Non-rating revenue and conflicts of interest

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ABSTRACT. Rating agencies produce ratings used by investors, but obtain most of their revenue from issuers, leading to a conflict of interest. We employ a unique data set on the use of non-rating services, and the associated payments, in India, to test if this conflict affects ratings quality. Agencies rate issuers that pay them for non-rating services higher (than agencies not hired for such services). Such issuers also have higher default rates. Both effects are increasing in the amount paid. These results suggest that issuers which hire agencies for non-rating services receive higher ratings despite having higher default risk.

Keywords: Credit ratings, agency problems, issuer-pays

JEL Codes: G20, G24, G28

1. Introduction

"I mean come on we pay you to rate our deals, and the better the rating the more money we make?!?! What's up with that? How are you possibly supposed to be impartial????" (Internal S&P email, United States of America v. McGraw-Hill Companies Inc., et al., No. 13-0779, C.D. Calif.)

"Separate ratings from consulting – just as accountants were compromised by their consulting assignments, ratings firms have similar issues." (Letter from Sean J. Egan and W. Bruce Jones, Egan-Jones Ratings Company, to Jonathan G. Katz, Secretary, SEC; November 10, 2002.)

Credit rating agencies are important information providers in credit markets, and the quality of the ratings they provide is important to the functioning of the financial system, for example by underlying a range of financial contracts and rules. Examples of the use of credit ratings include investment mandates, loan contracts (covenants), and financial regulation. Flawed ratings were critical to the recent financial crisis, when large losses on securities that had received overly optimistic ratings at issue contributed to destabilizing the financial system (Benmelech and Dlugosz, 2009a,b). A common view is that aggressive competition by rating agencies for business may have contributed to deteriorating credit standards in the boom years before the crisis. For example, rating agencies that made recommendations to securitization arrangers on how to structure products to receive a desired credit rating ended up subsequently rating the same securities.[1]

Fundamentally, the concerns with the ratings system are related to rating agencies' business model: their main revenue source is the companies whose securities they rate. These companies benefit from favorable (high) ratings on them or their securities. Therefore, the compensation arrangement leads to a conflict of interest between producers of ratings (the agencies) and users of ratings (such as investors). The heart of the problem is the flow of money from issuers to raters. This flow represents ratings fees, but also any payments for other services. In fact, rating

[1] "The Role and Impact of Credit Rating Agencies in the Subprime Credit Markets", Senate Hearing 110-931, September 26, 2007. See also the lawsuit filed by the US Department of Justice against S&P in 2013 asserting that S&P's ratings had been influenced by S&P's business relationships with investment banks that issued structured securities. The lawsuit was settled for $1.375 billion in February 2015.

agencies perform a variety of non-rating services (we use the term "consulting services" interchangeably). One example of such consulting services is "ratings assessment services", which encompass pre-rating analyses as well as assessments of the potential effect of a hypothetical transaction, such as a merger, spin-off, or share repurchase, on an issuer or security credit rating. Other non-rating services offered to issuers include risk management consulting, debt restructuring consulting, regulatory advice, and monitoring services.

In this paper, we study the relationship between issuers and raters and examine whether these commercial ties are correlated with differential ratings treatment. We exploit a recent change in regulation in India, which required Indian rating agencies (including local subsidiaries of S&P, Moody's, and Fitch) to disclose important details about their compensation arrangements with issuers of debt securities. These disclosures permit us to determine whether a given issuer pays a given rating agency for non-rating services, and, if so, the amount of fees paid. In the tests, we make use of the fact that many issuers receive ratings from multiple agencies, allowing us to control for issuer-year fixed effects. That is, we can identify the effect of a commercial relationship by comparing the rating assigned by an agency that has a deeper commercial relationship with the issuer to the rating assigned (to the same issuer) by another agency in the same year. This identification strategy alleviates concerns of selection bias stemming from the non-random assignment of the provision of non-rating services to different types of issuers.

First, we find that rating agencies that perform consulting services for an issuer on average rate such an issuer 0.3 notches higher (that is, closer to AAA) than agencies not hired for such services by the issuer. Additionally, we examine the amount paid for consulting. We find that issuers tend to obtain higher ratings the more non-rating revenue they generate for an agency. These effects are particularly large for issuers close to thresholds in the ratings spectrum that are important for regulatory and contracting purposes (such as BBB-). The strong apparent role for non-rating revenues may reflect that this business and the associated payment terms are quite fungible, that the amount can easily adjust in scope over time, and that non-rating services are quite profitable for the raters.

Finally, we study defaults. If higher ratings assigned by agencies to issuers that pay for non-rating services are warranted, then default frequencies should be similar for firms within a given rating category, whether or not these firms have a consulting relationship with the rating agency. If such issuers instead are treated more favorably, their ex-post default frequency would be higher than for other issuers with the same rating. We find support for the latter case: within a given rating category, firms that pay for non-rating services have higher one-year default rates than other firms; these effects are increasing in the amount of fees paid. This is our third finding: default rates are too high for non-rating services payments to be a sign (or a cause) of lower credit risk. The fact that issuers that obtain non-rating services—and, in particular, those that pay more—have higher ratings but also higher default rates is consistent with a conflict of interest interpretation.

Our findings point to the importance of understanding the entire commercial relationship between raters and rated firms (issuers). Given that non-ratings activities are important, this relationship likely cannot be understood without looking at the payments for such services as well as ratings fees. For example, Moody's reported in 2014 that Moody's Investor Services generated $2.4 billion in ratings-related revenues, while the group's other division, Moody's Analytics, generated $1.1 billion from selling services for *"measuring and managing risk"*.[2] Moody's non-rating services are quite profitable, with an operating margin of 20% in 2014. Non-rating profits grew 28% from 2013 to 2014, compared to 15% profit growth in the ratings division. Regulators have expressed concerns with regard to potential conflicts of interest that may occur when raters provide consulting services to issuers they rate. For example, according to a recent report to Congress by the SEC, *"[…] an NRSRO might issue a more favorable than warranted credit rating to an issuer or other party in order to obtain ancillary services business from them, or an issuer that purchases a large amount of ancillary services could pressure the NRSRO to issue a more favorable than warranted rating on that issuer"* (SEC, 2013). The European Commission describes the resulting problem in similar terms: *"Should these non-rating services give rise to significant, high-margin revenues from a rated client, a CRA has a clear incentive to continue this*

[2] This includes services marketed to fixed income investors, not just issuers. However, it is worth noting that many of these investors are themselves large issuers of fixed income securities.

lucrative relationship and look more favourably at the client's creditworthiness for rating purposes" (EC, 2008). Finally, the SEC (2003) has raised specific concerns about the aforementioned ratings assessment services: *"there are concerns that, to the extent a rating agency has already 'promised' a certain rating to an issuer's hypothetical scenario, pressure to match the actual rating to the promised rating is likely to be forceful, even if the ultimate analysis otherwise might not have supported the rating."* Rating agencies themselves have also expressed concerns about consulting. Referring to rating assessment services, then Fitch CEO Robin Monro-Davies stated in 2001 that *"(w)e looked at doing it and we saw the potential conflicts. If you guarantee a 'triple-A' [rating] to a company, it becomes more difficult to change your mind afterwards"*.[3]

Our results likely constitute a conservative estimate of the scope of the agency problem we study for at least two reasons. First, our estimates are based on fee data from publicly available regulatory disclosures mandated by a 2010 law change. It is therefore conceivable that the transparency introduced by the legislation has already diminished the prevalence of fee-driven ratings inflation in the period our sample covers. Second, our methodology centers on contemporaneous payment flows, while issuers and rating agencies have long-term relationships; past or future business, rents, or cash flows may be as important as those that are contemporaneous. Given the short time series dimension of our data, this cannot be investigated in great detail. We do find that the association between ratings and non-rating fees holds with a one-year lag.

Our sample concerns firms in India. Are they likely to be representative of financial markets more broadly? Indeed, we believe the results may indicate the relevance of the same issues elsewhere. India is English-speaking, its commercial law is influenced by UK law, and its financial institutions are relatively similar to those found in the OECD (La Porta, Lopez-de-Silanes, Shleifer, and Vishny, 1998). The role of ratings in India is similar to their role elsewhere (although public placements of corporate bonds are less important than in the US or Europe), and indeed, the leading Indian rating agencies are majority-owned by S&P, Moody's, and Fitch.

[3] "Credit-rating agencies: New interests, new conflicts", The Economist, April 12, 2001. S&P has been offering its "Ratings Evaluation Service" since 1997; Moody's and Fitch began offering their comparable "Rating Assessment Service" in 2000 and 2002, respectively.

As in the US, firewalls are in place between the ratings and non-ratings business; non-rating services are provided by dedicated subsidiaries of the raters. Indian accounting and financial data are generally of good quality. Finally, we believe that Indian credit markets are of interest in themselves. With a GDP of $2.2 trillion (2014), India is the seventh largest economy in the world; its stock market capitalization was $1.7 trillion in the same year (compared to, for example, $1.5 trillion for Germany).[4]

Our study constitutes some of the most pertinent evidence on conflicts of interest in ratings to date, consistent with less direct evidence from prior work. For example, large issuers (He, Qian, and Strahan, 2012) and issuers that provide more securitization business to rating agencies (Efing and Hau, 2015) receive higher ratings. Other indirect evidence of the conflict of interest comes from the impact of competition on ratings (Becker and Milbourn, 2011), and the finding that investor-paid ratings are more precise (Jian, Stanford, and Xie, 2012; Cornaggia and Cornaggia, 2013).[5] Bar-Isaac and Shapiro (2013), Bolton, Freixas, and Shapiro (2012), and Sangiorgi and Spatt (2011) propose relevant models of this agency problem. Our findings are consistent with the broad thrust of this literature, pointing to the basic conflict of interest when ratings are paid for by issuers.

The conflict of interest stemming from the provision of non-rating services is similar in nature to that between investors and accounting firms that offer non-audit services to their audit clients.[6] However, in contrast to accounting firms, rating agencies have not been subject to

[4] Data sources: market capitalization of listed domestic companies (% of GDP) from The World Bank's World Development Indicators; GDP from the World Economic Outlook Database prepared by the International Monetary Fund.

[5] Butler and Cornaggia (2012) examine a small sample of US bonds which includes fee data reported by the issuers in some bond prospectuses. In their sample, the amount paid to rating agencies is not statistically related to the rating a bond receives, although the error bounds are fairly wide, and the statistical power of their tests may be limited. However, it is also possible that the impact of fees differ across these settings.

[6] For a recent review of studies on how the provision of non-audit services affects audit quality, see Tepalagul and Lin (2015). A similar conflict of interest also arises in sell-side research, where analysts may publish more optimistic research about corporate clients in order to increase investment banking revenue (see, e.g., Ljungqvist, Marston, Starks, Wei, and Yan, 2007; Hong and Kacperczyk, 2010).

significant regulatory restrictions with regard to the provision of consulting.[7] Rating agencies have firewalls separating the ratings business from the non-ratings business. It is not clear that such organizational measures are effective at containing agency conflicts. For example, in the case of the ratings assessment services, the same ratings analysts who generate ratings also carry out the ancillary assessments (SEC 2003). Further, in SEC testimony regarding the role of raters in financial markets, a director of a large US financial services corporation stated that she was aware of at least one instance in which rating analysts themselves were soliciting non-rating services.[8]

In terms of regulatory policy, our empirical findings imply that there may be scope to better manage the inherent conflict of interest that partially compromises the quality of third party ratings, and handle the particular complication posed by raters offering consulting services to ratings clients. Mandating issuer disclosure of non-rating services purchased, as well as information on rating fees and other payments to rating agencies could help mitigate these agency problems (consistent with a suggestion by Sangiorgi and Spatt, 2011). A similar regulatory requirement exists for accounting firms, which have to disclose their accounting and consulting fees (separately) in 10-K statements to the SEC. Alternatively, rating agencies could be asked to disclose detailed fees and other revenues for individual issuers.

The rest of the paper is organized as follows. Section 2 discusses the institutional background. Section 3 discusses the data sources and describes the variable construction. We present the results in Section 4. Finally, Section 5 concludes.

[7] To the best of our knowledge, the only *prohibition* with regard to the provision of non-rating services is paragraph (c)(5) of Rule 17g-5 of the Securities Exchange Act, an amendment passed in April 2009. In short, this rule forbids a rating agency from rating its own work or that of an affiliate; for example, it would be prohibited from rating a structured product that was developed after consultations with the same rating agency. It is unclear how much this rule ultimately affects the rating process, as it may be quite difficult to separate inadmissible communications from acceptable feedback during the ratings process. The SEC recognizes that providing certain *"information during the rating process allows the person seeking the rating to make adjustments in response to the information provided by the NRSRO."* But the *"alternative–restricting the flow of information–would make the rating process more opaque."* (Amendments to Rule 17g-5, SEC Release No. 34-59342; File No. S7-13-08)

[8] SEC Hearing on the "Current Role and Function of the Credit Rating Agencies in the Operation of the Securities Markets", November 15, 2002, testimony by Cynthia L. Strauss.

