benabou and Laroque (1992) characterize the incentives of an insider to manipulate markets through strategic information disclosures. While credit rating agencies do in fact disclose information to the market, our interpretation of ours findings is not that the rating agencies were intentionally deceiving markets, but instead compromised ratings quality at the margin as competition increased.

reputation is diminished, less investment in information acquisition occurs in equilibrium.[9]

The implication of Chemmanur and Fulghieri (1994) could certainly be extended to credit rating agencies. An increasing body of work also specifically examines the role of reputation among credit rating agencies, both theoretically and empirically. For instance, Goel and Thakor (2010) characterize how reputational concerns provide a rating agency with incentives to invest in costly information acquisition. On the empirical side, Covitz and Harrison (2003) provide strong empirical evidence related to Moody's and S&P that suggests that reputation effects dominated any conflicts of interest in the industry. Their sample spans 1997–2002, which overlaps with the early part of our sample when Fitch was only beginning to build up market share in various industries. Most directly related to our work is that of Bar-Isaac and Shapiro (2010). In a model of endogenous reputation formation that explicitly characterizes the direct costs of providing high quality ratings, they show that if reputational losses are lower in the industry owing to perhaps increased competition, there are lesser incentives to provide accurate ratings. Our empirical results are exactly in line with the predictions of this model.

Because the market for ratings grew so much in recent years, it could be worth asking if the predictions of the reputational theories are scale-invariant. The reputational theories argue that competition can threaten quality by reducing future rents, but it appears likely that the massive expansion in the ratings industry during our sample period generated increases in total rents (see footnote 7 for a sense of the very high sustained growth rates), but these were concentrated in the structured products market, which is not the focus of our work. That said, the reputational argument still goes through as long as, holding market size constant, more competition corresponds to lower rents at the margin. If market size affects the payoff to high quality (more expected future business, as the firm's reputation for quality is maintained) and the payoff to low quality (more business or higher fee revenue from bond issuers) similarly, reputational concerns would appear unaffected by market size. If the market expansion is temporary, the incentives to cheat could be enhanced by market growth (because current profits from producing low quality become large relative to future rents).

A second explanation for our results related to ratings inflation could be the phenomenon of ratings shopping that has come to describe the process by which issuers shop around for good ratings and that ultimately the ratings we observe are the ones that were considered most positive by issuers. There is presumably greater scope for such shopping if there are more raters from which to choose. Skreta and Veldkamp (2009) and Bolton, Freixas, and Shapiro (2009) both provide theoretical models of the affect of ratings shopping on the quality of the ratings in the structured finance market.[10] Skreta and Veldkamp show that increases in asset complexity (such as the growth in mortgage-backed securities and collateralized debt obligations) leads to more ratings shopping and a systematic bias in disclosed ratings. Bolton, Freixas, and Shapiro find that rating agencies are more prone to inflate ratings as the fraction of naïve investors increases (i.e., those who follow disclosed ratings such as in Boot, Milbourn, and Schmeits, 2006). In both cases, increases in competition further exacerbate the problems.

While both of these theories are compelling in the market for ratings of structured products, the phenomenon of ratings shopping is likely to matter much less for the firms and corporate securities whose ratings we examine. As Spatt (2009) points out, ratings shopping can occur only if the security issuer gets to choose which credit ratings to purchase and have published. Such a luxury is not afforded to corporate issuers because both Moody's and S&P have a policy of rating essentially all taxable corporate bonds publicly issued in the US. Thus, even if an issuer refuses to pay for a rating, the raters publish it anyway as an unsolicited rating and thereby compromise any potential advantage of ratings shopping.[11] To the extent that shopping consists of some firms adding Fitch ratings, but no firms eliminating S&P and Moody's ratings, it would not affect our key dependent variable (the level of ratings issued by the incumbents).

Bongaerts, Cremers, and Goetzmann (2010) assess the prevalence of ratings shopping. They rely on data from 2002–2008 and find no support for ratings shopping in the corporate debt market.[12] Failure to find evidence of ratings shopping in this market is consistent with the earlier work of Cantor and Packer (1997), Jewell and Livingston (1999) and Covitz and Harrison (2003). In structured products, which are not included in our sample, the situation is different, because raters do not have access to the extensive public financial data that enable them to rate corporate debt based on public sources alone. Issuers of structured products can avoid a rating by withholding information about the issue from the agencies. In our data, only one piece of evidence suggests that shopping could take place. We find that S&P and Moody's bond ratings are slightly lower for bonds that have a Fitch rating (controlling for observables). This is consistent with firms seeking out Fitch when their ratings

[9] Not all reputational theories predict that competition will reduce quality. Competition may enhance the effectiveness of the reputational mechanism if the existence of competitive choice is required to make the loss of reputation a real threat, as in Hörner (2002).

[10] Bolton, Freixas, and Shapiro (2009) predict that ratings shopping, apart from affecting ratings directly, also leads to the sort of competitive dynamics that reduces the effect of reputations in maintaining quality, as suggested by, e.g., Bar-Isaac and Shapiro (2010). Hence, their model encompasses both the main explanations for the observed link between quality and competition, albeit not in the corporate security market.

[11] Which ratings are unsolicited (and, therefore, not paid for by the issuer) is not publicly known.

[12] Bongaerts, Cremers, and Goetzmann (2010) find that Fitch ratings tend to be higher than those issued by S&P and Moody's, but they reject this as evidence of ratings shopping or two important reasons. First, investors do not lower credit spreads in the instances in which Fitch enters a new rating that is higher (which would be the natural desire of the issuer attempting to shop for this third rating). Second, they do not find that Fitch enters with higher ratings at the critical investment-grade/high-yield cutoff (between the ratings categories BBB− and BB+).

appear low relative to other measures of credit quality. In other words, this could be interpreted as evidence for shopping.

However, this type of shopping cannot explain our findings on ratings informativeness and of how competition coincides with higher ratings. In fact, what we find at the aggregate industry level (when Fitch has a higher market share of rated bonds outstanding, the ratings of Moody's and S&P are higher) is the opposite direction of the bond-level finding (when Fitch rates a bond, it typically has low rating). Therefore, ratings shopping, which is arguably the most likely cause of endogeneity, appears to matter in the data but can be ruled out as an alternative explanation of our findings that higher competition coincides with more issuer-friendly ratings. If anything, ratings shopping leads to an underestimation of the effect of competition.

We conclude that competition most likely weakens reputational incentives for providing quality in the ratings industry and, thereby, undermines quality. The reputational mechanism appears to work best at modest levels of competition. There are a number of caveats and limitations to our findings and several qualifications to the conclusions we draw. First, we consider only corporate ratings, not ratings of CDOs, mortgage-backed securities, or other structured products.[13] Second, our findings have limited implications for the efficacy of reputational mechanisms in other imperfectly competitive settings, because the ratings industry is particular in many ways. For example, Hong and Kacperczyk (2010) find positive effects of competition among equity analysts [see also Chevalier and Ellison (1999) and Hong and Kubik (2003) for work on reputations and equity analysts]. These markets are different in many ways, including the underlying revenue model (equity analysts are paid indirectly by the institutional investors who use their recommendations, not by the firms they analyze) and the rate at which feedback occurs (equity analysts make short-term predictions, whereas many corporate bonds are first rated ten or even 20 years before they mature, before which time any evaluation of the rating's accuracy is typically incomplete).[14] Third, we disregard many potentially important aspects of reputation, such as how the reputational mechanism varies over firms' lifecycles (see Diamond, 1989) and how entry decisions are made (Mailath and Samuelson, 2001).

Our findings have important regulatory implications. As a policy matter, encouraging competition could reduce monopolistic (or, in the case of ratings, oligopolistic) rents, but our findings consistently suggest that it is not likely to improve quality. The fact that ratings quality seems to decrease with competition provides support for the standard economic theories of reputation (e.g., Klein and Leffler, 1981) as well as the related predictions about competition that Bolton, Freixas, and Shapiro (2009) provide for the ratings context. These findings indicate that quality in the ratings industry relies on rents that reward reputation-building activities, which are costly in the short run. The reduction of such rents reduces the amount of reputation-building, i.e., high quality production, in equilibrium. For policy makers and regulators, the benefits and costs of competition must be carefully compared.

In structured products, Fitch's presence was substantial early on, and no clear parallel exists to the changes we examine in the area of corporate bonds. This limits the applicability of our findings to the recent financial crisis, in which ratings of structured securities have been particularly called into question. However, a rich literature is emerging in this area, including Coval, Jurek, and Stafford (2008), Benmelech and Dlugosz (2009), Bolton, Freixas, and Shapiro (2009), Mathis, McAndrews, and Rochet (2009), and Skreta and Veldkamp (2009).

The rest of the paper is organized as follows. In Section 2, we discuss credit ratings and the underlying industry in more detail. In Section 3, we present the predictions of various theories and the methodology used to test them. We present the data in Section 4 and results in Section 5. Concluding remarks can be found in Section 6.

