



# How did increased competition affect credit ratings?

Bo Becker  
Todd Milbourn

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# How did increased competition affect credit ratings?

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Bo Becker and Todd Milbourn\*

**Abstract.** The credit rating industry has historically been dominated by just two agencies, Moody's and S&P, leading to longstanding 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 in fact increased competition affects the credit ratings market. 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.

**Key words:** Credit ratings; competition and reputation; information quality

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\* Harvard Business School (Becker) and Washington University in St Louis (Milbourn). Contact author's e-mail address: bbecker@hbs.edu. 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 NBER 2008 Summer Meeting, the NBER 2010 Summer Meeting on Credit Rating Agencies, MIT, Harvard Business School, Boston College, Boston University, Temple University, the Philadelphia Federal Reserve, Standard & Poors' Academic Council, the CEPR/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 course our own. An earlier draft of this paper was circulated under the title of "Reputation and competition: evidence from the credit rating industry".

## 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.<sup>1</sup> In addition, ratings are relied on extensively in regulation and private contracting, and 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 only hold securities with investment grade ratings (e.g., pension funds, money market funds) or are required to use different amount of capital based (e.g., insurance companies) on the ratings of securities they hold. For these reasons, ratings constitute a key channel of information dissemination in financial markets and are considered important by legislators, regulators, issuers and investors alike.<sup>2</sup> The quality of ratings is therefore quite 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 off, the industry is dominated by only three players – Moody’s, Standard & Poor’s (S&P), and Fitch – with Fitch only gaining prominence in the past decade or so.<sup>3</sup> 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 do not necessarily prefer accurate ones. Since 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.

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<sup>1</sup> 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 RMBS, CMOs, CDOs, etc.). See Table 1B for an overview of ratings categories.

<sup>2</sup> 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.

<sup>3</sup> The Securities and Exchange Commission (SEC) now recognizes 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.

The aforementioned features of the industry have raised questions about the quality of the ratings provided by these incumbent players. In particular, there is a broad consensus 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, the 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”<sup>4</sup> in testimony for a US Senate Committee on Banking, Housing, and Urban Affairs. 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 (S&P). 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. As noted by Nancy Stroker (Managing Director of Fitch Ratings), “[t]he 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.”<sup>5</sup> 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. Figure 1 characterizes the evolution of Fitch Ratings over time.

The emergence of Fitch as a larger player manifested itself in a significant increase in their market share. As detailed later in our data section, 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. Figure 2 highlights 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

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

<sup>5</sup> Drawn from the statement of Nancy Stroker, Group Managing Director Fitch Ratings, to the Committee on House Financial Services Subcommittee on Capital Markets, Insurance and Government Sponsored Enterprises June 29, 2005.

less than one in ten ratings in 1997, but approximately a third of ratings by 2007.<sup>6</sup> Also critical to the construction of our empirical tests is the fact that Fitch's aforementioned growth in the corporate ratings market has varied considerably across industries. The range of market shares can be seen from the 25<sup>th</sup> and 75<sup>th</sup> percentile lines plotted in Figure 2. Table 1C lists Fitch 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 didn't 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's rating to any corporate bond, and thus in situations where 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 junk-bond index. After this move to include Fitch's ratings as part of the classification, index classification was determined by the middle of the three 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 1C). 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, we focus on two dimensions of quality: 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 that 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

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<sup>6</sup> Figure 2 plots the 24-month rolling average of Fitch's market share in the 25<sup>th</sup> percentile, median, and 75<sup>th</sup> 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 1C (the specific industries that constitute the 25<sup>th</sup> percentile, median and 75<sup>th</sup> percentile lines varies over time).

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. Similarly 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.<sup>7</sup> Observe that ratings inflation may 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 may 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. Also, inflation will make regulation and contracting with ratings more difficult (since 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's 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 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 25<sup>th</sup> percentile), but only 2.2 times as likely when competition is high (market share at the 75<sup>th</sup> percentile).

Interpreting these results as evidence on the causal effect of competition on incumbent behavior is only valid 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. One possibility is that growth was driven by labor market frictions (i.e., staff with the requisite combination of financial and industry expertise were easier to find in some industries) or luck (some departments at Fitch were more successful and grew faster). However, there are several possible alternatives. The first relates to the endogeneity of Fitch's market share: could the market share in a particular industry be

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<sup>7</sup> Throughout the rest of the paper, when referring to credit ratings, we will use the term quality in the sense outlined above: stable category meanings and high correlation with prices and subsequent defaults.

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.<sup>8</sup>

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 which are rated by Fitch tend to have lower ratings from S&P and Moody's, the opposite of the aggregate pattern we observe in which industries where 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 where 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 bias being neglect by the incumbents). This story does not explain our results about ratings levels, and leaves unexplained the basic issue of why S&P and Moody's would neglect certain industries at all.<sup>9</sup> 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

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<sup>8</sup> 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, growing at 17% per year on average.

<sup>9</sup> 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.

default when competition is high. Fitch does not appear to have 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 onwards 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 where initial market share was high (such as for finance and insurance firms), and faster in industries where 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, there are several potential explanations that 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, it is possible that the empirical evidence reveals ratings shopping. We consider each of these explanations in turn.

Our findings of reduced ratings quality could be related to a reputation story. Since 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 may help sustain ratings quality (see Cantor and Packer (1994) and Smith and Ingo (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". Bloomberg news cites Moody's CEO Raymond McDaniel stating that "we are in a business where reputational capital is more important".<sup>10</sup> Former executive VP of Moody's Thomas McGuire stated in 1995 that

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<sup>10</sup> Bloomberg News March-11-2008, "Moody's, S&P Defer Cuts on AAA Subprime, Hiding Loss".



“what's driving us is primarily the issue of preserving our track record. That's our bread and butter.”<sup>11</sup>

There is a rich theoretical literature that 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,<sup>12</sup> but the role of reputation in financial market outcomes has been extensively explored as well. For example, Diamond (1989) models the incentives of firms (borrowers) to develop a reputation for choosing the appropriate project. On the other hand, Chemmanur and Fulghieri (1994) show how a bank's desire to acquire a reputation (in their case for making efficient negotiation versus liquidation decisions) provides them with an incentive to devote a large amount of resources to information production. However, if the desire to have a positive reputation is diminished, less investment in information acquisition will occur in equilibrium.<sup>13</sup>

The implication of Chemmanur and Fulghieri (1994) could certainly be extended to credit rating agencies. There is also an increasing body of work that 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 actually 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.