2. Institutional background

2.1. Corporate debt market in India

The Indian corporate debt market has experienced considerable growth in recent years: the 2008-2012 compound annual growth rate in the corporate credit-to-GDP ratio amounted to 18.4% (China: 22.6%, Korea: 8.5%, Singapore: 7.3%; Deutsche Bank Research, 2014). The ratio of non-financial corporate debt to GDP was 49.6% in 2012 (Deutsche Bank Research, 2014), while in the US it amounted to 66.7% (BIS and World Bank data). While bank-intermediated credit remains the main source of corporate debt finance in India, the Indian corporate bond market has significantly grown in recent years. From 2004 to 2013, corporate bond issuance increased by 62%, to 1.7% of GDP, which is less than in the US, but more than in many OECD countries.[9] As of December 2015, the total volume of outstanding corporate bonds in the Indian bond market amounted to approximately $287bn.[10]

The vast majority of Indian corporate bonds are privately placed (94% in 2012; SEBI, 2013). One reason for the dearth of public corporate bond issues are the stricter regulatory requirements and the associated costs compared to privately placed bonds. The secondary market for corporate debt securities in India is relatively thin. Total corporate debt turnover in the secondary market amounted to Rs7,386bn in 2012-2013; to put these numbers into perspective, total turnover on Indian stock exchanges amounted to Rs32,617bn (SEBI, 2013, Tables NY1 and 11).

2.2. Ratings and credit rating agencies in India

In India as in other economies, credit ratings are important for private contracting as well as regulation. For example, according to rules specified by the Insurance Regulatory and Development Authority in 2013, insurers in the pension and annuity business can invest at most 60% of assets in corporate bonds, which have to be rated AA- or higher. Mutual funds are

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[9] According to the figures for 2013, corporate bond issuance in India is less than in Germany (2.6%), UK (4.5%), and USA (4.6%), but exceeds corporate bond issuance of several OECD economies such as Turkey (1.0%), Austria (1.3%), and Denmark (1.4%); all figures are from IOSCO (2014).

[10] Retrieved from SEBI corporate bond statistics at http://www.sebi.gov.in/cms/sebi_data/statistics/corporate_bonds/outstandingcorpdata.html

permitted to invest in debt securities up to a BBB- rating. Bonds (including most types of privately placed bonds) require at least one rating by an eligible rating agency. Ratings are also required for the calculation of risk weights in banks for capital adequacy purposes.

Six agencies are currently recognized and regulated in India: CRISIL Limited, incorporated in 1987; India Ratings & Research (INDRA), incorporated originally as Duff and Phelps Credit Rating India Private Limited in 1996; ICRA Limited, incorporated in 1991; Credit Analysis & Research Ltd. (CARE), incorporated in 1993; Brickwork Ratings India Private Limited, incorporated in 2007; and SME Rating Agency of India Ltd. (SMERA), incorporated in 2005. In terms of revenue, CRISIL is India's largest rating agency, followed by ICRA and CARE.

Two features of Indian rating agencies are worth pointing out. First, several Indian agencies are owned by the large international agencies. As of September 2014, McGraw Hill Financial, the parent company of Standard & Poor's Ratings Services, owns 67% of CRISIL; Moody's Corporation owns 50% of ICRA; and INDRA is a wholly owned subsidiary of Fitch Ratings Inc. Second, aside from rating debt instruments, Indian rating agencies provide a variety of non-rating services, such as risk management services, industry analysis, business analytics, business process IT services, and management consulting. Firewalls separate the rating and non-rating business. For example, CRISIL's Firewall Policy aims to *"(i) ensure that Ratings Analysts and Research/Advisory Analysts have the freedom to express their respective opinions free from the improper influence of other CRISIL employees and free from the influence of the commercial relationships between CRISIL and third parties and (ii) protect the confidentiality of information given to Ratings analysts in connection with the rating process."*[11] Non-rating services are provided through specialized subsidiaries. As is the case in the US market, the non-rating business has grown in importance in India and accounts for a major and increasing part of rating agencies' revenues. For example, in the case of CRISIL (ICRA), the fraction of total revenue generated by rating services decreased from 40% (63%) in fiscal 2010 to 36% (54%) in fiscal 2013.

2.3. Regulation of rating agencies

[11] Retrieved from https://www.crisil.com/pdf/ratings/CRISILs-analytic-firewalls-policy.pdf

The Securities and Exchange Board of India (SEBI) was established in 1992 to promote the development of and to regulate the Indian securities markets. SEBI issued the first regulations related to rating agencies in 1999: the "SEBI (Credit Rating Agencies) Regulations, 1999" created the regulatory framework for the establishment, operation, and supervision of rating agencies.

Regulation was significantly tightened in May 2010 through the "Circular CIR/MIRSD/CRA/6/2010", which introduced additional transparency and disclosure requirements for rating agencies. These rules relate to the documentation and record keeping of certain aspects of the rating process; publication of detailed default studies to document the performance of assigned credit ratings; formulation of policies and internal guidelines for dealing with conflicts of interests; additional disclosures and duties for rating agencies that issue ratings of structured products; rules related to the assignment of unsolicited credit ratings; and public disclosure of rating procedures, credit rating histories and default rates. Finally, and most importantly for the purposes of this paper, Section 6.3 of the Circular covers disclosure requirements related to rating agency revenue:

"6.3 Income

[…]

6.3.3 A CRA shall disclose annually

6.3.3.1 its total receipt from rating services and non-rating services,

6.3.3.2 issuer wise percentage share of non-rating income of the CRA and its subsidiary to the total revenue of the CRA and its subsidiary from that issuer, and

6.3.3.3 names of the rated issuers who along with their associates contribute 10% or more of total revenue of the CRA and its subsidiaries."

The disclosures under point 6.3.3.2 of the Circular permit us to identify the issuers that generate non-rating revenue in addition to ratings revenue for the rating agency. While not required, some agencies publish additional revenue information on issuers that hire them for consulting. For example, CRISIL not only discloses the proportion of non-rating revenue to the total revenue from an issuer (as required by Section 6.3.3.2), but it also annually discloses the proportion of non-rating revenue from an issuer to *CRISIL's total revenue*. Similarly, in 2010 and 2011, ICRA reported the share of total revenue from an issuer to the total revenue of the ICRA

Group, provided the issuer obtained non-rating services. ICRA discontinued this additional reporting after 2011.

3. Data

Our sample spans the years 2010-2015. First, we obtain data on credit ratings and firms' industry classifications from the CMIE's Prowess database (September 2015 vintage). This source of high-quality corporate data has been used in several recent studies (e.g., von Lilienfeld-Toal, Mookherjee, and Visaria, 2012; Vig, 2013). Credit ratings are available for CRISIL, ICRA, CARE, Brickwork, and INDRA and are reported for each firm at the debt security level.[12] While specific debt instruments do not carry individual identifiers in the database, they are classified into instrument categories such as debentures, long-term loans, and term loans. We focus on non-structured instruments that are assigned medium- or long-term credit ratings by the agencies. Further, we retain only the ten most common instrument categories. The resulting sample consists of ten debt instrument categories (category designations are from CMIE's Prowess): debentures / bonds / notes/ bills; debt; fixed rate unsecured non-convertible debentures; fund based financial facility/instrument; long term loans; non-fund-based financial facility/instrument; term loans; cash; cash credit; and working capital loans. We verified that results are not sensitive to these sample selection procedures: results are similar if we include all non-structured instrument types with medium or long-term ratings in the sample.

Ratings are based on the following alphanumeric scale: AAA (highest creditworthiness), AA, A, BBB, BB, B, C, D (default); for the symbols "AA" to "C" the modifiers "+" and "-" are used to indicate the relative strength within the rating categories concerned.[13] The variable *Issuer*

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[12] In case of duplicate entries in the fields *rating date, rating agency, issuer, rating, status,* and *issue amount*, we keep only one such entry. Results are similar if we keep all entries. We also drop entries where the rating status is "withdrawn".

[13] While all agencies' alphanumeric ratings can be unambiguously mapped into this scale, the specific rating symbols differ in some cases across rating agencies and over time. For example, until 2011, ICRA denoted long term ratings with the symbols "LAAA", "LAA+", "LAA" etc., while CRISIL used "AAA", "AA+", "AA" etc. Following the 2011 SEBI Circular "Standardization of Rating Symbols and Definitions," rating agencies unified the ratings symbols. For example, CRISIL changed the long term rating symbols from "AAA", "AA+" etc. to "CRISIL AAA", "CRISIL AA+" etc. However, all these ratings are based on a 20 notch rating scale.

Rating exhibits variation at the issuer-rater-year level and is defined as follows. We first assign numerical values to the alphanumeric debt instrument ratings, with a value of one denoting the highest credit rating "AAA" and the value 19 denoting "C-". For each issuer, rating agency, and year, we average over the instruments' ratings to obtain the *Issuer Rating* from a given agency in a given year; we verified that taking the median or the maximum does not significantly change our results. To reduce the possible impact of outliers, we exclude 25 observations (corresponding to nine firm-years) from the sample in which the difference between the *Issuer Rating* from one agency and the average *Issuer Rating* assigned by the other rating agencies in that year is ten notches or higher in absolute terms. Including these observations in the sample does not, however, alter our results in any significant way.

In Section 4.3, we study defaults. The variable *Default in t+1* is defined at the firm-year level and takes the value of one in year *t* if a given issuer has a debt instrument on which it defaults in year *t+1* (irrespective of which agency rates that instrument); the variable takes a value of zero otherwise. We obtain the default information from CMIE's Prowess database.

Information on rating agencies' non-rating clients as well as issuer-specific revenue is from the "Regulatory Disclosures" sections of the agencies' websites. The relevant information is drawn from the disclosures related to SEBI's circular CIR/MIRSD/CRA/6/2010; of most interest to us are revenue disclosures referring to point 6.3.3 of the circular (see Section 2.3 for more details). The rating agencies only make current disclosures available on their websites. We obtain historical disclosures by contacting the rating agencies or use past records of the relevant sections of the agencies' websites as maintained on The Internet Archive.[14] Based on these compulsory disclosures, we find that ICRA, CRISIL, and CARE provided compensated non-rating services to Indian issuers, while Brickwork and INDRA did not. Furthermore, two of the rating agencies also voluntarily disclosed, for all consulting clients, the ratio of revenue per issuer to total agency revenue: CRISIL reported this information for each of its fiscal years 2010-

[14] CRISIL made available all past disclosures to us. All past disclosures from ICRA could be obtained from The Internet Archive. For CARE we can retrieve the relevant disclosures for the fiscal years 2012/2013, 2013/2014, and 2014/2015; we cannot ascertain whether CARE provided non-rating services in the prior years. Finally, to our knowledge, Brickwork and INDRA have not been providing non-rating services during our sample period.

2014, while ICRA did so for fiscal years 2010 and 2011. This information from the regulatory disclosures is used to construct the variables *Non-rating Services* and *Ln(Non-rating Issuer Revenue).*

Non-rating Services is a dummy variable that takes the value of one if an issuer obtains non-rating services from a rating agency in a given year, zero otherwise. The relevant information is available for the following agencies and sample years: years 2010 to 2014 for CRISIL; years 2010-2015 for ICRA, Brickwork, and INDRA; years 2013-2015 for CARE. CRISIL's fiscal year ends in December, so revenue information for the reporting period, e.g. January 2010 to December 2010, is coded as year 2010 in our sample. The other agencies' fiscal years end in March, so revenue information for the reporting period e.g. April 2010 to March 2011 is coded as 2011 in our sample.