2. Credit ratings: business model and regulation

A credit rating is an assessment of the creditworthiness of a corporation or security, based on the issuer's quality of assets, its existing liabilities, its borrowing and repayment history and its overall business performance. Ratings predict the likelihood of default on financial obligations and the expected repayment in the event of default. There are two main types of ratings. Bond ratings are provided for a vast majority of publicly traded bonds in the United States. Firm (or issuer) ratings are produced by each of the three main agencies for all US public firms that issue public debt. Credit ratings range from Aaa (or, equivalently, AAA) to D (see Table 2 for an overview of the ratings levels for the three main rating agencies and the numerical value assignments used in our empirical work).

Issuers seek ratings for a number of reasons, including to improve the marketability or pricing of their financial obligations, to increase their trustworthiness to business counterparties, or to sell securities to investors with preferences over ratings. Investors, financial intermediaries, and regulators use ratings as an indicator of the risk and likely repayment of securities. Also, certain categories of institutional investors are obliged by regulation to rely on ratings for their investment decisions. For example, the amount of capital required for banks and insurance companies who own securities varies with the credit rating. Also, regulatory constraints force some investors (e.g., insurance companies and savings and loan institutions) to hold debt securities only of investment grade (i.e., with a rating of BBB or better).

[13] Doherty, Kartasheva, and Phillips (2008) examine the effect of competitive entry among rating agencies of the insurance market. In contrast to our findings in the corporate bond arena, they find that going from one to two raters (S&P entered as a competitor to the incumbent A.M. Best) led to improved rating content, using a particular model of what ratings should be for individual cases.

[14] Other industries in which reputations have been studied empirically include auto mechanics (Hubbard, 2002), online trading (Cabral and Hortaçsu, 2006), and restaurants (Jin and Leslie, 2003, 2009).

Table 2
The ratings scale.
The table describes categories for credit ratings, as well as the numerical scale used in the paper. Multiple numerical values for a single rating level represents the number assigned to ratings with a + qualifier, no qualifier, and a − qualifier, respectively. The source for ratings definitions is Standard & Poor's (S&P) Ratings Definitions from March 17, 2008 (Standard and Poor, 2009).

Rating group	Rating agency		Numerical value assigned	Category definition
	Moody's	S&P, Fitch		
Investment grade	AAA	AAA	28	The obligor's capacity to meet its financial commitment on the obligation is extremely strong
	Aa	AA	24, 25, 26	The obligor's capacity to meet its financial commitment on the obligation is very strong
	A	A	21, 22, 23	Somewhat more susceptible to the adverse effects of changes in circumstances and economic conditions than obligations in higher-rated categories. However, the obligor's capacity to meet its financial commitment on the obligation is still strong
	Baa	BBB	18, 19, 20	Exhibits adequate protection parameters. However, adverse economic conditions or changing circumstances are more likely to lead to a weakened capacity of the obligor to meet its financial commitment on the obligation
	Ba	BB	15, 16, 17	Obligations rated 'BB', 'B', 'CCC', 'CC', and 'C' are regarded as having significant speculative characteristics. 'BB' indicates the least degree of speculation and 'C' the highest. While such obligations will likely have some quality and protective characteristics, these may be outweighed by large uncertainties or major exposures to adverse conditions
	B	B	12, 13, 14	
	Caa	CCC	9, 10, 11	
	Ca	CC	7	
	C	C	4	
Default	D	D	–	An obligation in payment default. The 'D' rating category is used when payments on an obligation are not made on the date due even if the applicable grace period has not expired, unless Standard & Poor's believes that such payments will be made during such grace period. The 'D' rating also will be used upon the filing of a bankruptcy petition or the taking of a similar action if payments on an obligation are jeopardized

Ratings are typically shared freely by the rating agencies whose revenues derive from charges to the firms whose credit quality is being assessed. Fees for bond ratings typically consist of a fixed fee per year coupled with a larger upfront fee, charged when the bond is first rated at the time of issuance.[15] Paying for firm ratings is voluntary, although raters consider only nonpublic information provided by the firm itself if they receive payment from the corporate issuer [see Jorion, Liu, and Shi (2005) regarding raters' access to nonpublic information]. Rating agencies also provide various other types of ratings, such as short-term credit opinions and various industry-specific ratings. They could also derive revenue from selling analysis and other services to investors.

Early on, rating agencies tried an alternative revenue model that charged users of ratings. This model suffers from being very dependent on the enforcement of contractual limits to how customers can share ratings information they receive. As pointed out by White (2002), the change from user-paid to issuer-paid ratings as the dominant model "in the early 1970s coincides with the spread of low-cost photo-copying" (p. 47). Rating agencies derive revenue from various sources apart from issuers' fees, such as subscriptions to historical databases.

The Securities and Exchange Commission (SEC) has designated certain firms as Nationally Recognized Statistical Rating Organizations (NRSROs), of which there are ten since 2008. The ratings of these firms can be used for various regulatory purposes, and many investors only will consider ratings by an NRSRO when making investment decisions. This could also make entry in the industry more difficult.[16] Some argue, as SEC commissioner Paul S. Atkins, that "the unintended consequence of the SEC's approach to credit rating agencies was to limit competition and information flowing to investors. The legislative history reflects a genuine concern that the SEC facilitated the creation of – and perpetuated – an oligopoly in the credit rating business. Indeed, today, three NRSRO-designated firms have more than 90 percent of the market share."[17]

3. Hypotheses and methodology

We aim to compare ratings quality under different intensities of competition. Our measures of quality are based on the idea that, ideally, ratings should have a stable meaning and accurately predict defaults. Various users of ratings could have slightly different views on this.

[15] Fees vary with the face value of a bond issue, but usually in a nonlinear way (i.e., they are capped). Also, active issuers could receive quantity discounts. In February 2008, S&P shared information about its rating fee structure, including that corporate issuers (including industrial and financial service companies) pay "up to 4.25 basis points for most transactions" and that the minimum fee is $67,500. Also, "S&P will consider alternative fee arrangements for volume issuers and other entities that want multi-year ratings services agreements" (Standard and Poor's, 2008, p. 2).

[16] See Boot, Milbourn, and Schmeits (2006) for both a discussion and model of such investor restrictions to hold only investment-grade debt securities.

[17] See "Speech by SEC Commissioner: Remarks to the Institute of International Bankers" by SEC commissioner Paul S. Atkins, March 3, 2008, http://www.sec.gov/news/speech/2008/spch030308psa.htm.

Legislators and regulators rely on ratings categories being consistent over time and across firms and industries, so that regulation can use ratings to control and limit risk-taking. The US Securities and Exchange Commission (2003) wants to promote "credible and reliable ratings"[18] (p. 9). Consistent ratings criteria could also be attractive for private contracting (e.g., for bond mutual funds that invest in certain ratings categories). Presumably, investors generally want ratings that are informative about risk and default.[19]

We use several complementary approaches to evaluate rating quality. Our first approach appeals to ratings level. We argue that lower quality ratings are on average higher ratings, that is, ratings closer to the AAA end of the spectrum, because this must be the universal desire of the issuers as the subject of the ratings. It is worth recalling why shifts along the rating scale are a problem. Such shifts could in theory allow similar information transmission. However, the practical requirements are fairly steep: All investors have to be able to decipher how the market structure is affecting ratings. In particular, the least sophisticated investors, who likely need ratings the most, are the least able to follow time-variation in the meaning of ratings categories. Even if information transmission is maintained as categories change meaning, regulation and legislation relying on ratings are adversely affected. Such rules tend to be slow-moving and not easily adapted. They, therefore, require ratings categories to have stable meanings. For these reasons, a shift in categories could generate considerable difficulty for users of ratings. Summing up, ratings levels are a natural place to investigate whether rated firms exert pressure on ratings firms, because issuers are likely to have the direct preferences about the level. Other measures of ratings quality, such as default prediction, are perhaps more important to the financial system, but less directly related to issuer preferences. A general increase in ratings levels is a direct implication of competition if competition leads to ratings reflecting issuer preferences instead of credit quality (as suggested by reputational models).

Some cross-sectional variation probably exists among firms with regard to their preferences for better ratings. We exploit cross-firm variation in the likely importance of ratings to various issuers. Specifically, we predict that any effect of competition would be stronger for firms with higher leverage as these rely more on debt to finance their operations and investment. Such a story is consistent with the survey evidence of Graham and Harvey (2001). This allows a difference-in-difference type test, in which we compare the effect of competition on ratings for different groups of firms. Using a range of measures of leverage, we find that the effect on ratings is higher for more levered firms, consistent with the idea that ratings tend to reflect issuer preferences more as competition increases.

Our second approach purports that high quality ratings should be informative about bond values, and here we use market prices of debt to assess the informativeness of ratings. Lower quality ratings mean that ratings reflect things other than expected repayment, and ratings levels thus are less correlated with bond yields. We examine the correlation of ratings with bond yields (conditional on various controls known to correlate with yields). That is, we ask if ratings contain information about bond values beyond easily observable characteristics such as bond covenants and firm fixed effects.