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<sup>11</sup> Institutional investor, 10-1995, “Ratings Trouble”.

<sup>12</sup> 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 our findings is not that the rating agencies were intentionally deceiving markets, but instead compromised ratings quality at the margin as competition increased.

<sup>13</sup> 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).

Since the market for ratings grew so much in recent years, it may 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, e.g., footnote 9 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 may in fact be enhanced by market growth (since 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.<sup>14</sup> Skreta and Veldkamp show that increases in asset complexity (such as mortgage-backed securities and CDOs) leads to more ratings shopping and a systematic bias in disclosed ratings. Bolton et al 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 only occur if the security issuer gets to choose which credit ratings to purchase and have published. Such a

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<sup>14</sup> Bolton, Shapiro and Freixas (2009) predict that ratings shopping, apart from affecting ratings directly, will also lead 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.

luxury is not afforded to corporate issuers since 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.<sup>15</sup> To the extent that shopping consists of some firms adding Fitch ratings, but no firms eliminating S&P and Moody's ratings, it won't 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.<sup>16</sup> 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 which enables 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, one piece of evidence suggests that shopping may take place. We find that S&P's 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 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 will lead us to underestimate the effect of competition.

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<sup>15</sup> Which ratings are unsolicited (and therefore, not paid for by the issuer) is not publicly known.

<sup>16</sup> Bongaerts, Cremers, and Goetzmann (2010) find that Fitch ratings tend to be higher than those issued by S&P and Moody's, but 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 on average higher ratings at the critical investment grade/high yield cutoff.

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 only consider corporate ratings, not ratings of CDOs, mortgage-backed securities or other structured products.<sup>17</sup> Second, our findings have limited implications for the efficacy of reputational mechanisms in other imperfectly-competitive settings, since the ratings industry is particular in many ways. For example, Hong and Kacperczyk (2008) 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 twenty years before they mature, before which time any evaluation of the rating's accuracy is typically incomplete).<sup>18</sup> Third, we disregard many potentially important aspects of reputation, such as how the reputational mechanism varies over firms' life-cycles (see Diamond (1989)) and how entry decisions are made (Mailath and Samuelson (2001)).

Our findings may shed light on some of the regulatory changes that have been contemplated and implemented for the credit ratings industry, including increased competition. . Further competition it is not likely to improve quality. Our 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. Aside from its effect on incumbent, competition might have other effects, including reducing monopolistic (or in the case of ratings, oligopolistic) rents, and adding information to financial markets (since raters sometimes give different ratings).

In structured products, Fitch's presence was substantial early on, and there is no clear parallel to the changes we examine in the area of corporate bonds. This of course limits the

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<sup>17</sup> 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.

<sup>18</sup> Other industries where reputations have been studied empirically include auto mechanics (Hubbard (2002)), online trading (Cabral and Hortaçsu (2006)), and restaurants (Jin and Leslie (2003, 2008)).

applicability of our findings to the recent financial crisis, where ratings of structured securities have been particularly called into question. However, there is a rich literature 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 (U.S.). Firm (or Issuer) ratings are produced by each of the three main agencies for all U.S. public firms that issue public debt. Credit ratings range from Aaa (or equivalently, AAA) to D (see Table 1B 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 because they wish 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. There are also regulatory constraints forcing some investors (e.g., insurance companies and Savings & Loan institutions) to only hold debt securities of investment grade (i.e., with a rating of BBB or better).

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 time of issuance.<sup>19</sup> Paying for firm ratings is voluntary, although raters will only consider non-public information provided by the firm itself if they receive payment from the corporate issuer (see Jorion et al. (2005) regarding raters' access to non-public information). Rating agencies also provide various other types of ratings, such as short-term credit opinions and various industry-specific ratings. They may 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”. Rating agencies derive revenue from various sources apart from issuers' fees, such as subscriptions to historical data bases.

The Securities and Exchange Commission (SEC) has designated certain firms as “Nationally Recognized Statistical Rating Organizations” (NRSROs).<sup>20</sup> The ratings of these firms can be used for various regulatory purposes, and many investors will only consider ratings by an NRSRO when making investment decisions. This may also make entry in the industry more difficult.<sup>21</sup> 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.”<sup>22</sup>

### **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

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<sup>19</sup> Fees vary with the face value of a bond issue, but usually in a non-linear way (i.e., they are capped). Also, active issuers may receive quantity discounts. In February, 2008, S&P shared information about their 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).

<sup>20</sup> There are ten such agencies since 2008 (see <http://www.sec.gov/divisions/marketreg/ratingagency.htm#nrsroorders>).

<sup>21</sup> See Boot, Milbourn and Schmeits (2006) for both a discussion and model of such investor restrictions to hold only investment grade debt securities.

<sup>22</sup> See “Speech by SEC Commissioner: Remarks to the Institute of International Bankers”, by SEC Commissioner Paul S. Atkins, March 3, 2008. Link to full speech is here: (<http://www.sec.gov/news/speech/2008/spch030308psa.htm>)

predict defaults. Various users of ratings may in fact have slightly different views on this. 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 SEC (2003) wants to promote “credible and reliable ratings”.<sup>23</sup> Consistent ratings criteria may 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.<sup>24</sup>

We use several complementary approaches to evaluate rating quality. Our first approach appeals to ratings level. We argue that lower quality ratings will be on average higher ratings, that is, ratings closer to the AAA end of the spectrum since 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 may 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, will be 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 will be 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 may 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).

There is probably some cross-sectional variation among firms with regards 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

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<sup>23</sup>Policy makers may also like ratings that do not fluctuate too much, in order to stabilize financial institutions. This is an aspect of quality where we do not expect competition to be particularly important (since neither issuer nor investor is likely to have a clear preference). We therefore leave this issue out of our empirical work.

<sup>24</sup>However, current holders of bonds may desire high ratings for the bonds they own. Especially under mark-to-market accounting rules, some investors may prefer not to get bad news in the form of downgrades.