The variable *Ln(Non-rating Issuer Revenue)* denotes the natural logarithm of (one plus) annual non-rating revenue paid to a given rating agency by a given issuer (in millions of Rupees). This variable is available for the majority of the issuers in the sample. For firms that do not obtain consulting services, this variable naturally takes a value of zero. For CRISIL-rated firms that obtain non-rating services from CRISIL, for the years 2010-2014, we also know the amount paid to CRISIL (and hence the variable *Ln(Non-rating Issuer Revenue)* is available). Furthermore, for ICRA-rated firms that also pay ICRA for non-rating services, sufficient information to construct the variable *Ln(Non-rating Issuer Revenue)* is available for the years 2010 and 2011, but not for the years 2012-2015.[15] In unreported regressions, using the raw (not in logs)

[15] CRISIL discloses for the years 2010-2014 the "Contribution of Non Rating Income" (Contribution), which is non-rating revenue from an issuer to total group revenue. For CRISIL-rated firms, the variable *Ln(Non-rating Issuer Revenue)* is Ln(1 + Contribution x total revenue of CRISIL in million Rupees). Note that Contribution is reported with a precision of four decimal places; therefore, in some instances, the variable *Ln(Non-rating Issuer Revenue)* takes the value of zero, even if payments for non-rating services have been made. Our results are unchanged if we replace such cases with a small non-zero revenue figure to distinguish these observations from cases where issuers do not obtain any non-rating services. ICRA discloses in 2010 and 2011 the "Share of Non Rating Income to Total Income from Issuer" (SNRITII) and the "Share of Total Income from Issuer to Total Income of Group ICRA" (STIITIGI). For ICRA-rated firms, the variable *Ln(Non-rating Issuer Revenue)* is Ln(1 + STIITIGI x SNRITII x total revenue of ICRA in million Rupees). We note that the variable *Ln(Non-rating Issuer Revenue)* uses some voluntarily disclosed information on fee payments by CRISIL and ICRA that are reported by the raters together with issuer-level fee income information mandated by the "Circular CIR/MIRSD/CRA/6/2010" (see Section 2.3 on the

issuer revenue, or using payments as a percentage of total rating agency revenue in a given year, produces similar results to reported regression using *Ln(Non-rating Issuer Revenue)*.

Finally, we use the product-market based industry classification system developed by CMIE to assign firms to industries; there are 145 such industries in our sample. We match the revenue information from the regulatory disclosure files to the ratings from Prowess using firm names.

Table A-1 in the Appendix provides a summary of the variable definitions and data sources.

4. Results

4.1. Summary statistics

We report summary statistics for the analysis of ratings and the provision of non-rating services in Table 1. Each observation in our sample is a firm-agency-year. Panel A shows a frequency distribution of observations with non-rating services. Our sample spans the years 2010-2015 and covers 26,760 firm-agency-years. There are 7,083 firms in our sample, of which 473 obtain non-rating services at some point during the sample period, corresponding to 1,165 observations (4.4% of the total) in our sample. The rest of the panel reports a breakdown by rating agency; for example, 7.9% of the sample observations with a CRISIL rating are associated with payments for non-rating services provided by CRISIL.

Panel B shows the incidence of firms with multiple raters in our sample. 19% (5,141 observations) of the sample corresponds to firms that receive ratings from more than one rating agency in a given year. As we discuss in Section 4.2, our main identification strategy relies on firms that use multiple raters. Panel C reports the propensity to use non-rating services by issuer rating category. This propensity markedly declines as credit quality decreases: while about 31% of AAA issuers use non-rating services, only 14% of AA issuers do, down to less than 1% of issuers below the investment-grade threshold. Finally, in Panel D of Table 1 we report the mean, standard deviation, minimum, and maximum of the variables *Issuer Rating, Non-rating Services,* and *Ln(Non-rating Issuer Revenue).* The average *Issuer Rating* in the sample is 9.04, which approximately corresponds to a BBB letter rating. The sample average of *Ln(Non-rating Issuer*

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exact disclosure requirements of the law). Total revenue of the raters is obtained from the annual consolidated financial statements available on the raters' websites.

Revenue) is 0.02, the sample maximum is 3.79. As can be seen from Panel A, many issuers do not pay for non-rating services. Among the issuers that do pay for non-rating services, the average and median payment amounts to approximately 1.65 and 0.52 million Rupees, respectively (not reported in the table).

Two features of our data are worth highlighting. First, the information on which issuers pay for non-rating services in which year is complete, because since 2010 it is mandatory for Indian raters (including local subsidiaries of S&P, Moody's, and Fitch) to annually report a list of issuers that pay for non-rating services, as well as the fraction of the total fees paid by those issuers that originate from non-rating services. We use this information to construct the indicator variable *Non-rating Services*. Second, we have information on the amount paid for non-rating services for 98.9% of the sample; considering only firms that pay for non-rating services, we have information on the amount paid for 75% (873 out of 1,165) of the observations (see Section 3 for more details on the variable construction).

In tests reported in Table A-2 of the Appendix, we investigate which firm characteristics are associated with the purchase of non-rating services. Financial services firms, firms with more assets, less leverage, more profitable firms, and listed firms, have a higher propensity to use non-rating services. The corresponding multi-variate regression has an adjusted R-squared of 12%. This suggests that a variety of possibly unobservable factors (such as a firm's dependence on ratings or need for advice) drive most of the decision to purchase non-rating services. As we discuss below, given our empirical strategy which compares simultaneous ratings of the same firm, this does not preclude identifying the effect of non-rating services on ratings.

Table 2 reports summary statistics for the sample used for the analysis of defaults in Section 4.3. The sample is smaller because it ends in 2014 (using default information until September 2015, however), and because we require firms in this sample to have at least two consecutive years of data. Panel A classifies observations by coarse rating category and default status. Panel B reports summary statistics for the variables used in our tests on defaults. According to Panel B, the average one-year default rate across all rating categories during the sample period is 3.8%. Panel C reports separate summary statistics for investment grade and high yield firms. In the investment grade sub-sample, the average one-year default rate is 1.3%, while it is 8.3% in the high yield sub-sample. In comparison, Standard & Poor's (2015) reports a global high yield corporate default rate of 2.2% per annum (2010-2014 average).

4.2. Non-rating revenue and credit rating levels

Do issuers that pay a rating agency for non-rating services obtain higher ratings from that rater? Fig. 1 provides a first look at the relevant data. It plots the distribution of ratings for issuers that obtain non-rating services and those that don't, after accounting for industry effects. The figure shows that issuers that generate non-rating revenue obtain a rating that is on average about three notches higher (that is, closer to AAA).

The difference in ratings between firms that hire a rater for non-rating services and those that do not as documented in Fig. 1 is likely to be driven by a number of different factors, some of which may be unobservable. As a consequence, the simple correlation between *Issuer Rating* and *Non-rating Services* does not necessarily reflect biased ratings. In order to narrow down the set of possible explanations, the tests that follow rely on *within-firm* or *within-firm-year* variation of the demand for non-rating services. This helps rule out a number of alternative explanations involving selection (i.e., which firms tend to use credit rating agencies for non-rating services). We first estimate parameters from the following regression model:

$$(Issuer\ Rating)_{i,j,t} = \alpha \cdot X_{i,j,\,t} + \beta_j + \gamma_i + \delta_t + \varepsilon_{i,j,t} \tag{1}$$

where i denotes the issuer, j the rating agency, and t the year. β, γ, and δ are fixed effects, and $X_{i,j,\,t}$ is a non-rating revenue measure. In different tests we measure non-rating revenue at the extensive margin (variable *Non-rating Services*), or at the intensive margin (variable *Ln(Non-rating Issuer Revenue)*). In all tables, we report standard errors that are adjusted for within-firm clustering of the error terms $\varepsilon_{i,j,t}$. The specification in Eq. (1) exploits within-firm variation, which helps address many identification challenges. However, the concern remains that there may be time-varying firm-level omitted variables related to both credit quality and the propensity to use consulting services. Therefore, our main specification employs *within-firm-year* variation for identification, corresponding to the following regression model:

$$(Issuer\ Rating)_{i,j,t} = \alpha \cdot X_{i,j,\,t} + \ \beta_{j\times t} + \gamma_{i\times t} + \varepsilon_{i,j,t} \quad (2)$$

Here, $\gamma_{i\times t}$ represents fixed effects for each issuer-year. This permits us to rule out that any firm-level omitted variables—even if time-varying—explain our results. That is, we identify the effect of payments for non-rating services on ratings through differences in the ratings assigned by different agencies *within* a given firm-year. Finally, to control for time-varying heterogeneity of raters and thereby rule out that differences across raters (e.g., some raters may be more conservative than others) are driving our results, we saturate the regression model with *agency x year* fixed effects (β_{jxt}). We implement these tests using ordinary least squares regressions.

Controlling for *issuer x year* fixed effects alleviates concerns about selection bias stemming from the non-random demand for non-rating services by different types of issuers. However, identifying within issuer-year is only possible for firms that have more than one rating and that use non-rating services from some but not all agencies which rate them. These firms may differ from the overall population of firms (i.e., those obtaining no non-rating services or acquiring such services from all raters), for example in terms of how much they care about credit ratings, or how opaque they are to financial markets. Other firms may have less ability to impact their ratings by paying consulting fees. This may, in principle, affect the external validity of the results estimated using this specification.

Table 3 reports results from tests with the dummy variable *Non-rating Services* as the explanatory variable. The specification in column 1 includes issuer, year, and agency dummies, while specification 2 employs *issuer x year* fixed effects in addition to agency fixed effects. Finally, specification 3 employs *agency x year* fixed effects instead of agency and year fixed effects. We find that the coefficients in all three specifications are significant at the 1% level and that they are of similar magnitude. According to these estimates, firms that pay a rating agency for non-rating services obtain a rating from that agency that is about 0.3 notches higher (that is, closer to AAA) than the average rating obtained from the other agencies in that year.

Next, we turn to the intensive margin: the association between the *amount* paid for non-rating services and the rating issued. Does paying more lead to a better rating? The conflict of interest hypothesis suggests that issuers that generate more financial value for a rating agency obtain better ratings. We first explore this question graphically. For this purpose, it is useful to define the variable *Rating Difference*, which for a firm with multiple ratings, is the difference between the *Issuer Rating* from one rating agency and the cross-sectional average of the ratings obtained from the other agencies in a given year. Fig. 2 plots the *Rating Difference* against the variable *Ln(Non-rating Issuer Revenue)* and fits a line. The figure shows that the more revenue an issuer contributes, the better is the rating that the issuer receives from that agency (compared to the rating obtained from other raters), on average. Because observations are correlated (the same rating may appear as part of the benchmark multiple times, or in both sides of the calculation of the *Rating Difference*), assessing statistical significance is not straightforward. We therefore turn to formal regression-based tests.

Table 4 reports results for regressions of ratings on the amount of payment flowing from issuers to raters. Specifications are similar to those reported in Table 3, but with *Ln(Non-rating Issuer Revenue)* as the explanatory variable of interest. The specification reported in column 1 employs issuer, agency, and year fixed effects; specification 2 employs *issuer x year* and agency fixed effects; finally, specification 3 includes *issuer x year* and *agency x year* fixed effects. In all three specifications, we find negative coefficients on the variable *Ln(Non-rating Issuer Revenue).* The coefficients are significant at the 1% level. In terms of economic magnitude, a doubling of fees corresponds to a higher rating by about 0.4 notches. The following back-of-the-envelope calculation further illustrates the economic magnitudes. Among issuers that pay for non-rating services, the median payment for non-rating services amounts to approximately 0.52 million Rupees. Using the point estimates of Table 4, a 0.4 notch ratings improvement would require a doubling of fee payments by the median issuer, to about 1.04 million Rupees. A one-notch ratings improvement would therefore be associated with a payment of around 2.6 million Rupees (around 38,000 US dollars at the current exchange rate). We emphasize that there is no evidence that such transactions—i.e., payments by issuers in exchange for higher ratings—take place. The fees we study in this paper are related to consulting work.

Overall, we interpret these results as consistent with a fee-driven conflict of interest between rating agencies and security issuers: when an issuer is directly important to an agency through the fees it generates, then ratings tend to be upward biased. Our results do not necessarily imply any special role for non-rating services. However, it is also possible that payments for non-rating services are important in their own right, perhaps because rating fees are fixed and there is more leeway in the pricing of non-rating services. That would imply that using non-rating services is a more direct way of transferring rents to a rating agency, and thus the key variable for predicting biased ratings. Consistent with this interpretation, the dummy for using non-rating services is associated with higher ratings (see Table 3).

We focus on the contemporaneous relationship between ratings and payment flows in Table 4. However, if the relationship between issuer and agency is long-term, past payments may affect current ratings. The time-series dimension of our data is somewhat limited, but we explore this relationship between ratings and current and past payments in Table 5. Column 1 reports a specification with firm, year, and agency fixed effects, while the regression underlying column 2 employs *issuer x year* as well as agency fixed effects; finally, specification 3 employs *issuer x year* and *agency x year* fixed effects. The results suggest that while contemporaneous payments matter, past payments may be even more important for determining current ratings.