Our third and final approach contends that, because ratings aim to predict default, we can test their predictive power econometrically as competition levels change. We relate default events three years out to current ratings, either to actual ratings categories or simply broad indicators for whether a firm is assigned an investment-grade rating, and allow the effect of ratings to vary with competition. Ratings are also meant to predict recovery rates in default, but data on these are much harder to collect (in part because bankruptcy proceedings can be lengthy and their outcomes complicated).

In all of the above tests, we rely on the use of Fitch's market share as a measure of competition, where market share is the number of bond ratings issued by Fitch as a fraction of those issued by the three raters in total. An advantage of using individual bond ratings is that it affords us a very large dataset. Another advantage is that the measure is simple and can easily be replicated. However, this is clearly not an ideal measure of competition, and revenue share would probably be preferable. Unfortunately, data on prices and revenue are not readily available. As a robustness test, we have also used an alternative measure of competition, the log of the number of ratings issued by Fitch in an industry-year. This variable is not mechanically affected by any decisions of S&P and Moody's and could therefore, be considered cleaner than Fitch's market share from an identification standpoint. Results with this alternative measure of competitive pressure are with few exceptions statistically stronger, and with slightly larger magnitudes than the results presented in the paper.[20]

4. Data

Data on bond ratings and market shares are drawn from the Mergent Fixed Income Securities Database (FISD). This database provides both issue- and issuer-specific data. We use data on ratings by S&P, Moody's, and Fitch of individual issues (bonds) to estimate the market share of Fitch in each industry-year cell. The total number

[18] Policy makers could also like ratings that do not fluctuate too much in order to stabilize financial institutions. This is an aspect of quality in which we do not expect competition to be particularly important (because neither issuer nor investor is likely to have a clear preference). We thereby leave this issue out of our empirical work.

[19] However, current holders of bonds could desire high ratings for the bonds they own. Especially under mark-to-market accounting rules, some investors could prefer not to get bad news in the form of downgrades.

[20] It might seem reasonable that Fitch can exert pressure only on the ratings of S&P and Moody's if Fitch itself on average offers friendly ratings. Fitch ratings are not included in our samples, but in unreported tests comparing Fitch bond ratings with those issued by the other two rating agencies, Fitch's ratings are 0.2 steps higher (controlling for bond fixed effects), consistent with competition through ratings levels.

of bond ratings used to calculate market shares is approximately 1.1 million. Each bond rating is matched to issuer data such as the main industry using the issuer's Committee on Uniform Security Identification Procedures code. There are more ratings around the year 2000 than in other years, but no year has fewer than 30,000 ratings. We define Fitch's market share as the fraction of all bond ratings in a year-industry cell performed by Fitch, where industries refer to the two-digit North American Industry Classification System (NAICS) industries and our sample years run from 1995 to 2006 (some of our tests do not use the first few years of data). Fig. 1 presents a moving average of monthly market shares for Fitch from 1998 to 2006.[21] Fitch's market share increases especially fast in 2000, coinciding with two acquisitions.[22] For each bond rating issued by Moody's or Standard and Poor's, we identify the preceding rating of the same bond, as well as whether the bond has been rated by Fitch. We have used four-digit industry classifications with very similar results throughout, but prefer two-digit industries for two reasons. First, using larger industries reduces the noise in market shares estimates, reducing measurement error. Second, it is not clear that narrow four-digit industries are competitively distinct (for credit rating agencies competing for business). The advantage of getting a larger number of distinct observations by using narrower industries does not seem to compensate for these disadvantages.

Firm ratings, default events, and accounting data are collected from the Compustat Industrial and Operating Segments databases. Compustat also contains S&P issuer credit ratings, updated annually. We define future default events as having a year-end corporate credit rating equal to D in three years.

We use bond transaction data from the Mergent FISD database to identify bond yields. This dataset covers all bond acquisitions and disposals (sales, redemptions) since 1995 by insurance companies. We exclude bonds denominated in foreign currencies, as well as any bonds that are callable, puttable, convertible, substitutable, or exchangeable. We also exclude US issues by foreign issuers (i.e., Yankee bonds). We drop defaulted bond issues, bonds denominated in foreign currency, and bonds with refund protection. We drop variable coupon bonds (because their yields to maturity are harder to calculate). We also require several control variables (such as issuer industry) to be available, and we drop bond trades with very high or very low sales prices to avoid data errors (this constraint does not affect our results). Most of these restrictions do not reduce the sample size much. We match each bond transaction to the most recent rating of the bond by Moody's or S&P and throw out any bonds with no ratings in the month preceding the transaction. If there is more than one rating on the same date, we use the median of the most recent ratings.

The remaining sample of bond transactions consists of a little more than 100,000 observations (each observation corresponds to one trade). For each bond transaction, we determine the yield to maturity implied by the price at which the trade took place (trades are quoted in terms of bond prices relative to bond face value), taking care to correctly time the coupons (typically semiannual) and final payment. We use a numerical procedure to estimate yields to maturity. Because of the sample restrictions (e.g., no floating rate bonds), this is straightforward and fairly fast, and the precise numerical procedure is not critical as determined by several robustness tests. We calculate yield spreads by subtracting the yield for the government bond with closest maturity (disregarding the timing of coupon payments) from the yield to maturity. Government bond yield data are from the Federal Reserve's H15 reports. For each bond in the sample, we identify the initial issue yield and match that to an initial credit rating.

An overview of the most important variables is presented in Table 3. In this table, the number of observations for Fitch's market share refers to the number of industry-year cells. Bond ratings categories are described in Table 2.

5. Empirical results

This section presents our evidence from the various tests of rating quality and how it is affected by changes in the competitive landscape of rating agencies.

5.1. Bond and firm credit rating levels

The first test concerns the level of firm credit ratings. We regress firm ratings on Fitch's market share. Results are presented in Table 4. In column 1, no controls are included. Errors are clustered by industry-year cell, because this is the level at which our variable of interest varies (this applies to most of our tests). In this sample, a significant positive correlation exists between Fitch's market share and the level of credit ratings issued by S&P or Moody's, suggesting that more competition pushes ratings toward the higher end of the rating spectrum (i.e., toward AAA). This pattern is clearly visible in Fig. 3, which plots the frequency of each rating for industry-years with high and low values for Fitch's market share. As the graph shows, all investment-grade ratings (i.e., BBB− and above) are more common under high competition, and all junk bond ratings (i.e., BB+ and below) are more common under low competition. In other words, the figure and the regression analysis offer complementary evidence that competition is correlated with higher ratings.

The estimated coefficients in Column 1 could be unreliable because no controls are included. In Column 2, we rectify this by including year and industry dummies. This pushes up the R^2 and reduces the coefficient and standard error on competition. The coefficient on Fitch's

[21] In tests, we use the total market share for each industry-year. This figure presents moving averages of total monthly market share across industries to provide a sense of the time path of Fitch's entry.

[22] Potentially, market share increases due to organic growth and increases due to acquisitions have different competitive impact, and including data from 2000 could make our results less representative. We have rerun our ratings levels regressions (Tables 3, 4, and 6) using only post-2000 data, or all years except 2000, and uncover qualitatively similar results.

Table 3
Summary statistics.

Each column presents the coefficient estimates from an ordinary least squares or logistic specification. Intercepts are not reported. The sample period is from 1995 until 2006. The left-hand-side variable is coded as follows: AAA=28, AA+=26, AA=25, AA−=42, A+=23, A=22, A−=21, BBB+=20, BBB=19, BBB−=18, BB+=17, BB=16, BB−=15, B+=14, B=13, B−=12, CCC=11, CC=7, and C=4. Firm characteristics are measured at the end of the previous fiscal year (using accounting data from Compustat). Leverage is debt over total assets. Yield spread is the yield to maturity minus the yield of the closest maturity treasury bond. EBITDAs earnings before interest, taxes, depreciation, and amortization.

	Firm credit rating	Bond credit rating	Fitch market share	Yield spread	Yield spread investment grade	Yield spread non investment grade	Yield spread at issue	Leverage	Debt/ EBITDA	Default in three years
Mean	18.092	23.080	0.212	194.6	129.4	530.1	164.9	0.368	3.798	0.010
Median	18	23	0.225	131.3	119.9	447.3	108.0	0.343	2.840	0.000
Standard deviation	3.930	4.943	0.142	252.7	139.9	390.8	158.3	0.203	4.073	0.101
Number of observations	19,756	686,990	429	1,110,955	92,949	18,006	7,520	19,756	19,300	18,651

market share remains positive and significant. The magnitude is modest but nontrivial. For a one standard deviation change in competition (0.142), average ratings are predicted to increase by 0.19. This corresponds to a one rating step upgrade (e.g., A− to A) of approximately one out of every five firms. Because the variable used to capture competition is likely to be noisy, the estimated coefficient is biased toward zero by measurement bias. The true magnitude could therefore, be larger than that implied by our coefficient estimate.[23] However, omitted firm heterogeneity could bias our findings either way. In Column 3, we include firm fixed effects (making industry fixed effects redundant), which absorb most of the variation in the dependent variable (firm ratings are fairly stable). Thus, the R^2 is now high (firm fixed effects explain over 80% of the variation in the left-hand-side variable). This regression also includes 18 accounting-based firm controls related to firm size, profitability, and indebtedness (see Table 4 for a description of the controls) to capture any time variation in firms' performance and credit worthiness. The estimated effect of competition remains positive and significant, and the implied magnitude is slightly smaller, corresponding to approximately one in nine firms. The significance of the coefficient is lower (10% level).