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, where 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 will reflect things other than expected repayment, and ratings levels will thus be 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 since 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 is 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 may 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.<sup>25</sup>

#### 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 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 Cusip. 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 2-digit North American Industry Classification System (NAICS) industries and our sample years run from 1995 to 2006 (some of our tests will not use the first few years of data). Figure 1 presents a moving average of monthly market shares for Fitch from 1998 to 2006.<sup>26</sup> Fitch's market share increases especially fast in 2000, coinciding with two acquisitions.<sup>27</sup> 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 4-digit industry classifications with very similar results throughout, but prefer 2-digit industries for two reasons. First, using larger industries reduces the noise in market shares estimates, reducing measurement error. Second, it's not clear that narrow 4-digit industries are actually 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

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<sup>25</sup> It may seem reasonable that Fitch can only exert pressure 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 to 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.

<sup>26</sup> In tests, we use the total market share for each industry-year. This figure presents moving averages of total monthly market share across industries in order to provide a sense of the time path of Fitch's entry.

<sup>27</sup> Potentially, market share increases due to organic growth and increases due to acquisitions have different competitive impact, and including data from 2000 may make our results less representative. We have rerun our ratings levels regressions (Tables 3, 4, 6) using only post-2000 data, or all years except 2000, and uncover qualitatively similar results.

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 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 one hundred thousand 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 semi-annual) 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 is 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 1A. 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 1B.

## 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 2. In column one, no controls are included. Errors are clustered by industry-year cell, since this is the level at which our variable of interest varies (this applies to most of our tests). In this sample, there is a significant positive correlation 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 Figure 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 one may be unreliable since no controls are included. In column two, we rectify this by including year and industry dummies. This pushes up the R-squared, and reduces the coefficient and standard error on competition. The coefficient on Fitch's market share remains positive and significant. The magnitude is modest but non-trivial. 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. Since the variable used to capture competition is likely to be noisy, the estimated coefficient is biased toward zero by measurement bias. The true magnitude may therefore be larger than that implied by our coefficient estimate.<sup>28</sup> On the other hand, omitted firm heterogeneity may potentially bias our findings either way. In column three, 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-squared is now high (firm fixed effects explain over 80% of the variation in the left hand side variable). This regression also includes eighteen accounting-based firm controls

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<sup>28</sup> Blume, Lim, and Mackinlay (1998) document 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.

related to firm size, profitability, and indebtedness (see Table 2 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 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 five, we run an ordered probit regression instead of OLS. This specification allows each cut-off to be estimated and so implicitly allows the effect of dependent variables to vary across different parts of the of the ratings scale. The regression therefore uses data more efficiently (although it may 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 2).

As a robustness test, we next collapse the data by industry-year cell, explaining the average (column five) or median (column six) 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 twenty five and 339 individual firm ratings (industry-years with less than twenty five firms are excluded). These specifications differ from that in column three in several ways. First, they avoid concerns about error correlations and repeated sampling of the same firm, since there are only 160 observations. Second, they put much less weight on cells with many bonds (since each industry-year cell is treated equally), which may 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 imply magnitudes similar to that implied by the coefficient estimate in column two (a one notch rating change for one in four or five firms), and significance somewhat higher than in column three. Overall, the firm rating results contained in Table 2 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 since 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 3, 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, since many firms have multiple bond issues outstanding at any given time and since many bonds are rated repeatedly. We include a range of fixed effects in order to control for observables. In column one, we report a regression of ratings on Fitch's market share, 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 will see 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 (of course, important aspects of a bond may change through time). In column two, 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 where competition causes low quality of 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 three we include a dummy variable equal to one if Fitch has rated the same bond during the calendar year in question.<sup>29</sup> The Fitch dummy enters with a negative sign, implying that individual bonds receiving a Fitch rating tends to be those where an incumbent agency's rating is low (conditional on regression controls). This suggests that if anything, selection effects will bias the coefficient on Fitch market share downward (since Fitch's market share will be higher in industry years where 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 market share is still positive and significant. These results are consistent with our interpretation that competition increase ratings, while firms with worse ratings seemingly gravitate towards into using Fitch (tending to generate a negative relation between Fitch's presence and ratings levels).<sup>30</sup> Adding up selection effects across many bonds therefore cannot explain our competition finding. The negative coefficient on Fitch's presence may 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, but again, such behavior provides no obvious advantage to the issuer.

Financial firms issue a large share of corporate bonds. In column four, we exclude issuers belonging to NAICS 52 from the sample in case bonds in this industry are fundamentally different from non-financial 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). Since the variation across cells in the number of bond ratings is even larger than for firm ratings, collapsed results may differ even more from the full panel results in this setting. The estimated competition coefficient for both average and median ratings is large and

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<sup>29</sup> 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).

<sup>30</sup> The negative coefficient on the Fitch dummy for individual bonds is less robust to reasonable variations in regression specification than our competition variable.

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 may 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 may be less biased. The pattern that firms with lower ratings tend to get a Fitch rating, seen in column three, was identified *within* industry-year cells. This pattern may be weaker or absent at the industry level (for example, because industry level presence is more driven 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 4, 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. These specifications allow us to include industry-year interaction fixed effects (i.e., approximately 400 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 which 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 there are some sophisticated investors who 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.<sup>31</sup> Secondly, re-writing 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. Since both S&P and Moody's have explicit policies to rate all taxable bonds from US issuers, and also to rate all issuers of such bonds, there is mostly likely very little selection into being rated at the firm level. Second, Fitch's market share may not correspond to a random experiment, causing either reverse causality (Fitch enters markets with high ratings) or omitted variable bias (some factor drives both higher ratings and entry by Fitch). We discussed above how 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 may 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 their market share in booming sectors where credit demand was high (perhaps overwhelming the capacity of S&P and Moody's 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 of assets (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 5. There seems to be no correlation between the various measures of demand for credit and Fitch's market share (one coefficient out of twenty five 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

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<sup>31</sup> For theories of ratings which rely on non-sophisticated (or naïve) investors, see the work of Boot, Milbourn and Schmeits (2006) and Bolton, Freixas and Shapiro (2010).



market shares.<sup>32</sup> 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. These theories predict that favoring issuers will 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 6. In column one, 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 25<sup>th</sup> to the 75<sup>th</sup> 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 specification.<sup>33</sup> 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, since most bond trades in the data are of bonds rated investment grade. Indeed, the effect of ratings is smaller for these firms, although still highly significant. The

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<sup>32</sup> An alternative way of incorporating these variables is to include them as controls in regressions similar to those in Table 2 and 3. 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.