The modest magnitudes we find in Tables 3 to 5 may mask interesting heterogeneity in the association between consulting fee payments and ratings. For example, an issuer with a low rating may have an incentive to obtain an additional (higher) rating from another rater, in particular if the issuer is close to but below an important threshold on the rating scale, such as AA- and BBB-, which is used for contracting and regulatory purposes (see Section 2.2). Indeed, we find evidence consistent with this conjecture in tests that we report in Table 6. Specifically, in Panel A, we consider a sub-sample of issuers that have at least one of the following ratings from a rating agency that they do not pay for consulting: A+, A, A-, BB+, BB, or BB- (i.e., close to but below an important threshold on the ratings scale). There are 11,582 observations (3,994 issuers) corresponding to such instances in the sample. We re-run regressions corresponding to Eq. (1) and Eq. (2) in this sub-sample. *Non-rating Services* is employed as the explanatory variable of interest in regressions corresponding to columns 1—3, while *Ln(Non-rating Issuer Revenue)* is employed in regressions corresponding to columns 4—6. As in Tables 3 and 4, we find that the coefficients on both revenue measures are statistically significant at the 1% level. However, the magnitudes reported in Panel A of Table 6 are about two to three times larger compared to the point estimates from our baseline regressions reported in Tables 3 and 4.

We conjecture that the effects shown in Panel A of Table 6 are driven by issuers with split ratings that are close to the AA- and BBB- thresholds, that is, issuers that may have benefited most from a higher rating. We confirm this hypothesis by selecting a narrower sub-sample of issuers that (i) in a given year obtain at least one “close” rating (A+, A, A-, BB+, BB, or BB-) from a rating agency that they do not pay for consulting, and that (ii) have at least two ratings in that year that are different from each other. The resulting sample consists of 1,765 observations (with 628 issuers). We repeat our tests in this sub-sample and report the results in Panel B of Table 6. Consistent with Panel A of that table, we find that the coefficients on the revenue measures are all statistically significant at the 1% level, with magnitudes about two to three times larger than those reported in Tables 3 and 4 (and, indeed, somewhat larger even than in Panel A of Table 6). For example, the estimate in column 3 of Panel B of Table 6 implies that in the sub-sample of issuers close to important regulatory thresholds, rating agencies rate issuers that hire them for non-rating services about one notch higher than agencies that are not paid for such services. In sum, Table 6 is consistent with the notion that the magnitude of the association between fee payments and ratings is larger close to economically important thresholds in the ratings spectrum. We note that the results in Table 6 have to be interpreted with caution due to the selection of these sub-samples based on values of the dependent variable.

A considerable number of firms that purchase non-rating services are financial services firms.[16] While only 2,756 (10.3%) of the total observations in the sample correspond to financial services firms, these firms contribute 464 of the 1,165 observations (40%) associated with payments for non-rating services. We would like to ascertain that our results are not specific to issuers in the financial services industry. One concern, for example, is that, as discussed in Section 2, bank-intermediated debt plays an important role in the Indian economy. Therefore,

[16] For the purposes of the following discussion, financial services firms are defined as firms that carry one of the following industry designations in the CMIE Prowess database: auto finance services, banking services, housing finance services, infrastructure finance services, other asset financing services, other fee based financial services, other financial services, other fund based financial services, other investment services, and securities broking.

banks may—directly or indirectly (through the firms they lend to)—have a large impact on rating agencies' revenues, which may affect the interpretation of our findings. For example, the prospect of rating large loan portfolios may give banks considerable bargaining power over rating agencies, which may lead to the assignment of positively biased ratings on the banks and the debt securities they issue.[17] At the same time, these unobserved sources of bargaining power could be correlated with the purchase of non-rating services. That is, whether or not a bank purchases non-rating services may just proxy for the depth of the commercial relationship it has with the rater, rather than indicating a special role for consulting payments *per se*.

To rule out that such effects drive our results, we repeat the main tests excluding financial services firms, such as banks, from the sample. Results are reported in Table 7, Panel A; columns 1—3 investigate the role of payments for non-rating services at the extensive margin (explanatory variable *Non-rating Services*), while columns 4—6 focus on the intensive margin of these payments (explanatory variable *Ln(Non-rating Issuer Revenue)*). We find that the results remain strongly supportive of a fee-driven conflict of interest and the special role played by non-rating services. The coefficients on the two revenue measures are statistically significant at the 5% level or higher in all specifications. Economic magnitudes are, overall, also similar to the estimates reported in Tables 3 and 4. Another possible concern associated with banks' bargaining power is the following. Issuers could be compelled by financial institutions to purchase non-rating services. This interpretation would imply that while raters still issue upward biased ratings to issuers that pay for non-rating services, the underlying reason why these payments are made is that banks want to lower capital charges on their loan portfolios. While we cannot rule out this explanation, we note that this observationally equivalent result would still be consistent with a fee-driven conflict of interest that operates through payments for non-rating services from issuers to raters.

[17] To determine risk weights for capital adequacy purposes, banks have to purchase ratings from eligible rating agencies. According to the regulator (Reserve Bank of India), banks "should use the chosen credit rating agencies and their ratings consistently for each type of claim, for both risk weighting and risk management purposes. Banks will not be allowed to 'cherry pick' the assessments provided by different credit rating agencies." This quote is from the RBI Master Circular "Prudential Guidelines on Capital Adequacy and Market Discipline - Implementation of the New Capital Adequacy Framework (NCAF)"; RBI/2008-09/68, DBOD.No.BP.BC. 11 /21.06.001/2008-09.

In Panel B of Table 7 we estimate the regressions only for issuers in the financial services industry. While the number of observations in this sub-sample is an order of magnitude smaller than in our main sample, we find again that payments for non-rating services are associated with more optimistic ratings; we note that the coefficients in specifications two and three are not statistically significant at conventional levels, while the other point estimates are significant at the 1% level.

A further robustness test concerns the functional form of our regression specifications corresponding to Eqs. (1) and (2). We implement these tests using linear regressions (see Tables 3 to 7). Two advantages of OLS regressions are that they provide direct estimates of marginal effects and that they can accommodate a large set of fixed effects without computational problems. An alternative would be to employ ordered probit (or logit) models. Such models are in principle well-suited for discrete outcomes which have a natural ordering but where the difference between different outcomes may not be meaningfully represented by a linear metric relating those outcomes. For example, in the case of ratings, the difference in credit risk between rating categories A and A- may be different from the difference in credit risk between categories B+ and B, even though the linear metric used to represent the ratings implies a difference of one in both cases. The disadvantage of such non-linear models, however, is that they may encounter computational and convergence problems when many fixed effects are employed in a panel setting (e.g., the incidental parameter problem), as is the case in our analysis.

While we generally prefer OLS models in our setting, for robustness, we have estimated all our tests using ordered probit models as well. We obtain very similar results. To conserve space, we only report the ordered probit specifications corresponding to our main results from Tables 3 and 4; however, we reproduce Tables 5 to 7 in the Appendix (see Tables A-4 to A-6). To make the estimation of ordered probit models computationally feasible, in light of the large number of fixed effects, we limit the sample to those instances in which issuers use multiple raters in a given year. These are precisely the observations that identify the coefficient of interest in specifications with *issuer x year* fixed effects, while leaving out data that only identifies fixed effects. This sub-sample consists of 5,141 observations (see Panel B of Table 1 which shows the incidence of firms with multiple raters in our main sample). First, we verify that OLS results using this sub-sample are consistent with the OLS results estimated in the full sample used in Tables 3 and 4: they are. In Appendix Table A-3, Panel A (Panel B), we show that results in this restricted sample are similar in economic and statistical significance to Table 3 (Table 4). The other tables are also similar when re-estimated with OLS in that sub-sample; we do not report those tables for brevity.

Having verified that the sub-sample is representative, we estimate ordered probit regressions. Table 8, Panel A, repeats Table 3 with ordered probit; Table 8, Panel B, repeats Table 4. The variable *Issuer Rating* is the average rating a firm receives for all instruments rated by a given agency in a given year; the variable is thus continuous (see Section 3). To be able to use *Issuer Rating* as the dependent variable in the ordered probit regressions, we round it to whole numbers. In this table, as well as Tables A-4 to A-6 in the Appendix, we find that both the statistical and economic significance is similar to the OLS results discussed above.

4.3. Non-rating revenue, ratings, and defaults

In the previous section, we found that an agency that receives non-rating revenue from a firm issues a higher rating for that firm than other agencies that are not paid for consulting by that firm. It is conceivable that these higher ratings are warranted (and thus that the benchmark ratings are too low). To see if this is the case, we examine ex-post default rates. If higher ratings given by agencies to issuers that purchase non-rating services are warranted, then default frequencies should be similar for firms within a given rating category, whether or not these firms have a consulting relationship with the rating agency. If such issuers instead get treated more favorably, their ex-post default frequency would be higher than for other issuers.

To address this point, we investigate one-year default rates (variable *Default in t+1*; see Section 3). Fig. 3 shows one-year default rates by rating category (see also Table 2, Panel A). The average one-year default rate across all rating categories is 3.8% during the 2010-2014 sample period. There are no defaults in the categories AAA and AA. Defaults happen in all categories below AA, and are increasingly frequent for worse ratings. In Fig. 4, we examine how the relationship between ratings and defaults depends on payment for non-rating services. Within each rating category, we separate issuers that obtain non-rating services from issuers that do not. Within each rating category, default rates are higher for firms that pay for non-rating services.

To formally test whether within-rating category differences in default rates between firms that pay for non-rating services and those that do not are jointly significant, we regress the variable *Default in t+1* on a revenue measure:

$$(Default\ in\ t+1)_{i,t} = \alpha \cdot X_{i,j,\,t} + \Psi_{i,j,t} + \varepsilon_{i,j,t} \tag{3}$$

where i denotes the issuer, j the rating agency, and t the year. $\Psi_{i,j,t}$ is a matrix of fixed effects, and $X_{i,j,\,t}$ is a non-rating revenue measure (*Non-rating Services*, or, in other specifications, *Ln(Non-rating Issuer Revenue)*). We cluster standard errors at the issuer level. We implement Eq. (3) with linear probability models estimated using OLS. For robustness, we have also implemented these tests with probit models; we report these tests in the Appendix (Tables A-7 to A-10) to conserve space.

Results are reported in Table 9. Columns 1-4 control for the rating by including the variable *Issuer Rating* as a regressor, while columns 5-7 include fixed effects for each of the 19 possible rating notches. In these latter specifications, we round *Issuer Rating* to whole numbers. In addition to these controls for the rating, columns 2 and 5 additionally include agency fixed effects; columns 3 and 6 additionally include agency, year, and industry fixed effects; and columns 4 and 7 additionally include *agency x year* and *industry x year* fixed effects. Finally, column 8 employs *industry x year* fixed effects and *agency x rating x year* fixed effects. The latter specification identifies our effect of interest using only variation within a given rating category assigned by a given rater in a given year; for example, for issuers rated A+ by CRISIL in 2013, the specification compares defaults between issuers that pay for non-rating services and those that do not. Because the dependent variable exhibits variation at the issuer-year level only (as opposed to issuer-agency-year level as in the tests discussed in Section 4.2), *issuer x year* fixed effects are not included in the default tests.

Across specifications, the coefficient on the variable *Non-rating Services* is positive and significant at the 1% level in all cases but one; in column 8, the relevant coefficient is significant at the 5% level. Overall, the results suggest that on average, controlling for the rating, firms that pay for non-rating services have higher default rates. Based on the estimates with rating fixed effects (columns 5-8), we find that such firms have a one percentage point higher default rate. As the average default rate in the sample is 3.8%, this corresponds to a difference of about 26% between firms that pay for non-rating services and those that do not.

As is evident from Fig. 3, the relationship between ratings and defaults is convex. Therefore, the association between the variables *Non-rating Services* and *Default in t+1* may differ between investment and non-investment grade (i.e., high yield) firms, respectively. To shed some light on this, we split the sample along the investment grade threshold. Results are reported in Table 10. Panel A shows results for the investment grade sub-sample (BBB- or above), while Panel B reports results for the high yield sub-sample (BB+ or below). We find statistically significant estimates for the coefficient on the variable *Non-rating Services* in most specifications, although, compared to Table 9, the precision is lower in most specifications, perhaps due to the lower number of observations in the sub-samples. In Panel A, the coefficient on *Non-rating Services* is around 0.007 on average, which suggests that the default rate of investment-grade firms that pay for non-rating services is about 0.7 percentage points higher than that of firms that do not. Given the relevant sample mean of 1.3% (see Table 2, Panel C), this implies a difference of about 54%. In the high yield sub-sample (Panel B of Table 10), the relevant coefficient is around 0.12, implying that high yield firms that pay for non-rating services have a 12 percentage point higher default rate. The average default rate in this sub-sample is 8.3%, suggesting a difference in default rates of more than 100%.