The ordinary least square (OLS) specifications implicitly treat every step of the left-hand-side variable as equal. There is no reason for this to be how ratings categories work, however. In Column 5, we run an ordered probit regression instead of OLS. This specification allows each cutoff to be estimated and so implicitly allows the effect of dependent variables to vary across different parts of the ratings scale. The regression, therefore, uses data more efficiently (although it could be less robust to certain econometric problems than OLS). The coefficient on Fitch's market share remains positive and significantly different from zero. The marginal effect of competition is estimated to be positive and significant at the 5% level for the rating categories AAA, AA+, AA, AA−, A+, A, A−, BBB+, and BBB. It is negative and significant at the 10% level for BBB− and negative and significant at the 5% level for all lower rating levels (these individual category effects are not reported in Table 4).

As a robustness test, we next collapse the data by industry-year cell, explaining the average (Column 5) or median (Column 6) of firm ratings in the industry and year with average (median) of all firm controls, as well as industry and year fixed effects. The cell averages are based on between 25 and 339 individual firm ratings (industry-years with fewer than 25 firms are excluded). These specifications differ from that in Column 3 in several ways. First, they avoid concerns about error correlations and repeated sampling of the same firm, because there are only 160 observations. Second, they put much less weight on cells with many bonds (because

[23] Blume, Lim, and Mackinlay (1998) show a trend toward tougher ratings standards in the period preceding our sample. Because our results include year fixed effects, any time trends in ratings levels are eliminated from the regressions. Average firm ratings are falling slightly over time in our sample.

Table 4
Predicting firm credit ratings with Fitch market share.

Each column presents the coefficient estimates from an ordinary least squares (OLS) or ordered probit specification. Intercepts are not reported. The sample period is from 1995 until 2006. The left-hand-side variable refers to credit opinion ratings by Standard and Poor's and is coded from 28 (AAA) to 1 (D). See Table 4 for details. Fitch market share is the fraction of bond ratings in an industry-year cell performed by Fitch Ratings. Firm characteristics are the log of sales, log of book value of assets, cash divided by total assets (and its square), EBITDA (earnings before interest, taxes, depreciation, and amortization) divided by total assets (and its square), cash flow over total assets (and its square), EBITDA over sales (and its square), cash flow over sales (and its square), PPE (property, plant, and equipment) over total assets (and its square), interest expense over EBITDA (and its square), and debt over total assets (and its square), all measured at the end of the previous fiscal year (using accounting data from Compustat). Industries are two-digit level North American Industry Classifications System (NAICS) industries. In Columns 5 and 6, data are collapsed by industry-year cell (averages and medians, respectively). Heteroskedasticity-robust standard errors for the coefficient estimates are in parentheses. Errors are clustered by industry × year cell in Columns 1 to 4. Significance at the10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

	Dependent variable: firm credit rating					
	OLS (1)	OLS (2)	OLS (3)	Ordered probit (4)	OLS average by cell (5)	OLS median by cell (6)
Fitch market share	2.395** (1.123)	1.325** (0.566)	0.784* (0.432)	0.3615** (0.156)	1.533*** (0.570)	1.754** (0.846)
Year fixed effects	No	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	No	Yes	No	Yes	Yes	Yes
Firm fixed effects	No	No	Yes	No	No	No
Firm controls	No	No	Yes	No	Yes	Yes
R^2	0.004	0.141	0.900	n/a	0.961	0.914
Number of observations	19,630	19,630	19,630	19,630	160	160

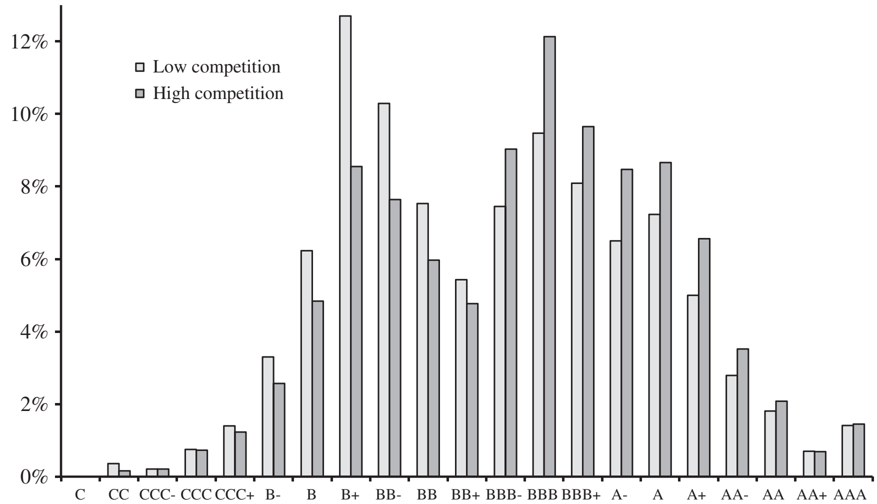

Fig. 3. Firm credit ratings distribution: high and low competition (Fitch market share above and below median).

each industry-year cell is treated equally), which could have an important effect on the estimated coefficients if the effect of competition is not homogenous. Third, all within-cell variation is thrown out. The estimates for Fitch's market share are significant and positive in both regressions, and they imply magnitudes similar to that implied by the coefficient estimate in Column 2 (a one notch rating change for one in four or five firms) and significance somewhat higher than in Column 3. Overall, the firm rating results contained in Table 4 suggest that ratings become more favorable to issuers when competition increases.

We turn now to ratings of individual bond issues (as opposed to the firms). Such tests should provide further evidence of how increases in competition among rating agencies affect ratings. For many purposes, bond ratings matter more than firm ratings because investment regulations tend to concern instrument and not issuer ratings. Also, thanks to the very large number of observations, we can control for dynamics more carefully than with firms. In Table 5, we report the estimates of regressions of the level for individual bond credit ratings on Fitch's market share. Each observation is a rating. The number of observations is very large, because many firms have multiple bond issues outstanding at any given time and many bonds are rated repeatedly. We include a range of fixed effects to control for observables. In Column 1, we report a regression of ratings on Fitch's market share,

Table 5
Predicting bond ratings with Fitch market share.

Each column presents the coefficient estimates from an ordinary least squares (OLS) regression. Intercepts are not reported. The sample period is from 1995 until 2006, except in Columns 5 and 6, which refer to 1996–2006. The left-hand-side variable refers to credit opinion ratings by Standard and Poor's and is coded from 28 (AAA) to 1 (D). See Table 4 for details. For Column 1 to 4, the unit of observation is an individual bond rating. For Columns 5 and 6, the unit of observation is industry-year cell, and all variables are the averages (Column 5) or medians (Column 6) of all observations in that cell. Cells with less than ten bond ratings are excluded. Fitch market share is the fraction of bond ratings in an industry-year cell performed by Fitch Ratings. Fitch rating (dummy) is a dummy variable taking the value one if Fitch issued a rating for the bond issue in the same calendar year as the rating was made. Industries are two-digit level North American Industry Classifications System (NAICS) industries. Previous rating refers to the same bond issue's preceding rating. Heteroskedasticity-robust standard errors for the coefficient estimates are in parentheses. Errors are clustered by industry × year cell. Significance at the10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

	Dependent variable: bond issue credit rating					
	OLS, all ratings	OLS, all ratings	OLS, all ratings	OLS, excludes NAICS 52	OLS, average, collapsed by cell; excludes NAICS 52	OLS, medians, collapsed by cell; excludes NAICS 52
	(1)	(2)	(3)	(4)	(5)	(6)
Fitch market share	0.4187**	0.5024**	0.5941***	0.6793**	2.061*	5.201***
	(0.187)	(0.220)	(0.198)	(0.336)	(1.214)	(1.782)
Fitch presence (dummy)			−0.0938**			
			(0.045)			
Maturity					0.0312	−0.205*
					(0.088)	(0.118)
Lagged rating (collapsed)					0.332***	0.242**
					(0.095)	(0.095)
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	No	Yes	No	Yes	Yes
Time to maturity fixed effects	Yes	Yes	Yes	Yes	No	No
Previous rating fixed effects	Yes	Yes	Yes	Yes	No	No
Bond issue fixed effects	No	Yes	No	Yes	No	No
R^2	0.941	0.959	0.941	0.904	0.908	0.842
Number of observations	368,811	368,811	368,811	146,366	176	176

controlling for year and industry fixed effects, as well as fixed effects for the lagged rating of the same bond (i.e., the most recent rating by either S&P or Moody's, whenever it occurred) and time to maturity (rounded to the nearest number of years) fixed effects. Competition enters with a positive sign, suggesting that more competition tends to increase ratings, consistent with the result for firm ratings. The coefficient on Fitch's market share implies that a one standard deviation increase in competition is expected to increase ratings by an average of 0.06 steps (that is, one in 17 bonds sees an increased rating of one step), a smaller effect than that estimated for firm-level credit ratings. Often, the same bond appears many times in our data. This means we can include bond issue fixed effects and estimate the effect of competition holding the subject of the rating fixed (important aspects of a bond could change through time). In Column 2, we include bond issue fixed effects (making industry fixed effects redundant). In this specification, Fitch's market share is again positively and significantly related to ratings (the estimated effect is approximately 20% larger than without bond fixed effects). This result rules out that our findings are driven by any time-invariant differences between bonds and is akin to studying changes in ratings.