<sup>33</sup> We have also included 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 may vary with bond age (not reported). Also, we have included controls based on estimated bond durations instead of maturities (not reported). These variations have only a marginal impact on the reported regression results.

interaction of Fitch's market share and ratings has a similar magnitude (relative to the average effect of ratings). In column four, 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 1A), 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, where the same bond can appear multiple times. One concern is that multiple trades capture the same information. We include bond controls, which may help reduce such concerns.<sup>34</sup> 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.<sup>35</sup> In column five, 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 two). 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 relationship between yields and ratings. An alternative way of assessing the informativeness of ratings is to study how they contribute to the R-squared. 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-squared 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

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<sup>34</sup> 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).

<sup>35</sup> Of course, it is possible that ratings are 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.

market share). For the high market share sample, the R-squared 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 really substantial impact on the level of some ratings, it could potentially explain our findings about informativeness as well (although this may not be very plausible). However, as mentioned in the introduction, ratings shopping is much more likely for other agencies than the incumbents, since S&P and Moody's tend to rate all US corporate bonds and issuers. Second, when multiple raters issue ratings, they tend to be fairly close to each other, so the scope even with Fitch's ratings seems modest.<sup>36</sup> Third, although researchers have searched for it, there is limited evidence for ratings shopping among US corporate bond issuers (see Cantor and Packer (1997) and 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

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<sup>36</sup> Ratings of the other firms provide very visible comparisons for raters, so they may prefer to not deviate too much from each other. The tactics of ratings is beyond the scope of our paper and does not really relate to the main implications from the reputational models, which concern informativeness and (the average) level of ratings.

ratings, where defaults are rare.<sup>37</sup> 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 7. Using a linear probability models (OLS), we regress indicators of future default on ratings and control variables. In column one, 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 non-investment 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 (25<sup>th</sup> percentile, 0.133) and only 2.2 times at high competition (75<sup>th</sup> percentile, 0.308). In column two, we replace the investment grade dummy with the numerical rating value (using the Hand, Holthausen and Leftwich scale), with similar results. The scale uses finer variation, but at the expense of imposing a particular numerical scale, which may 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 (25<sup>th</sup> percentile), and 1.5 times at high competition (75<sup>th</sup> percentile). The information content of ratings appears much diminished when competition increases.

The results in column one and two are consistent with lower quality ratings when competition is strong, but may 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 three,

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<sup>37</sup> 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 non-investment grade. The highest observed default frequency, 5.6%, is for the ratings category CCC+.

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 slightly (the interaction is now significant at the 1% level). The overall fit of this model is better: the R-squared is 2.4% (firm controls and the two sets of dummy variables contributes about half of the improvement each). Going from the 25<sup>th</sup> percentile of the competition measure to the 75<sup>th</sup> 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.<sup>38</sup> Second, however, after controlling for these important determinants, corporate ratings still help predict defaults, especially when competition is limited.

Defaults may 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 four. This specification leans very hard on the data, since there are fifty-three coefficients to estimate<sup>39</sup>, 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-squared. 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 7, 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-squared of

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<sup>38</sup> 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.

<sup>39</sup> 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.

57%. Since the collapsed data has 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 25<sup>th</sup> to the 75<sup>th</sup> 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 may also be consistent with ratings shopping: as competition increases, there are more ratings to choose from, and the actually published ratings become less representative of the average credit opinion of raters (as discussed in the introduction, 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 may have found it easier to gain market share where 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 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-squared. Ninety one such cells have at least one default and twenty observations, allowing us to estimate the model with all eighteen accounting ratios. The R-squared varies from 0.001 to 0.471. The variation in R-squared has no relation to Fitch’s market share.<sup>40</sup> We can also allow the eighteen controls to interact with Fitch’s market share, and the interactions are generally insignificant (joint F-stat 0.52 with p-value 0.473 using a model similar to column three). This suggests that reverse causality driven by preferential Fitch entry into difficult

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<sup>40</sup> We assessed this in several ways. Regressing R-squareds on market share with year and industry dummies gives a coefficient of -0.16, with a t-stat of 1.4. Regressing the square root of the R-squareds on market share with year and industry dummies gives a coefficient of -0.03, with a t-stat of 0.5. Weighting by the number of observations in each cell produces similar results (t-stats -0.39 and 0.56). The correlation and rank correlation between market share and the residual of R-squared after controlling for year and industry, are -0.076 (p-value 0.472) and -0.086 (p-value 0.419).

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 may 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 which is not subject to the same potential problem. We use this approach to repeat the Table 2 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 for that industry to the 2006 median market share (35.5%).<sup>41</sup> The intuition of the instrument is that a faster increase in competition is predicted in those industries where 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). Since this measure is predetermined, any concern about endogeneity (e.g., industries with high ratings attracting faster growth), is much weaker.<sup>42</sup> 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. On the other hand, the IV approach will yield 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 3, the latter may 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, will produce larger estimates. In addition, the instrument is less volatile than the actual market share, and if this reduces measurement error, there may be a smaller measurement error bias in our IV estimates.

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<sup>41</sup> Algebraically, the instrument for year  $t$  and industry  $i$  is  $\widehat{F}_{i,t} = F_{i,1995} + \frac{0.353 - F_{i,1995}}{2006 - 1995}t$ . Instead of 0.353, we have also used 1/3, with similar results.

<sup>42</sup> 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.

Results of IV regressions are reported in Table 8 which replicates the regressions in Table 2 (columns one to four), but replaces OLS with two-stage least squares estimates. The first stage t-stat and the F-test (not reported) are always significant at the 0.1% level (see Staiger and Stock (1997)). In column one, with no controls, the estimated coefficient is 5.7, which is larger than the corresponding OLS coefficient (which is 2.4, cf. Table 2). 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 which is insignificant at the 10% level (although fairly close), while the third and fourth columns, which include firm fixed effects, produce estimates which are significant at the 1% level. Since 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 may in fact 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 specifications. The most prudent interpretation of these results may 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 25<sup>th</sup> to the 75<sup>th</sup> 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.

Calls for more competition in the ratings industry, such as by the U.S. Department of Justice (1998, 2009), may deserve a caveat. For regulators and policymakers, 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 may obviously be benefits of competition in other areas, including reducing the level of rents in rating agencies and the additional information provided to financial markets by the additional ratings.