Next, we investigate whether this relationship between defaults and payments for non-rating services can also be observed at the intensive margin: within a rating category, are *higher* non-rating fee payments associated with higher defaults? Table 11 reports results of linear regressions in which the main explanatory variable is *Ln(Non-rating Issuer Revenue)*; otherwise, the regressions are the same as those reported in Table 9. We find that controlling for the issuers' ratings, the higher the non-rating fee payments, the higher is the probability of default. In these regressions, the coefficient of interest in column 8 (specification with *agency x rating x year* fixed effects) is not statistically significant, while it is significant at the 1% level in all other specifications. In Table 12, we again split the sample along the investment grade threshold. Panel A reports results for investment grade firms, while Panel B focuses on high yield issuers. Overall, we find similar patterns as in Table 10, with smaller (and more precise) point estimates of the coefficient of the variable *Ln(Non-rating Issuer Revenue)* in the investment grade sub-sample; indeed, none of the coefficients of interest in Panel B are statistically significant at conventional levels.

In sum, the empirical analysis of ratings, default rates, and payments for non-rating services suggests that the higher ratings assigned to issuers that pay rating agencies for non-rating services are not warranted: within a given rating category, firms that pay for non-rating services have higher one-year default rates than other firms. Furthermore, there is evidence that these effects are increasing in the amount paid for non-rating services, at least in some sub-samples. Finally, the association between the payment for non-rating services and defaults is stronger for high yield firms than for investment grade firms; however, the estimates in the non-investment grade sub-sample are less precise.

4.4. Discussion

We find that firms that pay for non-rating services receive higher ratings and that the more they pay, the higher the rating is. This is consistent with issuers effectively paying for higher ratings. Alternatively, agencies learn that firms that pay for consulting have lower credit risk. For example, the provision of non-rating services may enable a rater to obtain additional information about an issuer that is useful in assessing credit risk, and perhaps higher consulting fee payments proxy for the rater's effort in acquiring such information. This in itself cannot explain our results on ratings, as such information should not be positive—that is, implying lower credit risk—on average. However, it is conceivable that firms that have hidden qualities that imply low default risk obtain non-rating services in part to enable the rater to uncover such qualities. In this case, such firms should have lower default rates, which is the opposite of what we find. Another possibility is that obtaining additional non-rating services (such as risk-management advice) reduces credit risk, but the improvement is discernible only by the rating agency providing such services, not by other raters, at least initially. This argument is also inconsistent with our findings on defaults, as such firms should have lower default risk.

Overall, our results suggest that (higher) payments for non-rating services are associated with more optimistic ratings, but also with higher ex post default rates. This may reflect rating agencies "selling" upward biased ratings. Alternatively, by hiring raters for consulting work, issuers could learn how to game raters' models and "fool" raters into believing they are higher quality borrowers. It is not possible to separate these stories with our data. However, we believe that this moral distinction — determining the "culprit" of the inflated ratings — distracts from the key financial issue of ratings quality. That is, whatever the exact mechanism is, our results suggest that the flow of payments for non-rating services is associated with lower ratings quality. On the margin (the effects we find are relatively modest in size), the integrity of the financial system is impaired by this link between commercial relationships and ratings precision.

5. Conclusion

Issuer-paid credit ratings play an important role in Indian credit markets, as elsewhere. These ratings give investors access to a public signal that can be used for contracting and screening securities, without incurring fees. However, issuer-paid ratings involve a fundamental conflict of interest, since the paying party has an interest in upward biased ratings. There is mounting indirect evidence on where and how this conflict is important, for example, when competition is high (Becker and Milbourn, 2011) and when individual issuers represent large shares of total business (He, Qian, and Strahan, 2012; and Efing and Hau, 2015). However, there is no evidence to date on whether actual payment flows relate to optimistic ratings. Do favored issuers generate more business? Pay higher fees per rating? Commit to their raters with longer contracts? Raters also receive revenues from consulting. Because these activities and the associated payment terms are likely to be quite fungible and scalable, and the business is quite profitable for the raters, it is conceivable that the provision of such non-rating services could further impair the objectivity and, in turn, the quality of credit ratings.

In this paper, we use a unique data set based on agencies' reports of consulting relationships and the associated revenue from individual issuers to assess whether the provision of non-rating services and the amounts paid for such services are related to the level of ratings. We find that an agency which receives non-rating revenue from an issuer rates that issuer more positively than other agencies. The magnitude is relatively modest: on average, paying for non-rating services is associated with 0.3 notch higher ratings, and big payers only see a slightly more substantial ratings improvement. There is some evidence, however, that these effects are larger in magnitude around important regulatory thresholds in the ratings spectrum, such as BBB-. We also find that, within rating categories, default rates are higher for firms that have paid for non-rating services, and that default rates are increasing in the amount paid for such services. This suggests that the better ratings obtained by firms that pay (more) for non-rating services are not a reflection of lower credit risk.

Our findings are consistent with two points of the literature: corporate credit ratings perform relatively well and are less subject to bias than structured ratings (Cornaggia, Cornaggia, and Hund, 2015 make an explicit comparison; see also Benmelech and Dlugosz, 2009a,b), but corporate ratings are not immune to bias (e.g., Becker and Milbourn, 2011; Alp, 2013; Baghai, Servaes, and Tamayo, 2014; Dimitrov, Palia, and Tang, 2015). Our study adds an important piece of evidence: the fundamental agency problem in ratings can operate through higher past and contemporaneous payment flows from issuers to raters, and especially through non-rating fees.

Do our results point to any policies for maintaining the integrity of credit ratings? Reducing the opportunities for rating agencies to perform non-rating services for their clients seems like one possibility, because these revenues are especially associated with bias. Such activities could even be prohibited entirely. This may certainly have negative side effects, which we have not considered. As an alternative, increased disclosure may facilitate scrutiny by investors and outsiders of the role non-rating fees play. If data of the type we use was routinely available for the large fixed income markets, there would be scope for outsiders to assess the risk of bias in individual ratings. For corporate issuers, who typically issue annual reports and other public accounting statements, disclosure of the type mandated for their relationships with accountants might prove a template.

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Table 1. Summary statistics – main sample

Panel A reports a frequency distribution of firm-agency-years with non-rating services, as well as a breakdown by rating agency. The sample spans the years 2010-2015. Panel B tabulates the incidence of firms with multiple ratings in our sample, reported separately for firms that purchase non-rating services and those that do not. Panel C tabulates by rating category observations associated with the purchase of non-rating services and those that are not. Panel D reports the mean, standard deviation, minimum and maximum of the variables used in the study of ratings. *Issuer Rating* is the rating an issuer receives from a given rating agency in a given year, with a value of one denoting the highest credit rating "AAA" and the value 19 denoting "C-". *Non-rating Services* is a dummy variable that takes the value of one if an issuer pays for non-rating services from a given rating agency in a given year, zero otherwise. *Ln(Non-rating Issuer Revenue)* is the natural logarithm of one plus non-rating revenue (in million Rupees) paid by an issuer to the rating agency. The variables are defined in more detail in Section 3 of the paper and in Table A-1 of the Appendix.

Panel A

Full sample		
	Frequency	Percent
Non-rating Services = 0	25,595	95.65
Non-rating Services = 1	1,165	4.35
Total	*26,760*	*100*
CRISIL only		
	Frequency	Percent
Non-rating Services = 0	9,299	92.13
Non-rating Services = 1	794	7.87
Total	*10,093*	*100*
ICRA only		
	Frequency	Percent
Non-rating Services = 0	7,962	96.26
Non-rating Services = 1	309	3.74
Total	*8,271*	*100*
CARE only		
	Frequency	Percent
Non-rating Services = 0	5,071	98.79
Non-rating Services = 1	62	1.21
Total	*5,133*	*100*
Brickwork Ratings only		
	Frequency	Percent
Non-rating Services = 0	852	100
INDRA only		
	Frequency	Percent
Non-rating Services = 0	2,411	100

Panel B

	Non-rating Services		
Number of Raters	No	Yes	*Total*
1	21,016	603	*21,619*
2	3,809	307	*4,116*
3	577	182	*759*
4	169	67	*236*
5	24	6	*30*
Total	*25,595*	*1,165*	*26,760*

Panel C

Rating Category	Non-rating Services No	Yes	*Total*
AAA	761	339	*1,100*
AA	2,468	417	*2,885*
A	4,111	194	*4,305*
BBB	8,336	155	*8,491*
BB	6,818	44	*6,862*
B	2,800	12	*2,812*
C	301	4	*305*
Total	*25,595*	*1,165*	*26,760*

Panel D

	Obs.	Mean	Std. Dev.	Min.	Max.
Issuer Rating	26,760	9.044	3.838	1.000	19.000
Non-rating Services	26,760	0.044	0.204	0.000	1.000
Ln(Non-rating Issuer Revenue)	26,468	0.020	0.173	0.000	3.792

Table 2. Summary statistics – default sample

This table shows summary statistics for the variables used in the analysis of default rates in Section 4.3. The sample spans the years 2010-2014. Panel A reports the number of defaults by rating category. Panel B reports the mean, standard deviation, minimum and maximum of the variables used in the study of defaults. *Default in t+1* is defined at the firm-year level and takes the value of one in year *t* if a given company has a debt instrument on which the company defaults in year *t+1* (irrespective of which agency rates that instrument); the variable takes a value of zero otherwise. The other variables were defined in Table 1. Panel C reports summary statistics for the default sample, split along the investment grade threshold.

Panel A

	AAA	AA	A	BBB	BB	B	C	Total
Default in t+1 = 0	899	2,219	3,037	5,796	4,322	1,592	136	18,001
Default in t+1 = 1	0	0	25	134	248	248	51	706
Total	*899*	*2,219*	*3,062*	*5,930*	*4,570*	*1,840*	*187*	*18,707*

Panel B

	Obs.	Mean	Std. Dev.	Min.	Max.
Default in t+1	18,707	0.038	0.191	0.000	1.000
Issuer Rating	18,707	8.823	3.888	1.000	18.000
Non-rating Services	18,707	0.053	0.225	0.000	1.000
Ln(Non-rating Issuer Revenue)	18,508	0.027	0.200	0.000	3.792

Panel C

Investment grade sub-sample (BBB- or higher)

	Obs.	Mean	Std. Dev.	Min.	Max.
Default in t+1	12,110	0.013	0.114	0.000	1.000
Issuer Rating	12,110	6.661	2.914	1.000	10.429
Non-rating Services	12,110	0.079	0.269	0.000	1.000
Ln(Non-rating Issuer Revenue)	11,925	0.041	0.247	0.000	3.792

High yield sub-sample (BB+ or lower)

	Obs.	Mean	Std. Dev.	Min.	Max.
Default in t+1	6,597	0.083	0.276	0.000	1.000
Issuer Rating	6,597	12.792	1.715	10.500	18.000
Non-rating Services	6,597	0.007	0.081	0.000	1.000
Ln(Non-rating Issuer Revenue)	6,583	0.001	0.027	0.000	1.506

Table 3. Ratings and the provision of non-rating services

This table reports the coefficients for linear regression models estimating the association between ratings and the provision of non-rating services. Each observation corresponds to an issuer-agency-year. The variables are defined in Table 1. The sample period is 2010-2015. Heteroskedasticity-robust standard errors, clustered by issuer, are reported below coefficients. * denotes estimates that are significantly different from zero at the 10% level, ** at the 5% level, and *** at the 1% level.

	(1)	(2)	(3)
		Issuer Rating	
Non-rating Services	-0.281***	-0.326***	-0.299***
	(0.058)	(0.068)	(0.068)
Issuer F.E.	x		
Year F.E.	x		
Agency F.E.	x	x	
Issuer x Year F.E.		x	x
Agency x Year F.E.			x
Observations	26,760	26,760	26,760
Adjusted R-squared	0.937	0.941	0.943

Table 4. Ratings and payments for non-rating services

This table reports the coefficients for linear regression models estimating the association between ratings and revenue from issuers. Each observation corresponds to an issuer-agency-year. The variables are defined in Table 1. The sample period is 2010-2015. Heteroskedasticity-robust standard errors, clustered by issuer, are reported below coefficients. * denotes estimates that are significantly different from zero at the 10% level, ** at the 5% level, and *** at the 1% level.