The statistically robust link between competition and poor incumbent ratings quality is consistent with theories in which competition causes lower quality ratings, but also with theories that imply the reverse direction of causality. We attempt to address endogeneity concerns by controlling for whether a bond is rated by Fitch. Controlling for Fitch's presence in individual bonds addresses the concern that Fitch tends to rate bonds with either high or low ratings (and hence that competition is correlated with the left-hand-side variable due to reverse causality). In particular, we might find a positive correlation between competition and ratings if Fitch systematically rates bonds with high ratings. In Column 3 we include a dummy variable equal to one if Fitch has rated the same bond during the calendar year in question.[24] The Fitch dummy enters with a negative sign, implying that individual bonds receiving a Fitch rating tends to be those in which an incumbent agency's rating is low (conditional on regression controls). This suggests that, if anything, selection effects bias the coefficient on Fitch market share downward (because Fitch's market share is higher in industry years when many bonds have a Fitch rating). In other words, whereas bonds in industry-year cells with a big Fitch presence (what we interpret as competition) tend to receive higher ratings, the particular bonds that are rated by Fitch within an industry-year cell tend to have low ratings. The estimated coefficient on Fitch's market share is still positive and significant. These results are consistent with our interpretation that competition increase ratings, while firms with worse ratings

[24] Varying the time window has only a minor impact on the regression results. For example, using a dummy equal to one for bonds for which Fitch issued a rating ever, or issued a rating at the time of issue, yields very similar regression results (the coefficient on Fitch's market share is similar).

seemingly gravitate toward using Fitch (tending to generate a negative relation between Fitch's presence and ratings levels). Adding up selection effects across many bonds, therefore, cannot explain our competition finding. The negative coefficient on Fitch's presence could be consistent with ratings shopping if firms tend to ask for a Fitch rating if they are disappointed with their ratings from S&P and Moody's. However, such behavior provides no apparent advantage to the issuer.

In our sample, financial firms issue a large share of corporate bonds. In Column 4, we exclude issuers belonging to NAICS 52 from the sample in case bonds in this industry are fundamentally different from nonfinancial firms' bonds. The sample size is cut in approximately half, and the estimated coefficient is somewhat larger, corresponding to an upgrade of roughly one in ten bonds for a one standard deviation increase in Fitch's market share. We next collapse the data by industry-year cell, as done for firm ratings, explaining the average or median of ratings in the industry and year with average (median) maturity and lagged ratings, as well as industry and year fixed effects. The cell averages are based on between ten and 7,914 individual bond ratings (industry-years with less than ten observations are excluded). Because the variation across cells in the number of bond ratings is even larger than for firm ratings, collapsed results could differ even more from the full panel results in this setting. The estimated competition coefficient for both average and median ratings is large and significant (at the 10% level for averages, 1% for medians). The implied magnitudes are larger than in the individual bond regressions (corresponding to an upgrade of one in three bonds for averages and two in three bonds for medians). This could reflect any of several factors. First, the method puts more weight on industry-year cells with few bond ratings. Perhaps the effect of competition is stronger for industries with limited numbers of bonds outstanding, potentially reflecting the sophistication of investors. Second, all within-cell variation is thrown out. Third, to the extent that endogeneity biases coefficients against our findings (because firms are more interested in a third rating when S&P and Moody's issue relatively low ratings), the collapsed results could be less biased. The pattern that firms with lower ratings tend to get a Fitch rating, seen in Column 3, was identified within industry-year cells. This pattern could be weaker or absent at the industry level (e.g., perhaps industry level presence is driven more by Fitch's access to skilled labor).

We next consider cross-sectional variation in the impact of competition on firm ratings. The effect of competition should be felt more acutely for those firms that are likely to care more about their ratings. We use firm indebtedness to identify firms with a greater concern for ratings. In Table 6, we interact Fitch's market share with four measure of indebtedness: leverage (debt over assets), long-term leverage (long-term debt over assets), a high leverage dummy (leverage is above the median in the firm's industry), and debt divided by EBITDA (earnings before interests, taxes, depreciation, and amortization). These specifications allow us to include industry-year interaction fixed effects

Table 6
Predicting rating levels with Fitch market share–interactions with leverage.

Each column presents the coefficient estimates from an ordinary least squares (OLS) or logistic specification. Intercepts are not reported. The sample period is from 1995 until 2006. The left-hand-side variable refers to firm credit opinion ratings by Standard and Poor's and is coded from 28 (AAA) to 1 (D). See Table 4 for details. Fitch market share is the fraction of bond ratings in an industry-year cell performed by Fitch Ratings. Firm characteristics are the log of sales, log of book value of assets, cash divided by total assets (and its square), EBITDA (earnings before interest, taxes, depreciation, and amortization) divided by total assets (and its square), cash flow over total assets (and its square), EBITDA over sales (and its square), cash flow over sales (and its square), PPE (property, plant, and equipment) over total assets (and its square), interest expense over EBITDA (and its square), debt over total assets (and its square), all measured at the end of the previous fiscal year (using accounting data from Compustat). Leverage is debt over total assets, long term leverage is long-term debt over assets, the high leverage dummy is equal to one if debt over assets is above 0.2324 (the sample median). Industries are two-digit level North American Industry Classifications System (NAICS) industries. The standard errors for the coefficient estimates are in parentheses and are clustered by industry × year cell. Significance at the10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

	Dependent variable: firm credit rating			
	OLS (1)	OLS (2)	OLS (3)	OLS (4)
Fitch market share × leverage	6.010*** (1.645)			
Fitch market share × long-term leverage		5.317*** (1.708)		
Fitch market share × high leverage dummy variable			1.587** (0.682)	
Fitch market share × debt/EBITDA				0.3806*** (0.129)
Debt/EBITDA				0.3221*** (0.0483)
Firm controls	Yes	Yes	Yes	Yes
Industry × year fixed effects	Yes	Yes	Yes	Yes
R^2	0.589	0.599	0.588	0.629
Number of observations	19,630	19,630	19,630	19,630

(i.e., approximately four hundred dummies), thereby reducing any concern about omitted variables that are correlated with Fitch's market share and vary within industries and years. Without exception, the interactions of competition and debt are positive and highly significant. This suggests that the effect of competition is disproportionately felt for firms that are more likely to care about their ratings because they rely heavily on debt financing. This is consistent with the argument that competition makes ratings more responsive to firm preferences.

Regressions of ratings levels, at both the firm and security level, with and without extensive control variables, estimated either in full or collapsed panels, consistently suggest that a high Fitch market share coincides with higher ratings. Before we address possible econometric concerns with these results and then turn to tests of the information content of ratings, we want to emphasize how problematic ratings inflation is for the use of credit ratings in the financial system. Suppose some sophisticated investors can filter out ratings inflation and extract the credit information in ratings that change with competition. This leaves the least informed investors at a disadvantage, thereby diminishing the value of credit ratings to the financial system.[25] Also, rewriting contracts and regulation is costly and slow.

5.2. Identification issues raised by ratings level results

There are two main identification concerns with our results. First, certain firms or bonds might be more likely to be rated and thus show up in our data. Because both S&P and Moody's have explicit policies to rate all taxable bonds from US issuers, and also to rate all such issuers, there is mostly likely very little selection into being rated. Second, Fitch's market share might not correspond to a random experiment, suggesting either reverse causality (Fitch enters markets with high ratings) or an omitted variable bias (some factor drives both higher ratings and entry by Fitch). Interestingly, the most likely reverse causality works against our findings, as firms with low ratings are more eager to ask for a third opinion. This pattern is confirmed directly in bond-level regressions. Hence, reverse causality could bias the coefficient estimates on Fitch's market share to zero, but most likely cannot explain our findings. Omitted variable bias is harder to rule out conclusively. One possibility is that Fitch found it easier to grow its market share in booming sectors where credit demand was high (perhaps overwhelming S&P's and Moody's capacity to rate bonds). In other words, overall market growth drove an increased market share for Fitch.