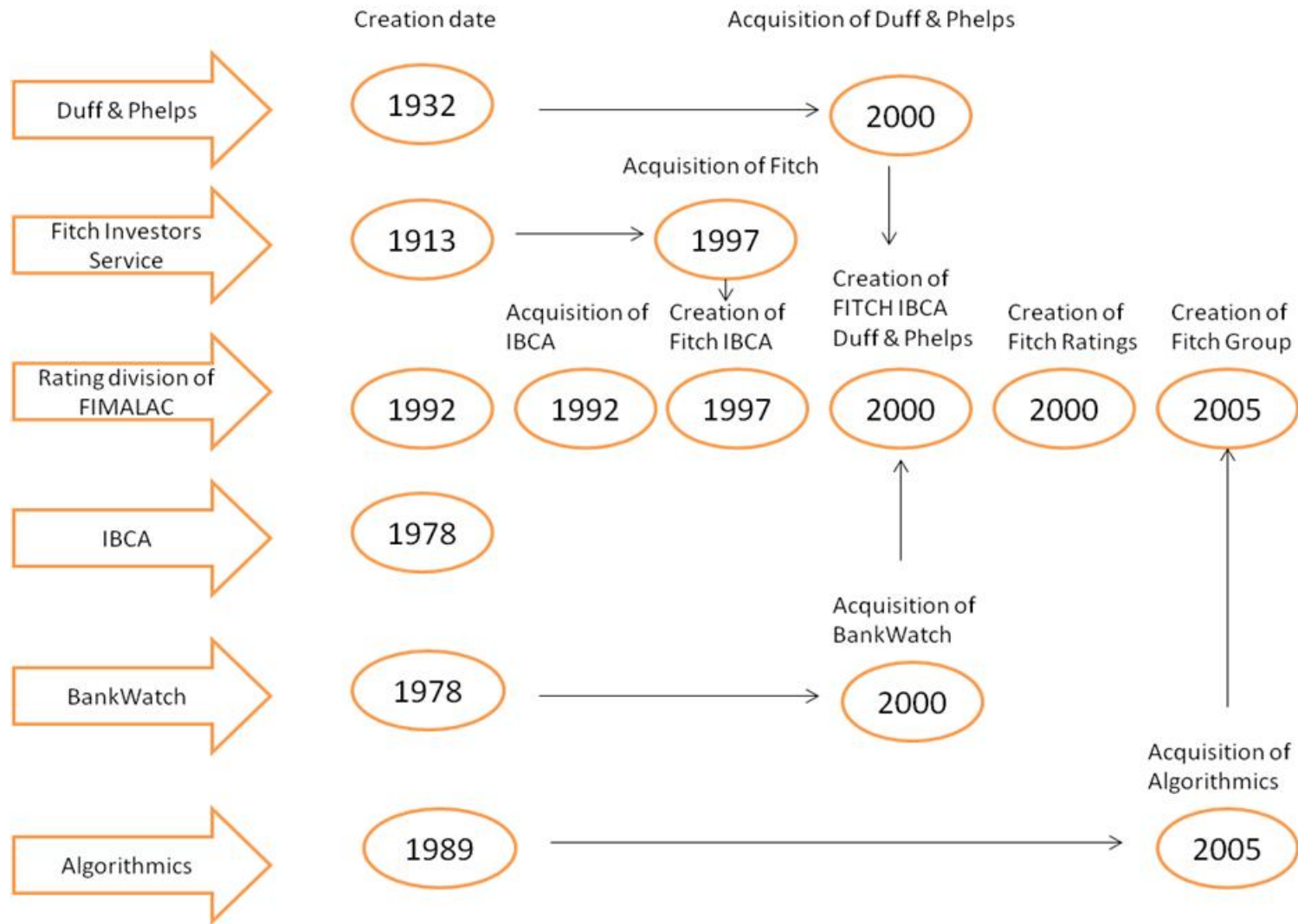
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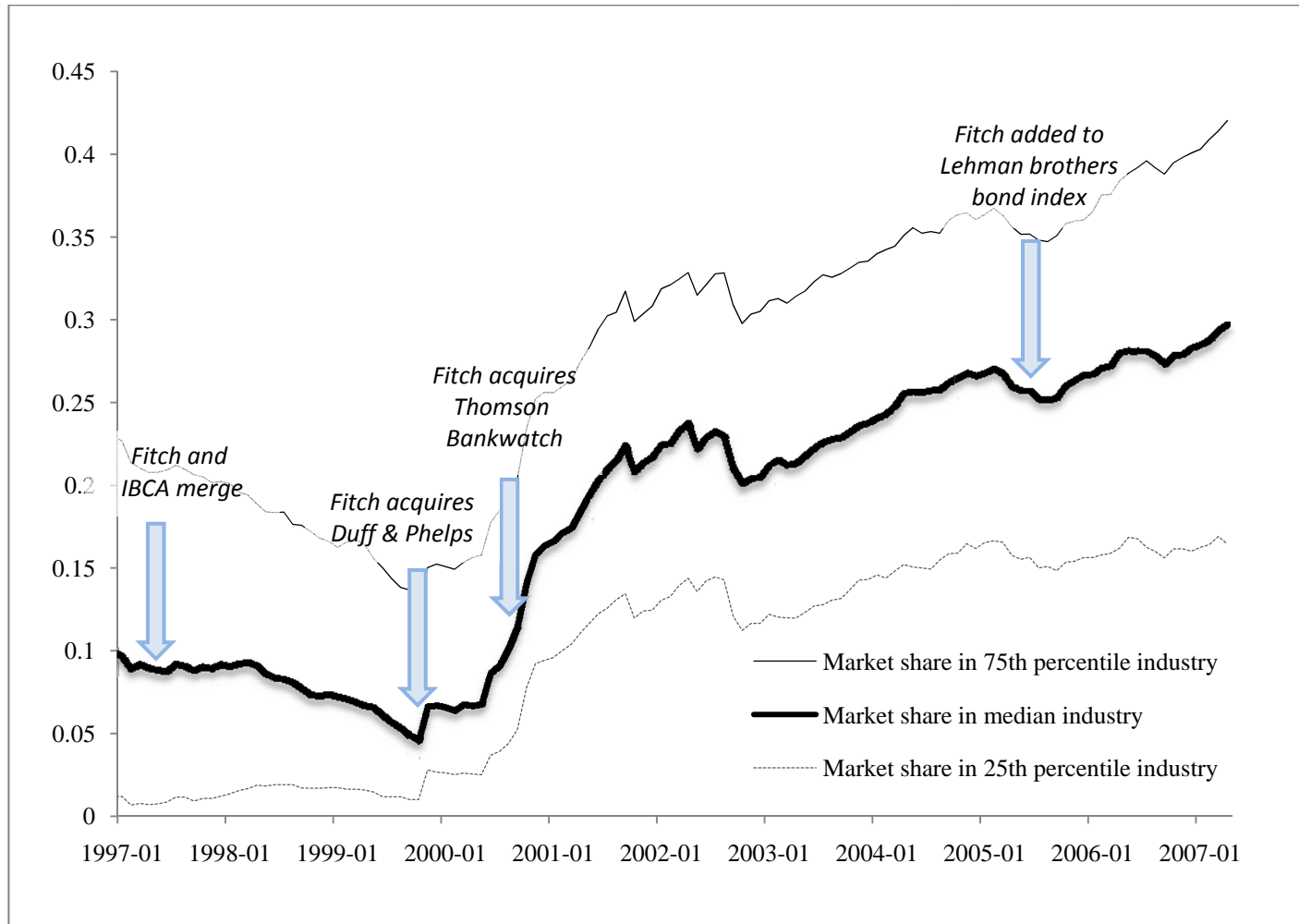
**Figure 1: The Evolution of Fitch Ratings<sup>43</sup>**