	(1)	(2)	(3)
		Issuer Rating	
Ln(Non-rating Issuer Revenue)	-0.414***	-0.404***	-0.362***
	(0.058)	(0.063)	(0.065)
Issuer F.E.	x		
Year F.E.	x		
Agency F.E.	x	x	
Issuer x Year F.E.		x	x
Agency x Year F.E.			x
Observations	26,468	26,468	26,468
Adjusted R-squared	0.936	0.938	0.939

Table 5. Ratings and past payments for non-rating services

This table reports the coefficients for linear regression models estimating the association between ratings and non-rating revenue from issuers. Each observation corresponds to an issuer-agency-year. *Lag[·]* is the lag operator and denotes one-year lags of the relevant variable. The variables are defined in Table 1. The sample period is 2010-2015. Heteroskedasticity-robust standard errors, clustered by issuer, are reported below coefficients. * denotes estimates that are significantly different from zero at the 10% level, ** at the 5% level, and *** at the 1% level.

	(1)	(2)	(3)
		Issuer Rating	
Ln(Non-rating Issuer Revenue)	-0.255***	-0.164*	-0.120
	(0.065)	(0.090)	(0.089)
Lag[Ln(Non-rating Issuer Revenue)]	-0.223***	-0.198**	-0.215***
	(0.056)	(0.087)	(0.081)
Issuer F.E.	x		
Year F.E.	x		
Agency F.E.	x	x	
Issuer x Year F.E.		x	x
Agency x Year F.E.			x
Observations	16,811	16,811	16,811
Adjusted R-squared	0.950	0.954	0.954

Table 6. Ratings and non-rating services: sub-samples for issuers close to important thresholds in the ratings spectrum

This table reports the coefficients for linear regression models estimating the association between ratings and the purchase of non-rating services by issuers. Each observation corresponds to an issuer-agency-year. The variables are defined in Table 1. The sample period is 2010-2015. These tests focus on issuers that are close to an important "threshold" on the rating scale (AA- or BBB-), which is used for contracting and regulatory purposes (see Section 2.2). Specifically, in Panel A, the sample contains issuers that in a given year obtain at least one of the following "close" ratings from a rating agency that they do not pay for consulting: A+, A, A-, BB+, BB, or BB-. In Panel B, the tests focus on issuers that (i) in a given year obtain at least one "close" rating (A+, A, A-, BB+, BB, or BB-) from a rating agency that they do not pay for consulting, and that (ii) have at least two ratings in that year that are different from each other. Heteroskedasticity-robust standard errors, clustered by issuer, are reported below coefficients. * denotes estimates that are significantly different from zero at the 10% level, ** at the 5% level, and *** at the 1% level.

Panel A: Issuers close to AA- or BBB- thresholds

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable:	Issuer Rating					
Non-rating Services	-0.742***	-0.927***	-0.848***			
	(0.258)	(0.232)	(0.221)			
Ln(Non-rating Issuer Revenue)				-1.084***	-1.176***	-1.020***
				(0.169)	(0.146)	(0.175)
Issuer F.E.	x			x		
Year F.E.	x			x		
Agency F.E.	x	x		x	x	
Issuer x Year F.E.		x	x		x	x
Agency x Year F.E.			x			x
Observations	11,582	11,582	11,582	11,561	11,561	11,561
Adjusted R-squared	0.934	0.871	0.874	0.934	0.871	0.873

Panel B: Issuers with split ratings close to AA- or BBB- thresholds

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable:			Issuer Rating			
Non-rating Services	-1.125***	-1.209***	-1.024***			
	(0.313)	(0.271)	(0.269)			
Ln(Non-rating Issuer Revenue)				-1.286***	-1.300***	-1.043***
				(0.148)	(0.136)	(0.197)
Issuer F.E.	x			x		
Year F.E.	x			x		
Agency F.E.	x	x		x	x	
Issuer x Year F.E.		x	x		x	x
Agency x Year F.E.			x			x
Observations	1,765	1,765	1,765	1,752	1,752	1,752
Adjusted R-squared	0.861	0.855	0.861	0.860	0.854	0.859

Table 7. Ratings and non-rating services: issuers in the financial services sector versus issuers in other sectors

This table reports the coefficients for linear regression models estimating the association between ratings and the purchase of non-rating services by issuers. Each observation corresponds to an issuer-agency-year. The variables are defined in Table 1. The sample period is 2010-2015. The sample in Panel A excludes financial services firms, while the sample in Panel B focusses on a sample of only financial services firms. Heteroskedasticity-robust standard errors, clustered by issuer, are reported below coefficients. * denotes estimates that are significantly different from zero at the 10% level, ** at the 5% level, and *** at the 1% level.

Panel A: Excluding issuers in financial services

	(1)	(2)	(3)	(4)	(5)	(6)
	Issuer Rating					
Non-rating Services	-0.150**	-0.249***	-0.247***			
	(0.072)	(0.083)	(0.083)			
Ln(Non-rating Issuer Revenue)				-0.264***	-0.310***	-0.277**
				(0.094)	(0.114)	(0.114)
Issuer F.E.	x			x		
Year F.E.	x			x		
Agency F.E.	x	x		x	x	
Issuer x Year F.E.		x	x		x	x
Agency x Year F.E.			x			x
Observations	24,004	24,004	24,004	23,859	23,859	23,859
Adjusted R-squared	0.926	0.928	0.929	0.926	0.926	0.927

Panel B: Only issuers in financial services

	(1)	(2)	(3)	(4)	(5)	(6)
				Issuer Rating		
Non-rating Services	-0.320***	-0.075	-0.078			
	(0.088)	(0.105)	(0.102)			
Ln(Non-rating Issuer Revenue)				-0.370***	-0.272***	-0.257***
				(0.077)	(0.084)	(0.088)
Issuer F.E.	x			x		
Year F.E.	x			x		
Agency F.E.	x	x		x	x	
Issuer x Year F.E.		x	x		x	x
Agency x Year F.E.			x			x
Observations	2,756	2,756	2,756	2,609	2,609	2,609
Adjusted R-squared	0.961	0.963	0.965	0.960	0.961	0.962

Table 8. Ratings and non-rating services – ordered probit regressions

This table reports the coefficients of ordered probit regression models estimating the association between ratings and the provision of non-rating services in Panel A, and between ratings and consulting revenue from issuers in Panel B. Each observation corresponds to an issuer-agency-year. In these tests, the dependent variable *Issuer Rating* is rounded to whole numbers. The variables are defined in Table 1. The sample period is 2010-2015. This sub-sample only consists of observations in which issuers have multiple raters in a given year (see Table 1, Panel B). Heteroskedasticity-robust standard errors, clustered by issuer, are reported below coefficients. * denotes estimates that are significantly different from zero at the 10% level, ** at the 5% level, and *** at the 1% level.

Panel A: Ordered probit specifications corresponding to Table 3

	(1)	(2)	(3)
		Issuer Rating	
Non-rating Services	-0.592***	-0.616***	-0.577***
	(0.108)	(0.151)	(0.156)
Issuer F.E.	x		
Year F.E.	x		
Agency F.E.	x	x	
Issuer x Year F.E.		x	x
Agency x Year F.E.			x
Observations	5,141	5,141	5,141
Pseudo R-squared	0.584	0.649	0.657

Panel B: Ordered probit specifications corresponding to Table 4

	(1)	(2)	(3)
		Issuer Rating	
Ln(Non-rating Issuer Revenue)	-0.752***	-0.970***	-0.933***
	(0.093)	(0.154)	(0.164)
Issuer F.E.	x		
Year F.E.	x		
Agency F.E.	x	x	
Issuer x Year F.E.		x	x
Agency x Year F.E.			x
Observations	4,979	4,979	4,979
Pseudo R-squared	0.582	0.649	0.657

Table 9. Ratings, defaults, and the provision of non-rating services

This table reports the coefficients for linear regression models estimating the association between default rates and the provision of non-rating services. Each observation corresponds to an issuer-agency-year. The variables are defined in Tables 1 and 2. In columns 5 to 8, *Issuer Rating* is rounded to whole numbers and one dummy variable per rating notch is included. The sample period is 2010-2014 (using default information until September 2015). Heteroskedasticity-robust standard errors, clustered by issuer, are reported below coefficients. * denotes estimates that are significantly different from zero at the 10% level, ** at the 5% level, and *** at the 1% level.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Default in t+1							
Non-rating Services	0.027***	0.034***	0.027***	0.029***	0.015***	0.014***	0.015***	0.011**
	(0.004)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Issuer Rating	0.010***	0.010***	0.011***	0.011***				
	(0.000)	(0.000)	(0.001)	(0.001)				
Constant	-0.053***							
	(0.003)							
Issuer Rating F.E.					x	x	x	
Agency F.E.		x	x		x	x		
Year F.E.			x			x		
Industry F.E.			x			x		
Industry x Year F.E.				x			x	x
Agency x Year F.E.				x			x	
Agency x Issuer Rating x Year F.E.								x
Observations	18,707	18,707	18,707	18,707	18,707	18,707	18,707	18,707
Adjusted R-squared	0.039	0.042	0.054	0.056	0.062	0.073	0.076	0.103

Table 10. Ratings, defaults, and the provision of non-rating services: investment-grade versus high yield firms

This table reports the coefficients for linear regression models estimating the association between default rates and the provision of non-rating services. Each observation corresponds to an issuer-agency-year. The variables are defined in Tables 1 and 2. Panel A shows results for the sample of investment-grade firms, while Panel B reports results for the high yield sub-sample. In columns 5 to 8, *Issuer Rating* is rounded to whole numbers and one dummy variable per rating notch is included. The sample period is 2010-2014 (using default information until September 2015). Heteroskedasticity-robust standard errors, clustered by issuer, are reported below coefficients. * denotes estimates that are significantly different from zero at the 10% level, ** at the 5% level, and *** at the 1% level.

Panel A: Investment grade

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
				Default in t+1				
Non-rating Services	0.003	0.007**	0.008**	0.008**	0.006**	0.006**	0.007**	0.005
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Issuer Rating	0.003***	0.004***	0.003***	0.003***				
	(0.000)	(0.000)	(0.000)	(0.000)				
Constant	-0.010***							
	(0.002)							
Issuer Rating F.E.					x	x	x	
Agency F.E.		x	x		x	x		
Year F.E.			x			x		
Industry F.E.			x			x		
Industry x Year F.E.				x			x	x
Agency x Year F.E.				x			x	
Agency x Issuer Rating x Year F.E.								x
Observations	12,110	12,110	12,110	12,110	12,110	12,110	12,110	12,110
Adjusted R-squared	0.007	0.009	0.015	0.016	0.010	0.015	0.017	0.022

Panel B: High yield

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
				Default in t+1				
Non-rating Services	0.132**	0.134**	0.112*	0.129**	0.129**	0.107*	0.124*	0.129**
	(0.064)	(0.065)	(0.064)	(0.065)	(0.065)	(0.064)	(0.065)	(0.065)
Issuer Rating	0.028***	0.030***	0.029***	0.029***				
	(0.003)	(0.003)	(0.003)	(0.003)				
Constant	-0.282***							
	(0.033)							
Issuer Rating F.E.					x	x	x	
Agency F.E.		x	x		x	x		
Year F.E.			x			x		
Industry F.E.			x			x		
Industry x Year F.E.				x			x	x
Agency x Year F.E.				x			x	
Agency x Issuer Rating x Year F.E.								x
Observations	6,597	6,597	6,597	6,597	6,597	6,597	6,597	6,597
Adjusted R-squared	0.032	0.037	0.069	0.087	0.043	0.073	0.090	0.114

Table 11. Ratings, defaults, and payments for non-rating services

This table reports the coefficients for linear regression models estimating the association between default rates and payments for non-rating services. Each observation corresponds to an issuer-agency-year. The variables are defined in Tables 1 and 2. In columns 5 to 8, *Issuer Rating* is rounded to whole numbers and one dummy variable per rating notch is included. The sample period is 2010-2014 (using default information until September 2015). Heteroskedasticity-robust standard errors, clustered by issuer, are reported below coefficients. * denotes estimates that are significantly different from zero at the 10% level, ** at the 5% level, and *** at the 1% level.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Default in t+1							
Ln(Non-rating Issuer Revenue)	0.020***	0.026***	0.018***	0.019***	0.008***	0.008***	0.008***	0.003
	(0.003)	(0.003)	(0.003)	(0.003)	(0.002)	(0.003)	(0.003)	(0.003)
Issuer Rating	0.010***	0.010***	0.011***	0.011***				
	(0.000)	(0.000)	(0.001)	(0.001)				
Constant	-0.051***							
	(0.003)							
Issuer Rating F.E.					x	x	x	
Agency F.E.		x	x		x	x		
Year F.E.			x			x		
Industry F.E.			x			x		
Industry x Year F.E.				x			x	x
Agency x Year F.E.				x			x	
Agency x Issuer Rating x Year F.E.								x
Observations	18,508	18,508	18,508	18,508	18,508	18,508	18,508	18,508
Adjusted R-squared	0.039	0.041	0.053	0.055	0.062	0.073	0.076	0.103

Table 12. Ratings, defaults, and payments for non-rating services: investment-grade versus high yield firms

This table reports the coefficients for linear regression models estimating the association between default rates and payments for non-rating services. Each observation corresponds to an issuer-agency-year. The variables are defined in Tables 1 and 2. Panel A shows results for the sample of investment-grade firms, while Panel B reports results for the high yield sub-sample. In columns 5 to 8, *Issuer Rating* is rounded to whole numbers and one dummy variable per rating notch is included. The sample period is 2010-2014 (using default information until September 2015). Heteroskedasticity-robust standard errors, clustered by issuer, are reported below coefficients. * denotes estimates that are significantly different from zero at the 10% level, ** at the 5% level, and *** at the 1% level.