We test this directly by regressing Fitch's market share on leads and lags of five proxies for ratings demand in an industry: the number of ratings issued, the log of the total amount of outstanding debt of Compustat firms in an industry, the annual change in this variable, an asset-weighted average of the ratio of return on assets (ROA, EBITDA over assets) in Compustat firms in the industry, and the median of ROA across Compustat firms in the industry. We separately regress each of the industry-year observations of one of the credit demand proxies on Fitch's market share, controlling for industry and time fixed effects. Results are presented in Table 7. There seems to be no correlation between the various measures of demand for credit and Fitch's market share (one coefficient out of 25 is estimated to be significant at the 10% level, which is slightly fewer than the expected number from a random sample with no relation). These tests do not explain what drives Fitch's market share but shows that ratings demand is not likely a main driver of relative market shares.[26] Furthermore, the "easy entry in good times" explanation for the ratings results presented above has no implication for the informativeness of ratings. The reputational theories do, however, in that they predict that favoring issuers compromise the information content (i.e., putting more weight on rater's preferences when determining ratings implies less weight on rater's information about credit quality). We turn to these tests next and return to the discussion of which theories are consistent with the various findings after that.

5.3. Bond yields and ratings

The next step is to examine how the information content of ratings responds as competition changes. To do this, we test how the conditional correlation between ratings and bond yields responds to competition. The dependent variable is the yield spread to the closest maturity Treasury bond. Results are reported in Table 8. In Column 1, we control for a recent credit rating by S&P or Moody's as well as Fitch's market share. We also include industry fixed effects and bond characteristics as controls (e.g., time to maturity and size of bond issue). Bond trades occur at different times, and interest rates and risk premia are likely to be an important source of time series variation in yields, so we include fixed effects for each date (specifically, each month). The coefficient on credit ratings is negative and significant, confirming that bonds with better credit ratings trade at lower yields, controlling for other observable factors. The coefficient on the interaction of credit rating and Fitch's market share is positive and significant, implying that the correlation of credit ratings and bond yields is lower when there is more competition. Going from the 25th to the 75th percentile of competition, the effective coefficient on ratings falls by a third. This is consistent with the view that competition reduces the information content of ratings. This result is robust to the inclusion of year-industry fixed effects, as seen in Column 2. This regression produces results that are very similar to the previous

[25] For theories of ratings that incorporate unsophisticated (or naïve) investors, see the work of Boot, Milbourn, and Schmeits (2006) and Bolton, Freixas, and Shapiro (2009).

[26] An alternative way of incorporating these variables is to include them as controls in regressions similar to those in Tables 4 and 5. Doing this has a very limited effect on the coefficient estimates on Fitch's market share. This is also consistent with the interpretation that Fitch's entry is not simply about market growth.

Table 7
Fitch's market share and segment characteristics.

Each coefficient estimate refers to one ordinary least squares (OLS) specification (different rows represent regressions that differ only in the timing of the independent variable). Each regression includes year and industry fixed effects. For each regression, the coefficient estimate for Fitch's market share is reported. The sample period is from 1995 until 2006. Number of ratings issued is the log of the aggregate number of credit ratings issued for bonds in an industry. Industry debt is the log of the total amount of outstanding debt of Compustat firms in an industry. The change in industry debt is the log of industry debt minus its previous value. Industry profitability is an asset-weighted average of the ratio of EBITDA (earnings before interest, taxes, depreciation, and amortization) to assets in Compustat firms in the industry and industry profitability (median) is the median EBITDA-asset ratio across all Compustat firms in the industry. Fitch market share is the fraction of bond ratings in an industry-year cell performed by Fitch Ratings. The number of observations is 266 or fewer (some observations are lost due to lags). The standard errors for the coefficient estimates are in parentheses and are heteroskedasticity-robust. Significance at the10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

Timing of Fitch's market share	Independent variable: Fitch's market share				
	Number of ratings issued (1)	Industry debt (dollars) (2)	Change in industry debt (dollars) (3)	Industry profitability (4)	Industry profitability (median) (5)
Lead ($t+2$)	0.1831	−0.1079	−0.0885	−0.0108	0.0085
	(0.4055)	(0.1937)	(0.2039)	(0.0272)	(0.0156)
Lead ($t+1$)	0.0194	0.0824	0.2870	−0.0167	0.0039
	(0.4210)	(0.1913)	(0.1794)	(0.0248)	(0.0155)
Simultaneous (t)	0.1474	−0.0617	−0.1813	−0.0086	0.0112
	(0.4151)	(0.1739)	(0.1541)	(0.0251)	(0.0158)
Lag ($t+1$)	0.2968	−0.2615	−0.1362	0.0151	−0.0008
	(0.3367)	(0.1673)	(0.1584)	(0.0245)	(0.0149)
Lag ($t+2$)	0.2015	−0.3075*	0.1018	0.0213	0.0221
	(0.3190)	(0.1768)	(0.1577)	(0.0237)	(0.0165)
Industry fixed effects	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes
Number of observations	≤266	≤266	≤266	≤266	≤266

specification.[27] Next, we exclude speculative-grade bonds, in case they have a different relation to ratings than investment grade bonds. The sample is only slightly smaller, because most bond trades in the data are of bonds rated investment grade. The effect of ratings is smaller for these firms, although still highly significant. The interaction of Fitch's market share and ratings has a similar magnitude (relative to the average effect of ratings). In Column 4, we instead exclude trades of bond rated investment grade and focus exclusively on speculative-grade observations. The coefficient estimate is about 2.9 times higher. This lines up closely with the standard deviation of the left-hand-side variable (cf. Table 3), which is 2.8 times larger (the median of the dependent variable is 3.7 times larger for non-investment-grade bond trades). Thus, the reduced correlation between yields and ratings is comparable for the two groups of bonds. In other words, the economic magnitude appears fairly similar across investment and non-investment-grade bonds.

These tests are based on trades of bonds, in which the same bond can appear multiple times. One concern is that multiple trades capture the same information. We include bond controls, which could help reduce such concerns.[28] However, a more direct way of addressing this is to look at the price at issue. The Mergent FISD database contains yield spreads at issue and we can match these to early ratings using the same process as for the secondary market trades.[29] In Column 5, we use the yield spread at issue as dependent variable. As with the data on secondary market trades, the implied correlation between credit ratings and bond yields is weaker when Fitch's market share is higher. The result is highly statistically significant. The magnitude is slightly lower than that found in the trade data (i.e., Column 2). However, the standard deviation of yields is lower at issue (the coefficient is 56% lower, the standard deviation is 37% lower), so the economic magnitude of the estimates is similar. Across ratings levels and both at issuance and in the secondary market, it appears that competition reduces the correlation between ratings and bond yields. In other words, the bond market suggests that ratings are less informative when competition is high.

So far, we have discussed the slope of the relation between yields and ratings. An alternative way of assessing the informativeness of ratings is to study how they

[27] We also include the interaction of date (i.e., month) fixed effects and the natural log of time to maturity to absorb any variation in how bond premia could vary with bond age (not reported). Also, we include controls based on estimated bond durations instead of maturities (not reported). These variations have only a marginal impact on the reported regression results.

[28] We have tried clustering errors by bond issue and consistently get much higher significance than reported in the tables (where errors are clustered by industry-year combinations).

[29] Ratings could be less (or more) important at issue than for later trades. Thus, there is not necessarily an expectation that the coefficient will be the same as for secondary market trades.

Table 8
Bond yields and ratings—the effect of Fitch market share.

Each column presents the coefficient estimates from an ordinary least squares (OLS) regression. Intercepts are not reported. Each observation is the yield to maturity of a bond in one transaction. The sample period is from 1995 until 2006. The dependent variable is the yield to maturity minus the yield to maturity of the government bond with the closest maturity. Credit ratings are bond credit ratings issued by Standard and Poor's and Moody's (reported by the Margent Fixed Income Securities Database), and represent the latest preceding the transaction (if several were issued simultaneously, we use the average), not older than three months. Fitch market share is the fraction of bond ratings in an industry-year cell issued by Fitch Ratings. Industries are two-digit level North American Industry Classifications System (NAICS) industries. Bonds are excluded if they have nonstandard features (see text for details), negative yields, or yields above 20%. The standard errors for the coefficient estimates are in parentheses and are clustered by industry × year cell. Significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

	Dependent variable: yield spread				
	OLS, all trades (1)	OLS, all trades (2)	OLS, investment grade only (3)	OLS, noninvestment grade only (4)	OLS, initial issue (5)
Credit rating × Fitch market share	0.766***	0.968***	0.430***	1.253**	0.430***
	(0.162)	(0.214)	(0.114)	(0.523)	(0.)
Credit rating	−0.569***	−0.620***	−0.272***	−1.102***	−0.287***
	(0.162)	(0.063)	(0.003)	(0.164)	(0.034)
Fitch market share	−14.160**				
	(3.544)				
Log of time to maturity	−1.174***	−1.203***	−1.121***	−3.414***	0.666***
	(0.168)	(0.165)	(0.125)	(0.493)	(0.085)
Log of time to maturity, squared	0.251***	0.268***	0.278***	0.495***	−0.113***
	(0.035)	(0.035)	(0.027)	(0.115)	(0.022)
Log of offering amount	−0.223**	−0.302***	0.366***	0.665	−0.260
	(0.101)	(0.108)	(0.071)	(1.581)	(0.352)
Log of offering amount, squared	0.002	0.006	−0.019***	−0.018	−0.007
	(0.004)	(0.004)	(0.003)	(0.063)	(0.015)
Date fixed effects (month–year)	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	No	No	No	No
Year–industry fixed effects	No	Yes	Yes	Yes	Yes
R^2	0.484	0.503	0.444	0.398	0.697
Number of observations	110,955	110,955	92,949	18,006	7,427

contribute to the R^2. To do this, we run first-stage regressions with all controls except ratings and then regress residuals from the first stage on bond ratings. In a second stage, done separately for subsamples by Fitch market share, we can examine how R^2 varies. These tests agree with the *t*-tests from regression coefficients. For example, splitting the sample in half by competition, we find that ratings explain more of the residuals (from a regression on all controls apart from ratings and market share). For the high market share sample, the R^2 is 0.081, and for the low market share sample, 0.141 (the estimated coefficients on ratings are −0.094 and −0.215, respectively, significantly different from zero and each other). Similar patterns are evident for other sample splits. In other words, also by this measure we find that ratings are more informative when competition is low.