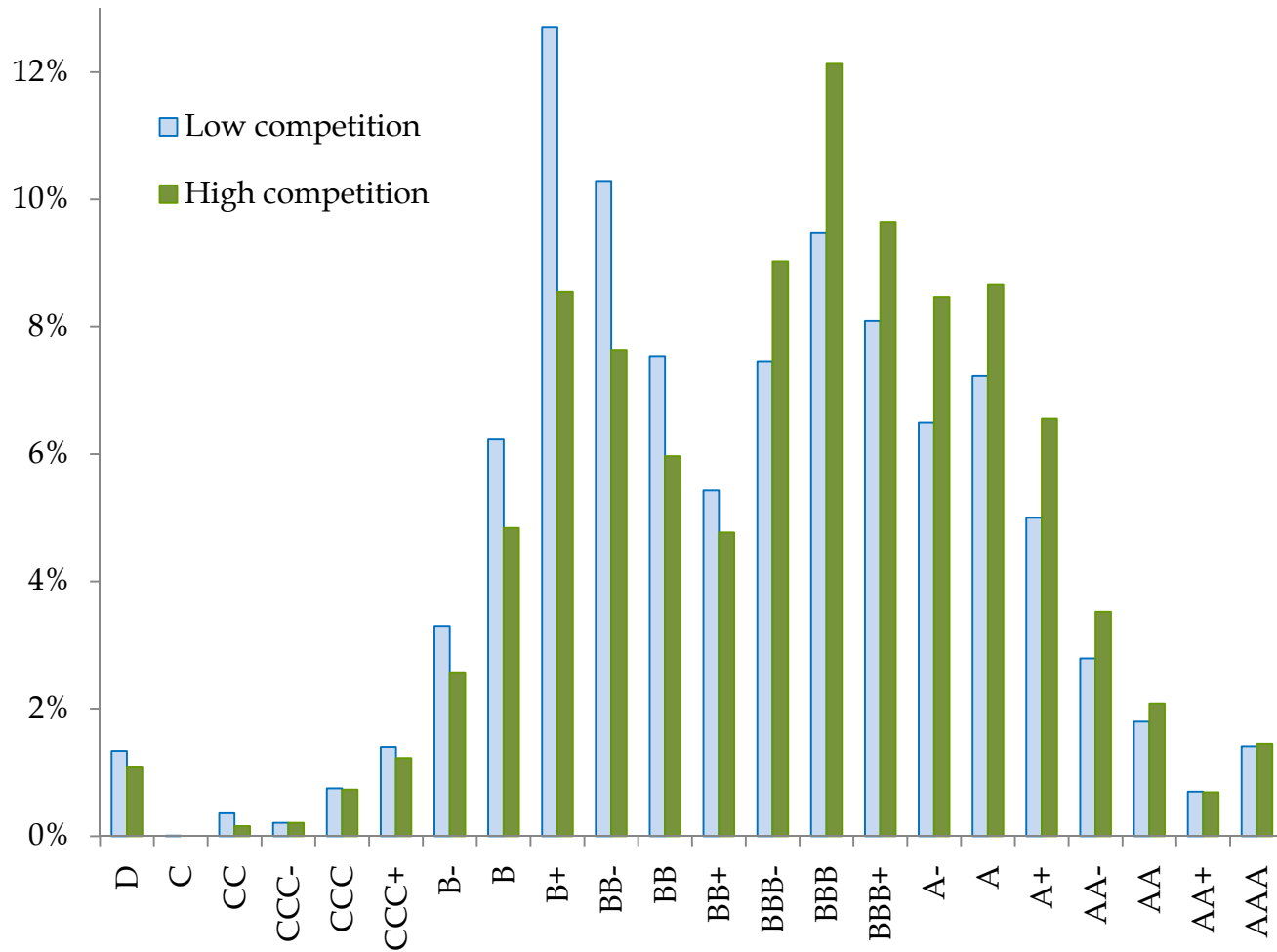
<sup>43</sup> This figure is based on a figure found at [http://www.fitchratings.com/creditdesk/public/group\\_timeline.cfm](http://www.fitchratings.com/creditdesk/public/group_timeline.cfm)

**Figure 2.**

Fitch market share (by industry and month): rolling 24-month averages of 25th, 50th and 75th percentile industries



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



**Table 1A: Summary statistics**

	<b>Firm credit rating</b>	<b>Bond credit rating</b>	<b>Fitch market share</b>	<b>Yield spread</b>	<b>Yield spread – Investment grade</b>	<b>Yield spread – non-investment grade</b>	<b>Yield spread at issue</b>	<b>Leverage</b>	<b>Debt/ EBITDA</b>	<b>Default in t+3</b>
<b>Mean</b>	18.092	23.080	0.212	194.6	129.4	530.1	164.9	0.368	3.798	0.010
<b>Median</b>	18	23	0.225	131.3	119.9	447.3	108.0	0.343	2.840	0.000
<b>Standard Deviation</b>	3.930	4.943	0.142	252.7	139.9	390.8	158.3	0.203	4.073	0.101
<b>Observations</b>	19,756	686,990	429	1110,955	92,949	18,006	7,520	19,756	19,300	18,651

**Notes:** Each column presents the coefficient estimates from an OLS or logistic specification. Intercepts 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.