Panel A: Investment grade

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
				Default in t+1				
Ln(Non-rating Issuer Revenue)	0.003	0.006***	0.007***	0.007***	0.004**	0.005**	0.006**	0.002
	(0.002)	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)	(0.003)	(0.003)
Issuer Rating	0.003***	0.004***	0.003***	0.003***				
	(0.000)	(0.000)	(0.000)	(0.000)				
Constant	-0.010***							
	(0.002)							
Issuer Rating F.E.					x	x	x	
Agency F.E.		x	x		x	x		
Year F.E.			x			x		
Industry F.E.			x			x		
Industry x Year F.E.				x			x	x
Agency x Year F.E.				x			x	
Agency x Issuer Rating x Year F.E.								x
Observations	11,925	11,925	11,925	11,925	11,925	11,925	11,925	11,925
Adjusted R-squared	0.007	0.009	0.015	0.016	0.009	0.015	0.016	0.022

Panel B: High yield

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
				Default in t+1				
Ln(Non-rating Issuer Revenue)	0.149	0.164	0.102	0.194	0.166	0.108	0.201	0.197
	(0.172)	(0.174)	(0.169)	(0.193)	(0.179)	(0.173)	(0.194)	(0.191)
Issuer Rating	0.028***	0.030***	0.029***	0.029***				
	(0.003)	(0.003)	(0.003)	(0.003)				
Constant	-0.281***							
	(0.033)							
Issuer Rating F.E.					x	x	x	
Agency F.E.		x	x		x	x		
Year F.E.			x			x		
Industry F.E.			x			x		
Industry x Year F.E.				x			x	x
Agency x Year F.E.				x			x	
Agency x Issuer Rating x Year F.E.								x
Observations	6,583	6,583	6,583	6,583	6,583	6,583	6,583	6,583
Adjusted R-squared	0.031	0.036	0.068	0.086	0.042	0.072	0.090	0.113

Fig. 1. Ratings of firms with and without non-rating services

This figure shows the distribution of issuer ratings for firms that obtain non-rating services and those that do not, after accounting for differences due to industry effects. Specifically, we plot the residuals from the following regression: $(\text{Issuer Rating})_{i,j,t} = \gamma_{i \to k} + \varepsilon_{i,j,t}$ where *i* denotes the firm, *k* the industry, *j* denotes a rating agency, *t* denotes the year, and $\gamma_{i \to k}$ are industry dummies.

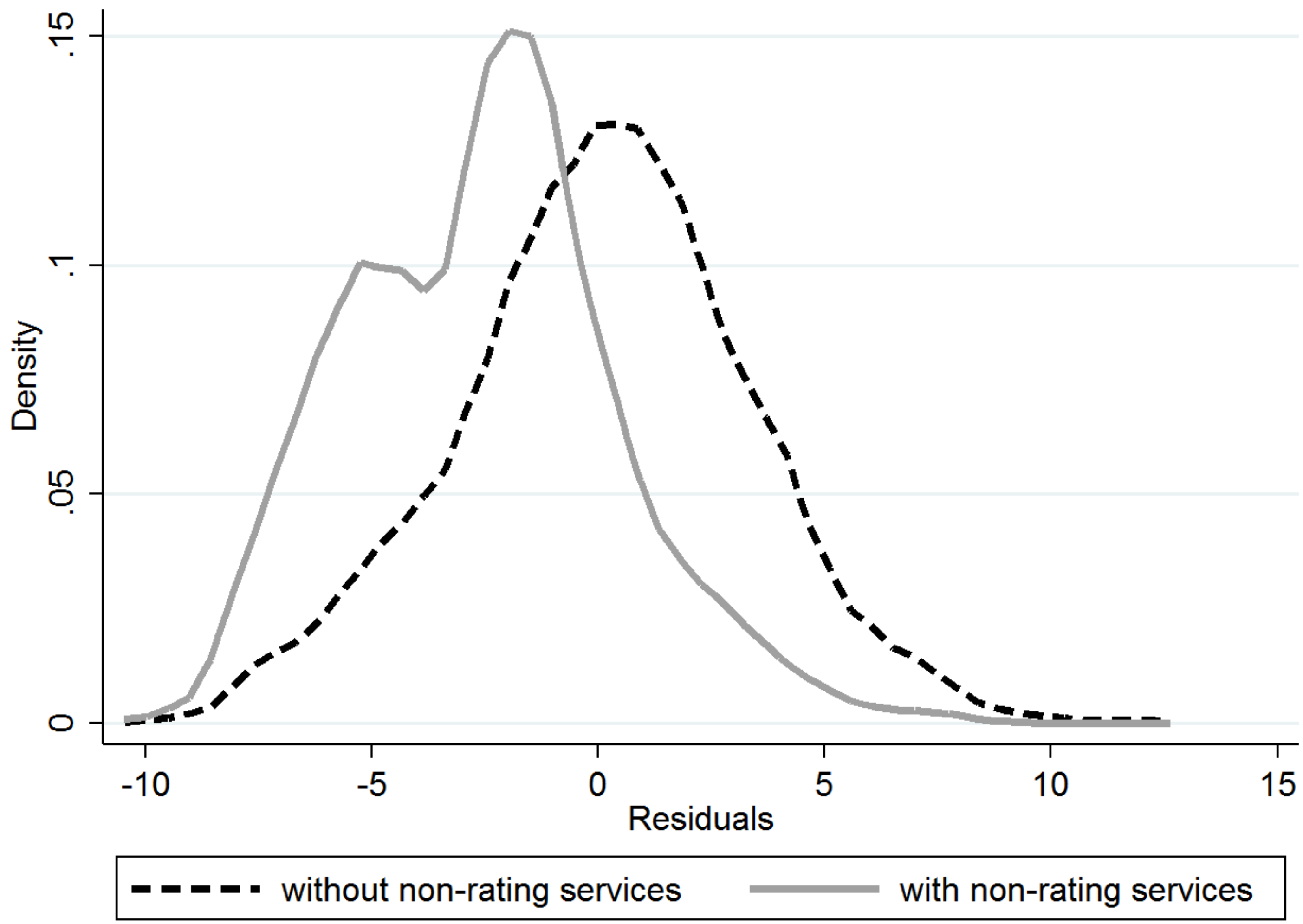


Fig. 2. Non-rating revenue and ratings

This figure plots the *Rating Difference* (the difference between the *Issuer Rating* from one rating agency minus the cross-sectional average of the ratings obtained from the other agencies in that year) against the variable *Ln(Non-rating Issuer Revenue)* and fits a linear prediction plot. *Issuer Rating* and *Ln(Non-rating Issuer Revenue)* are defined in Table 1. The sample underlying the figure consists of observations in which issuers have multiple ratings and where those issuers pay an agency for consulting (i.e., where the variable *Non-rating Services* takes the value of one).

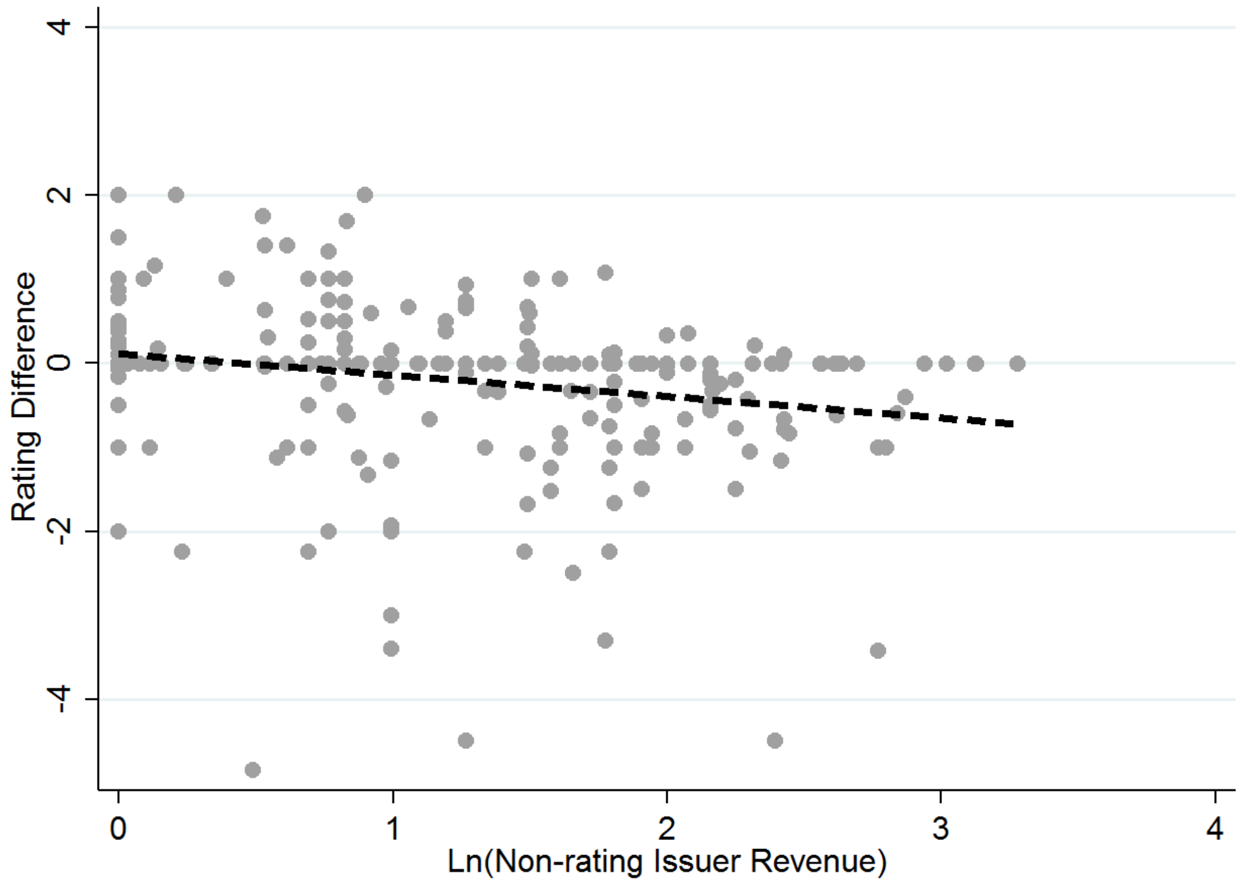


Fig. 3. Ratings and default rates

The figure shows one-year default rates by rating category. Observations are divided into coarse *Issuer Rating* categories. For each of the rating categories, the fraction of firms that default in the following year is shown on the vertical axis.