The bond yield results show that the correlation of ratings and yields declines as competition increases. In other words, bond yields (and spreads) are less related to credit ratings when Fitch has a high market share. In addition, ratings explain more of the variation in yields when competition is low, consistent with the slope findings. The implication is that credit ratings contain less yield-relevant information when competition is stronger. This is consistent with theories that predict lower quality (less informative) ratings when there is more competition.

Ratings shopping, the ability of issuers to choose the best ratings from among a set of possible rating agencies, also appears consistent with the correlation of Fitch's market share with higher ratings levels. If ratings shopping had a substantial impact on the level of some ratings, it could potentially explain our findings about informativeness as well (although this might not be very plausible). However, ratings shopping is much more likely for other agencies than the incumbents, because S&P and Moody's tend to rate all US corporate bonds and issuers. Also, when multiple raters issue ratings, they tend to be fairly close to each other, so the scope even with Fitch's ratings seems modest.[30] Moreover, although researchers have searched for it, limited evidence exists for ratings shopping among US corporate bond issuers (see Cantor and Packer, 1997; Jewell and Livingston, 1999).

5.4. Predicting default

We next examine what is perhaps the most direct measure of informativeness for credit ratings: their ability to predict defaults. This test is attractive because it directly examines the ability of ratings to predict the most important credit events. The disadvantage is that corporate defaults are rare, limiting the power of this test. This limit is likely to be especially problematic for higher

[30] Ratings of the other firms provide very visible comparisons for raters, so they could prefer to not deviate too much from each other. The tactics of ratings is beyond the scope of our paper and does not relate to the main implications from the reputational models, which concern informativeness and (the average) level of ratings.

Table 9
Default prediction—the effect of Fitch market share.

Each column presents the coefficient estimates from an ordinary least squares (OLS) regression. Intercepts are not reported. Each observation is one firm-year in which firm-level controls can be identified and the firm is identified as defaulting or not defaulting in three years. The sample period is from 1995 until 2005. Fitch market share is the fraction of bond ratings in an industry-year cell issued by Fitch Ratings. Industries are two-digit level North American Industry Classifications System (NAICS) industries. Firm characteristics are the log of sales, log of book value of assets, cash divided by total assets (and its square), EBITDA (earnings before internet, taxes, depreciation, and amortization)divided by total assets (and its square), cash flow over total assets (and its square), EBITDA over sales (and its square), cash flow over sales (and its square), PPE (property, plant, and equipment) over total assets (and its square), interest expense over EBITDA (and its square), debt over total assets (and its square), and the log of sales and the log of assets, all measured at the end of the previous fiscal year (using accounting data from Compustat). In Column 5, data are averaged by industry-year cell. The standard errors for the coefficient estimates are in parentheses and are clustered by industry × year cell in Column 1 to 4 and heteroskedasticity robust in all columns. Significance at the10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

	Default in three years, OLS (1)	Default in three years, OLS (2)	Default in three years, OLS (3)	Default in three years, OLS (4)	Fraction default in three years by industry-year cell, OLS (5)
IG dummy × Fitch market share	0.089***				
	(0.030)				
IG dummy	−0.033***				
	(0.067)				
Rating × Fitch market share		0.0123***	0.0123***	0.0063*	0.0070***
		(0.070)	(0.001)	(0.0038)	(0.001)
Rating		−0.0045***	−0.0049***		−0.0094**
		(0.0009)	(0.0011)		(0.004)
Fitch market share	−0.080***	−0.253***	−0.229***	−0.116	−0.121***
	(0.028)	(1.250)	(0.085)	(0.080)	(0.023)
Year fixed effects	No	No	Yes	Yes	Yes
Industry fixed effects	No	No	Yes	Yes	Yes
Year and industry FE × rating	No	No	No	Yes	No
Firm controls	No	No	Yes	No	Yes
R^2	0.008	0.001	0.024	0.024	0.571
Number of observations	18,707	18,650	15,661	18,650	189

ratings, where defaults are rare.[31] It can be argued that ratings should ideally predict default both conditionally and unconditionally, i.e., ratings should be informative about raw probabilities without taking any other information into account, as well as providing predictive power beyond what easily measurable accounting data can. The information transmission function of ratings concerns conditional predictability, whereas the risk classification function concerns unconditional predictability.

Tests of the ability of ratings to predict default at the three-year horizon are presented in Table 9. Using a linear probability models (OLS), we regress indicators of future default on ratings and control variables. In Column 1, default in three years is regressed on a dummy for investment-grade rating, Fitch's market share, and an interaction of these. All three variables are highly significant. The coefficient on the investment-grade dummy is negative and significant at the 1% level, implying that firms rated investment grade are less likely to default than those rated noninvestment grade. The interaction is positive, meaning that the difference between investment-grade and speculative-grade default rates falls with competition. The magnitude of this effect is large. Speculative-grade firms are predicted to be 4.7 times as likely to default in three years as investment-grade firms at median competition, but 7.7 times as likely with low competition (25th percentile, 0.133) and only 2.2 times at high competition (75th percentile, 0.308). In Column 2, we replace the investment-grade dummy with the numerical rating value (using the Hand, Holthausen, and Leftwich, 1992, scale), with similar results. The scale uses finer variation, but at the expense of imposing a particular numerical scale, which could be inappropriate. As it turns out, the fit is slightly better, and the magnitude of the interaction remains large and significant at the 1% level. The predicted default probability of a B+ (the most common non-investment-grade rating) firm is 2.1 times that of a BBB-rated firm (the most common investment-grade rating) at median competition, 2.4 times at low competition (25th percentile), and 1.5 times at high competition (75th percentile). The information content of ratings appears much diminished when competition increases.

The results in Columns 1 and 2 are consistent with lower quality ratings when competition is strong but could be affected by the absence of controls. We now examine how well ratings predict default after controlling for observables such as accounting data. In Column 3, year and industry fixed effects are included, as well as the full set of firm controls. The significance and magnitude of the coefficient estimates for the variables of interest change

[31] In our sample, there are no default events at the three-year horizon for firms rated AA−, AA, AA+, or AAA. There are 186 events that we can map to controls three years before, of which 40 (21.5%) were rated investment grade and 146 (78.5%) were rated noninvestment grade. The highest observed default frequency, 5.6%, is for the ratings category CCC+.

slightly (the interaction is now significant at the 1% level). The overall fit of this model is better: The R^2 is 2.4% (firm controls and the two sets of dummy variables contributes about half of the improvement each). Going from the 25th percentile of the competition measure to the 75th percentile, the effective slope on ratings falls by almost two-thirds. This establishes several interesting points. First, defaults are better predicted by ratings together with firm accounting data than by ratings alone. In other words, ratings are not sufficient statistics for the information in accounting data. Similarly for time and industry dummies, ratings do not fully incorporate all the time- and industry-variation in default rates.[32] Second, after controlling for these important determinants, however, corporate ratings still help predict defaults, especially when competition is limited.

Defaults could be harder to predict in some years and in some industries. This could lead to smaller differences in default probabilities between investment- and non-investment-grade firms at those times or in those industries. To control for this, we include interactions of ratings with all the year and industry fixed effects. The results are reported in Column 4. This specification leans very hard on the data, because there are 53 coefficients to estimate,[33] using a sample with less than two hundred defaults. The year and industry interactions are not well estimated with joint Chi-tests of 3.18 (significantly different from zero at the 7.4% level) and 2.07 (significantly different from zero at the 15.0% level). The model also does no better than the model with firm controls in terms of R^2. The coefficient estimate for the interaction of ratings and Fitch's market share is slightly lower than the previous regression with firm controls. It remains significant at the 10% level.

In the last column of Table 9, we collapse data by industry-year cell. The dependent variable is the fraction of firms in a cell default within three years and ranges from zero (in about three-quarters of cells) to 0.0144. This is well explained by the linear model, which has an R^2 of 57%. Because the collapsed data have discarded all within-cell variation in default probabilities, this regression is identified only from across-cell variation. The coefficient estimate for the ratings–competition interaction is positive and significant as in the full panel regressions, but of slightly lower magnitude. The coefficient estimate for ratings drops by 14% going from the 25th to the 75th percentile of the competition measure.