**Table 1B: Ratings scales**

Rating group	<u>Rating agency</u>		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.

\* Multiple numerical values for a single rating level represent ratings with a + qualifier, no qualifier, and a - qualifier, respectively.

\*\* Source for ratings definitions is Standard & Poor's Ratings Definitions from 17-Mar-2008.

**Table 1C: Fitch market share by 2-digit NAICS industry early and late in sample**

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

**Notes:** Row presents the straight average of annual market shares (the main measure of competition), for the earlier and later halves of the sample period. Market share is the fraction of instrument ratings for corporate bonds issued by firms in a 2-digit NAICS industry which have been issued by Fitch, as oppose to Moody's and S&P.

**Table 2. Predicting firm credit ratings with Fitch market share**

Regression model	Dependent Variable: firm credit rating					
	OLS	OLS	OLS	Ordered Probit	OLS - Average by cell	OLS - Median by cell
	(1)	(2)	(3)	(4)	(5)	(6)
<b>Fitch market share</b>	2.395 ** (1.123)	1.325 ** (0.566)	0.784 * (0.432)	0.3615 ** (0.156)	1.533 *** (0.570)	1.754 ** (0.846)
<b>Year Fixed Effects</b>		X	X	X	X	X
<b>Industry Fixed Effects</b>		X		X	X	X
<b>Firm Fixed Effects</b>			X			
<b>Firm controls</b>			X		X	X
<b>R<sup>2</sup></b>	0.004	0.141	0.900	n/a	0.961	0.914
<b>N</b>	N = 19,630	N = 19,630	N = 19,630	N = 19,630	N = 160	N = 160

**Notes:** Each column presents the coefficient estimates from an OLS or ordered probit specification. Intercepts 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 1 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 it's square), EBITDA divided by total assets (and it's square), cash flow over total assets (and it's square), EBITDA over sales (and it's square), cash flow over sales (and it's square), PPE over total assets (and it's square), interest expense over EBITDA (and it's square), debt over total assets (and it's square), all measured at the end of the previous fiscal year (using accounting data from Compustat). Industries are 2-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 column (1) to (4).

\* significant at 10%; \*\* significant at 5%; \*\*\* significant at 1%

**Table 3. Predicting bond ratings with Fitch market share**

		<b>Dependent Variable: bond issue credit rating</b>					
<b>Regression model</b>	OLS	OLS	OLS	OLS	OLS - average	OLS - medians	
<b>Sample</b>	All ratings	All ratings	All ratings	Excludes NAICS52	Collapsed by cell; excludes NAICS 52	Collapsed by cell; excludes NAICS 52	
	(1)	(2)	(3)	(4)	(5)	(6)	
<b>Fitch market share</b>	0.4187 ** (0.187)	0.5024 ** (0.220)	0.5941 *** (0.198)	0.6793 ** (0.336)	2.061 * (1.214)	5.201 *** (1.782)	
<b>Fitch presence (dummy)</b>			-0.0938 ** (0.045)				
<b>Maturity</b>					0.0312 (0.088)	-0.205 * (0.118)	
<b>Lagged rating (collapsed)</b>					0.332 *** (0.095)	0.242 ** (0.095)	
<b>Year Fixed Effects</b>	X	X	X	X	X	X	
<b>Industry Fixed Effects</b>	X	-	X	-	X	X	
<b>Time to maturity Fixed Effects</b>	X	X	X	X	-	-	
<b>Previous rating Fixed Effects</b>	X	X	X	X	-	-	
<b>Bond Issue Fixed Effects</b>	-	X	-	X	-	-	
<b>R<sup>2</sup></b>	0.941	0.959	0.941	0.904	0.908	0.842	
<b>N</b>	N = 368,811	N = 368,811	N = 368,811	N = 146,366	N = 176	N = 176	

**Notes:** Each column presents the coefficient estimates from an OLS regression. Intercepts 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 1 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 2-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 in column (1) to (4).

\* significant at 10%; \*\* significant at 5%; \*\*\* significant at 1%

**Table 4. Predicting rating levels with Fitch market share - interactions with leverage**

Regression model	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	X	X	X	X
Industry * Year Fixed Effects	X	X	X	X
R <sup>2</sup>	0.589	0.599	0.588	0.629
N	N = 19,630	N = 19,630	N = 19,630	N = 19,630

**Notes:** Each column presents the coefficient estimates from an OLS or logistic specification. Intercepts 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 1 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 it's square), EBITDA divided by total assets (and it's square), cash flow over total assets (and it's square), EBITDA over sales (and it's square), cash flow over sales (and it's square), PPE over total assets (and it's square), interest expense over EBITDA (and it's square), debt over total assets (and it's 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 2-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.

\* significant at 10%; \*\* significant at 5%; \*\*\* significant at 1%

**Table 5. Fitch's market share and segment characteristics**

<b>Dependent variable:</b>	<b>Independent Variable: Fitch's market share</b>				
	# Ratings issued	Industry debt (\$)	Change in ind. debt (\$)	Industry profitability	Ind. profitability (median)
<b>Timing of Fitch's market share</b>	(1)	(2)	(3)	(4)	(5)
<b>Lead (t+2)</b>	0.1831 (0.4055)	-0.1079 (0.1937)	-0.0885 (0.2039)	-0.0108 (0.0272)	0.0085 (0.0156)
<b>Lead (t+1)</b>	0.0194 (0.4210)	0.0824 (0.1913)	0.2870 (0.1794)	-0.0167 (0.0248)	0.0039 (0.0155)
<b>Simultaneous (t)</b>	0.1474 (0.4151)	-0.0617 (0.1739)	-0.1813 (0.1541)	-0.0086 (0.0251)	0.0112 (0.0158)
<b>Lag (t+1)</b>	0.2968 (0.3367)	-0.2615 (0.1673)	-0.1362 (0.1584)	0.0151 (0.0245)	-0.0008 (0.0149)
<b>Lag (t+2)</b>	0.2015 (0.3190)	-0.3075 * (0.1768)	0.1018 (0.1577)	0.0213 (0.0237)	0.0221 (0.0165)
<b>Industry Fixed Effects</b>	X	X	X	X	X
<b>Year Fixed Effects</b>	X	X	X	X	X
<b>N</b>	$N \leq 266$	$N \leq 266$	$N \leq 266$	$N \leq 266$	$N \leq 266$

**Notes:** Each coefficient estimate refers to one OLS specification (different rows represent regressions which 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 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.