The regression results for the interaction of Fitch's market share and credit ratings all suggest that ratings quality is lower when competition is high. This is consistent with reputational models predicting less willingness to invest (through quality) in reputations when competition increases. It could also be consistent with ratings shopping: as competition increases, there are more ratings to chose from, and the published ratings become less representative of the average credit opinion of raters (the scope for ratings shopping is probably limited for US corporate debt, however). We discussed above why reverse causality is unlikely to explain the higher ratings that coincide with a higher Fitch market share and also how credit demand is unlikely to be an important omitted variable. Another possible omitted variable problem has to do with the precision of ratings. Fitch could have found it easier to gain market share when credit quality was hard to judge. This could lead simultaneously to poor predictability of ratings and high Fitch market share. If this mechanism generates our results, we cannot infer that competition is harmful to ratings quality. We can test the hypothesis that informational opaqueness drives entry with a measure of how difficult it is to predict default. To construct such a measure, we estimate a linear probability model of default, with firm controls but without ratings, separately for each industry-year cell, and record the R^2. Ninety-one such cells have at least one default and 20 observations, allowing us to estimate the model with all 18 accounting ratios. The R^2 varies from 0.001 to 0.471. The variation in R^2 has no relation to Fitch's market share.[34] We can also allow the 18 controls to interact with Fitch's market share, and the interactions are generally insignificant (joint F-statistic 0.52 with p-value 0.473 using a model similar to Column 3). This suggests that reverse causality driven by preferential Fitch entry into difficult information environments is not an important driver of the correlation between Fitch's market share and the predictive power of ratings.

5.5. Instrumental variables

The empirical strategy of this paper relies on industry-level variation in the extent to which Fitch competes with the incumbent rating agencies. We have argued that endogeneity is unlikely to explain our results but could, in fact, understate the impact of competition on ratings levels. An econometric approach to addressing endogeneity of the market share is to find an instrument that is not subject to the same potential problem. We use this approach to repeat the Table 4 tests using instrumental variables (IV). We employ Fitch's predicted market share as an instrument for the actual market share. To construct predicted market share, we begin with Fitch's market share in an industry in 1995 and make a linear projection

[32] This is consistent with cyclical default rates (e.g., Fons, 1994). This likely reflects conscious policy by raters. Adjusting ratings for the business cycle or other factors that simultaneously shift all or most default probabilities would require constantly moving ratings up and down the ratings scale, something raters probably want to avoid.

[33] The last few years of the sample are lost due to the three-year lag used in defining future defaults, and the corresponding year fixed effects and interactions drop out. Some industries experienced no defaults of public firms during the sample period, so the fixed effect and interactions corresponding to those industries drop out of probit specifications.

[34] We assess this in several ways. Regressing R^2s on market share with year and industry dummies gives a coefficient of -0.16, with a t-statistic of 1.4. Regressing the square root of the R^2s on market share with year and industry dummies gives a coefficient of -0.03, with a t-statistic of 0.5. Weighting by the number of observations in each cell produces similar results (t-statistics -0.39 and 0.56). The correlation and rank correlation between market share and the residual of R^2 after controlling for year and industry are -0.076 (p-value 0.472) and -0.086 (p-value 0.419), respectively.

Table 10
Predicting bond and firm ratings with Fitch market share—instrumental variables.

Each column presents the coefficient estimates from an ordinary least squares (OLS) or ordered probit specification. Intercepts are not reported. The sample period is from 1996 until 2006. The left-hand-side variable refers to credit opinion ratings by Standard and Poor's and is coded from 28 (AAA) to 1 (D). See Table 4 for details. Fitch market share is the fraction of bond ratings in an industry-year cell performed by Fitch Ratings. Fitch rating (dummy) is a dummy variable taking the value one if Fitch issued a rating for the bond issue in the same calendar year as the rating was made. Industries are two-digit level North American Industry Classifications System (NAICS) industries. Previous rating refers to the same bond issue's preceding rating. The standard errors for the coefficient estimates are in parentheses and are clustered by industry × year cell. Significance at the10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

Second stage	Dependent variable: firm credit rating			
	2SLS, all ratings (1)	2SLS, all ratings (2)	2SLS, all ratings (3)	2SLS, all ratings (4)
Fitch market share (instrumented)	5.7475** (1.941)	14.290 (10.011)	6.074*** (2.254)	11.771*** (2.299)
Year fixed effects	No	Yes	Yes	Yes
Industry fixed effects	No	Yes	Yes	Yes
Firm controls	No	No	No	Yes
Firm fixed effects	No	No	Yes	Yes
First stage				
Predicted market share	0.8815*** (0.0107)	0.3419*** (0.0189)	0.2965*** (0.0242)	0.2910*** (0.0245)
First stage R^2	0.289	0.719	0.744	0.772
Second stage R^2	0.003	0.108	0.882	0.900
Number of observations	16,810	16,810	16,810	16,810

for that industry to the 2006 median market share (35.5%).[35] The intuition of the instrument is that a faster increase in competition is predicted in those industries in which Fitch starts out with a low presence early in the sample.

The start- and end-years of 1995 and 2006 are excluded. The instrument is highly correlated with the actual market share (the unconditional correlation is 0.463, significant at the 0.1% level). Because this measure is predetermined, any concern about endogeneity (e.g., industries with high ratings attracting faster growth) is much weaker.[36] The instrumental variable estimates are predicted to be smaller than those from OLS if there is positive correlation between ratings and competition due to reverse causality (i.e., Fitch was attracted to industries with high ratings). This is the concern we are trying to address. Meanwhile, the IV approach yields a larger estimated coefficient than OLS if there is negative correlation between ratings and competition (e.g., due to reverse causality). Based on the negative coefficient on the Fitch dummy in Table 5, the latter could seem more likely. In other words, ratings shopping would cause OLS to underestimate the effect of competition on ratings, and IV, being free of this bias, produces larger estimates. In addition, the instrument is less volatile than the actual market share, and if this reduces measurement error, there could be a smaller measurement error bias in our IV estimates.

Results of IV regressions are reported in Table 10, which replicates the regressions in Table 4 (Columns 1 to 4) but replaces OLS with two-stage least squares estimates. The first-stage t-statistic and the F-test (not reported) are always significant at the 0.1% level (see Staiger and Stock, 1997). In Column 1, with no controls, the estimated coefficient is 5.7, which is larger than the corresponding OLS coefficient (which is 2.4, cf. Table 4). The estimated coefficient is significant at the 5% level. In the other columns, regressions with additional controls are reported. The coefficients are consistently larger than the OLS estimates. The implied magnitudes are on the order of a one-step increase in the ratings of half of all bonds for a one standard deviation increase in competition. The second column, with industry and year fixed effects, provides a coefficient that is insignificant at the 10% level (although fairly close), while the third and fourth columns, which include firm fixed effects, produce estimates that are significant at the 1% level. Because the IV estimates are consistently larger than the OLS estimates, it is likely that some form of endogeneity is operating against our finding, implying that the true effect of competition could be larger than the OLS findings suggest. It is also possible that no endogeneity affects our OLS results, but that measurement error in the measure of competition biases the coefficient toward zero, while the instrument is less noisy. Again, the higher IV coefficients would be more indicative of the impact of competition that we have uncovered throughout the paper. The instrumental variables estimates are, however, more complicated and less consistent across

[35] Algebraically, the instrument for year t and industry i is $\hat{F}_{i,t} = F_{i,1995} + t(0.353 - F_{i,1995})/(2006-1995)$. Instead of 0.353, we have also used 1/3, with similar results.

[36] Market shares in 1995 might still be endogenous but, generally, that would tend to yield the opposite bias. This is because a high market share in 1995 predicts a low increase in market share after 1995.

specifications. The most prudent interpretation of these results could be to confirm the significance of a negative causation from competition to ratings levels, without inferring too much about magnitudes.

6. Conclusions

Credit ratings perform a function of critical importance to the financial system. We find that the entry of a third major rating agency coincides with lower overall quality, as measured by both the levels and informational content of incumbents' ratings. The negative link between competition and quality is econometrically robust and unlikely to be explained by the sources of reverse causality and omitted variables bias we examine. It also appears unlikely that ratings shopping or growth in overall market share can explain these patterns.

The effect of competition on incumbent quality is of substantial economic magnitude. A one standard deviation increase in Fitch's market share is predicted to increase the average firm and bond rating by between a tenth and half of a step (and increases it significantly more for more highly levered firms). Moving from the 25th to the 75th percentile of our competition measure reduces the conditional correlation between ratings and bond yields by about a third and reduces the conditional predictive power for default events at a three-year horizon by two-thirds.

Our results have potential policy implications. For regulators, it is worth considering that increasing competition in the ratings industry involves the risk of impairing the reputational mechanism that seemingly underlies the provision of good quality ratings. There could obviously be benefits of competition in other areas. Nevertheless, calls for more competition, such as by the US Department of Justice (1998), deserve a caveat. For bond markets, it is clear that relying on third party ratings paid for by issuers is a system with limitations. Our empirical findings suggest that the system works better when competition is not too severe.

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