\* significant at 10%; \*\* significant at 5%; \*\*\* significant at 1%

**Table 6. Bond yields and ratings - the effect of Fitch market share**

Dependent Variable	Yield spread	Yield spread	Yield spread	Yield spread	Yield spread
Regression model	OLS	OLS	OLS	OLS	OLS
Sample	All trades	All trades	Inv. Grade only	Non-inv. Grade only	Initial issue
	(1)	(2)	(3)	(4)	(5)
<b>Credit rating * Fitch market share</b>	0.766 *** (0.162)	0.968 *** (0.214)	0.430 *** (0.114)	1.253 ** (0.523)	0.430 *** (0.)
<b>Credit rating</b>	-0.569 *** (0.162)	-0.620 *** (0.063)	-0.272 *** (0.003)	-1.102 *** (0.164)	-0.287 *** (0.034)
<b>Fitch market share</b>	-14.160 ** (3.544)				
<b>Log of time to maturity</b>	-1.174 *** (0.168)	-1.203 *** (0.165)	-1.121 *** (0.125)	-3.414 *** (0.493)	0.666 *** (0.085)
<b>Log of time to maturity, squared</b>	0.251 *** (0.035)	0.268 *** (0.035)	0.278 *** (0.027)	0.495 *** (0.115)	-0.113 *** (0.022)
<b>Log of offering amount</b>	-0.223 ** (0.101)	-0.302 *** (0.108)	0.366 *** (0.071)	0.665 (1.581)	-0.260 (0.352)
<b>Log of offering amount, squared</b>	0.002 (0.004)	0.006 (0.004)	-0.019 *** (0.003)	-0.018 (0.063)	-0.007 (0.015)
<b>Date Fixed Effects (Month - Year)</b>	X	X	X	X	X
<b>Industry Fixed Effects</b>	X				
<b>Year - Industry Fixed Effects</b>		X	X	X	X
<b>R<sup>2</sup></b>	0.484	0.503	0.444	0.398	0.697
<b>N</b>	N = 110,955	N = 110,955	N = 92,949	N = 18,006	N = 7,427

**Notes:** Each column presents the coefficient estimates from an OLS regression. Intercepts 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 Poors and Moody's (reported by FISD), 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 2-digit level North American Industry Classifications System (NAICS) industries. Bonds are excluded if they have non-standard 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.

\* significant at 10%; \*\* significant at 5%; \*\*\* significant at 1%

**Table 7. Default prediction - the effect of Fitch market share**

<b>Dependent Variable</b>	<b>Default in t+3</b>	<b>Default in t+3</b>	<b>Default in t+3</b>	<b>Default in t+3</b>	<b>Fraction default in t+3 by industry-year cell</b>
<b>Regression model</b>	OLS (1)	OLS (2)	OLS (3)	OLS (4)	OLS (5)
<b>IG dummy * Fitch market share</b>	0.089 *** (0.030)				
<b>IG dummy</b>	-0.033 *** (0.067)				
<b>Rating * Fitch market share</b>		0.0123 *** (0.070)	0.0123 *** (0.001)	0.0063 * (0.0038)	0.0070 *** (0.001)
<b>Rating</b>		-0.0045 *** (0.0009)	-0.0049 *** (0.0011)		-0.0094 ** (0.004)
<b>Fitch market share</b>	-0.080 *** (0.028)	-0.253 *** (1.250)	-0.229 *** (0.085)	-0.116 (0.080)	-0.121 *** (0.023)
<b>Year Fixed Effects</b>			X	X	X
<b>Industry Fixed Effects</b>			X	X	X
<b>Year and Industry FE * Rating</b>				X	
<b>Firm controls</b>			X		X
<b>R<sup>2</sup></b>	0.008	0.001	0.024	0.024	0.571
<b>N</b>	N = 18,707	N = 18,650	N = 15,661	N = 18,650	N = 189

**Notes:** Each column presents the coefficient estimates from an OLS regression. Intercepts not reported. Each observation is one firm-year where firm level controls can be identified and where 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 2-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 it's square), EBITDA divided by total assets (and it's square), cash flow over total assets (and it's square), EBITDA over sales (and it's square), cash flow over sales (and it's square), PPE over total assets (and it's square), interest expense over EBITDA (and it's square), debt over total assets (and it's 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 is 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.

\* significant at 10%; \*\* significant at 5%; \*\*\* significant at 1%



**Table 8. Predicting bond and firm ratings with Fitch market share - Instrumental Variables**

<b>Dependent Variable: firm credit rating</b>				
<b>Regression model</b>	2SLS All ratings (1)	2SLS All ratings (2)	2SLS All ratings (3)	2SLS All ratings (4)
<b>Second stage</b>				
<b>Fitch market share (instrumented)</b>	5.7475 ** (1.941)	14.290 (10.011)	6.074 *** (2.254)	11.771 *** (2.299)
<b>Year Fixed Effects</b>	-	X	X	X
<b>Industry Fixed Effects</b>	-	X	X	X
<b>Firm controls</b>	-	-	-	X
<b>Firm fixed effects</b>	-	-	X	X
<b>First stage</b>				
<b>Predicted market share</b>	0.8815 *** (0.0107)	0.3419 *** (0.0189)	0.2965 *** (0.0242)	0.2910*** (0.0245)
<b>First stage R<sup>2</sup></b>	0.289	0.719	0.744	0.772
<b>Second stage R<sup>2</sup></b>	0.003	0.108	0.882	0.900
<b>N</b>	N = 16,810	N = 16,810	N = 16,810	N = 16,810

**Notes:** Each column presents the coefficient estimates from an OLS or ordered probit specification. Intercepts 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 1 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 2-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.

\* significant at 10%; \*\* significant at 5%; \*\*\* significant at 1%