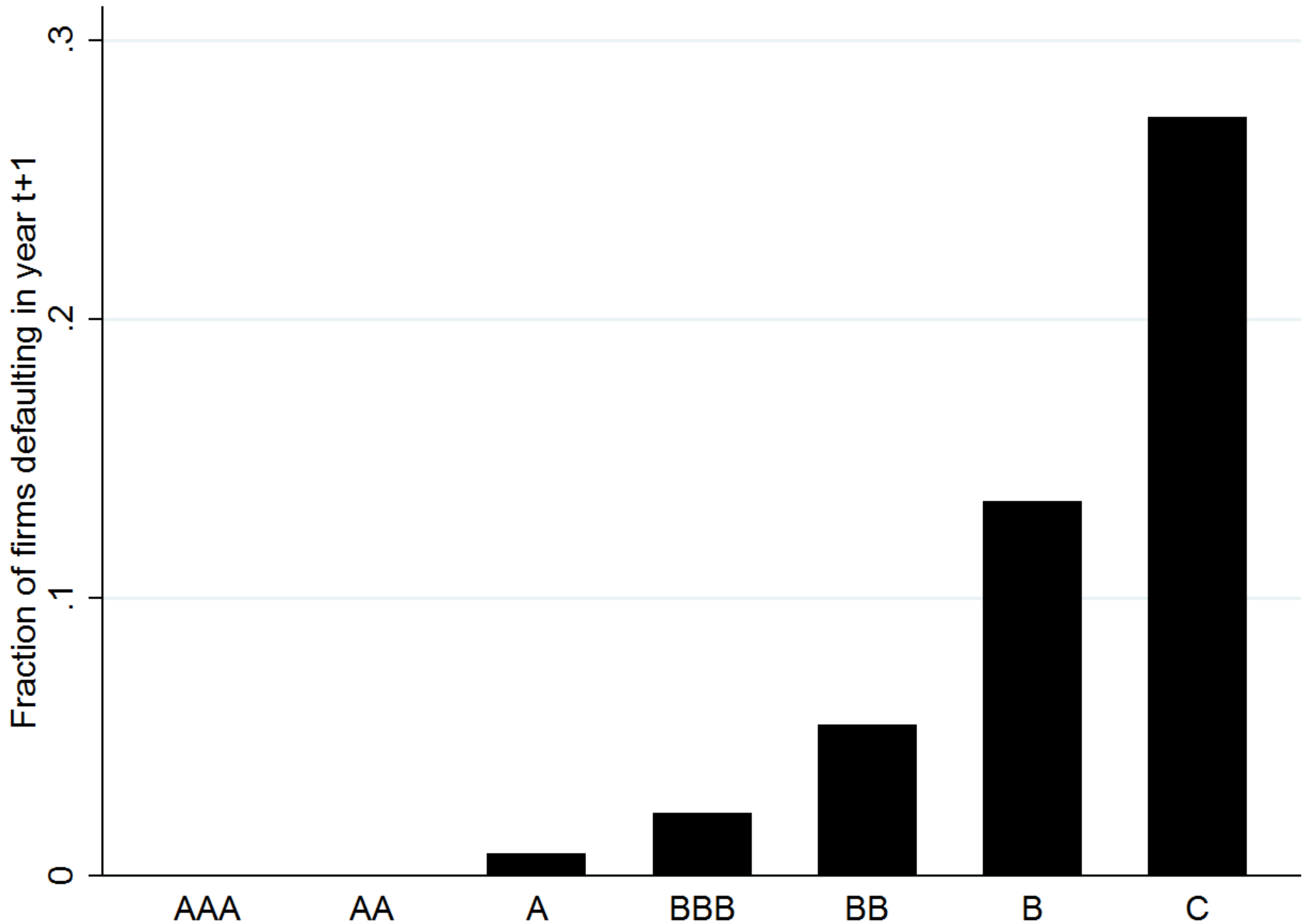
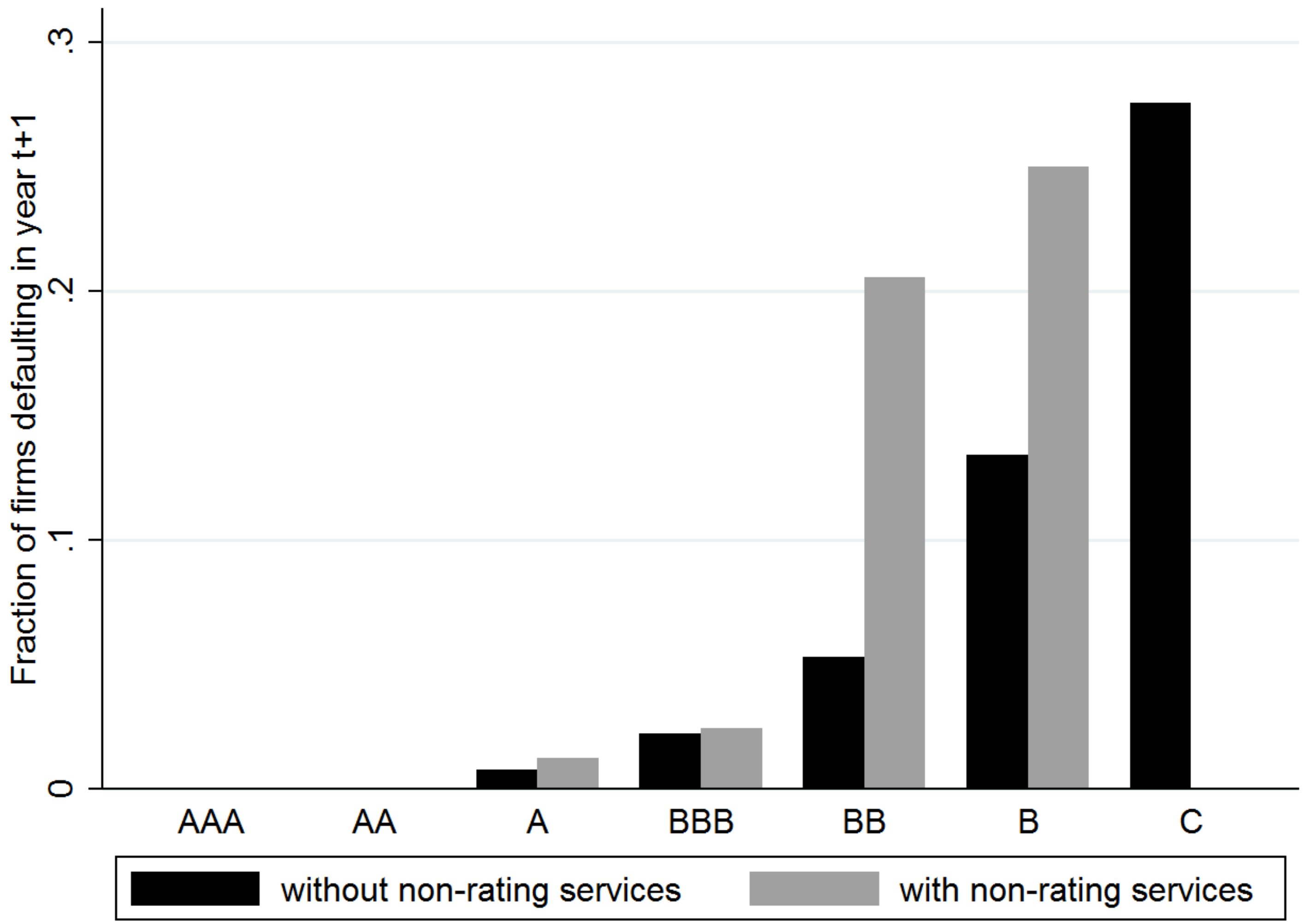


Fig. 4. Ratings and default rates: the role of non-rating services

The figure shows one-year default rates by rating category; for each rating category, default rates are separately reported for firms that pay for non-rating services and those that do not.



Non-rating revenue and conflicts of interest

Appendix

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This Appendix contains additional results and robustness tests referred to in the main draft.

Table A-1 contains detailed definitions of the variables used in this study.

Table A-2 provides an answer to the question which types of firms purchase non-rating services from rating agencies. Given our identification strategy (which compares simultaneous ratings of the same firm) this is not econometrically important per se for our results on the impact of non-rating services on ratings. However, this question is potentially relevant for understanding the broader role of consulting for ratings. We investigate which types of firms are associated with the purchase of non-rating services by regressing the *Non-rating Services* indicator variable on firm characteristics. In these regressions, we collapse the variable *Non-rating Services* from the issuer-agency-year to the issuer-year level: it takes a value of one if the issuer pays any rating agency for non-rating services in a given year. In Panel A of Table A-2 we report summary statistics on those firm characteristics, which use information from CMIE's Prowess database. Panel B shows regression results; column 1 reports the coefficients from a linear probability model, while column 2 reports results from a probit model. Both regressions additionally contain year fixed effects, so the coefficients can be interpreted as cross-sectional comparisons. We find that financial services firms, firms with more assets, firms with less leverage, more profitable firms, and listed firms, all have a significantly higher propensity to use non-rating services. Given that the adjusted R-squared is only 12% (see column 1 in Panel B), it is fair to say that we do not have a good econometric model of the purchase decision. Of course, a reasonable theory, which we do not directly test here, is that some firms are more dependent on ratings and therefore more likely to buy consulting services.

Table 8 in the draft re-estimated the main tests reported in Tables 3 and 4 using ordered probit models. The remaining tables in this Appendix re-estimate all other results using (ordered) probit models. As discussed in Section 4.2, to make the estimation of ordered probit models computationally feasible, in light of the large number of fixed effects we employ, we limit the sample to those observations in which issuers use multiple raters in a given year. This sub-sample consists of 5,141 observations. First, we verify that OLS results using this sub-sample are consistent with the OLS results estimated in the full sample used in the draft: they are. In Table A-3, Panel A (Panel B), we show that results in the restricted sample are similar to Table 3

(Table 4) in the draft. Tables 5 to 7 are also similar when re-estimated with OLS in that sub-sample; we do not report these tables for brevity. Having verified that the sub-sample is representative, we estimate ordered probit regressions. Tables A-4 to A-6 repeat, respectively, Tables 5 to 7 with ordered probit. We note that in Table A-4, we do not report a specification with issuer, agency, and year fixed effects as this particular specification encountered convergence problems in the maximum likelihood procedure; we do report the other two specifications (corresponding to columns 2 and 3 of Table 5). In these tables, we find that both the statistical and economic significance is similar to the OLS results reported in the draft.

For the probit versions of the default tables (Tables 9 to 12 in the draft), we start with the same sample as in the paper, as we did not encounter any computational difficulties. The results are reported in Tables A-7 through A-10 below. Note that the number of observations varies across specifications as the software used to estimate the probit models automatically drops observations from the analysis when one or more covariates (such as one of the fixed effects) perfectly predicts the outcome of interest. This is standard practice when dealing with so-called separation in limited dependent variable models. The probit results are generally similar to the OLS results, although the variable *Ln(Non-rating Issuer Revenue)* is not significant for predicting defaults in the probit tests.

Table A-1. Variable definitions

This table contains detailed definitions of the variables used in this study.

<u>*Issuer Rating:*</u> This variable represents the rating that an issuer receives from a rater in a given year. We obtain alphanumeric debt instrument ratings by the rating agencies CRISIL, ICRA, CARE, Brickwork Ratings, and INDRA from the CMIE Prowess database. We first assign numerical values to these alphanumeric instrument ratings, with a value of one denoting the highest credit rating "AAA" and the value 19 denoting "C-". Then, for each issuer, rating agency, and year, we average over the instruments' ratings to obtain an issuer-level credit rating. The variable *Issuer Rating* is rounded to whole numbers in default regressions in which issuer rating fixed effects are employed (Tables 9—12), and in ordered probit regressions in which this variable is used as the dependent variable (Table 8).

<u>*Rating Difference:*</u> the difference between the *Issuer Rating* from one rating agency minus the cross-sectional average of the *Issuer Ratings* from the other agencies (using the ratings from up to four other agencies). Ratings are from the CMIE Prowess database. This variable is only used in Fig. 2.

<u>*Non-rating Services:*</u> This indicator variable takes the value of one if an issuer pays a given rating agency for non-rating services in a given year, zero otherwise. The relevant information is available for the following agencies and years: years 2010 to 2014 for CRISIL; years 2010-2015 for ICRA, Brickwork Ratings, and INDRA; years 2013-2015 for CARE. The information is from the "Regulatory Disclosures" sections of the agencies' websites. Some years' disclosures could not be obtained (for CARE in the years 2010-2012) because raters only have to maintain the current year's disclosures on their websites.

<u>*Ln(Non-rating Issuer Revenue):*</u> the natural logarithm of (one plus) annual non-rating revenue paid to a given rating agency by a given issuer (in million Rupees). For firms that do not obtain consulting services (instances in which the variable *Non-rating Services* is zero), this variable naturally takes a value of zero. For issuers that do pay for non-rating services (instances in which the variable *Non-rating Services* is one), detailed fee information to construct the variable *Ln(Non-rating Issuer Revenue)* is available for CRISIL-rated firms for the years 2010-2014, and for ICRA-rated firms for the years 2010 and 2011 (but not for the years 2012-2015).

Specifically, CRISIL discloses for the years 2010-2014 the "Contribution of Non Rating Income" (Contribution), the non-rating revenue from an issuer to total group revenue. For CRISIL-rated firms, the variable *Ln(Non-rating Issuer Revenue)* is then Ln(1 + Contribution x total revenue of CRISIL in million Rupees). ICRA discloses in 2010 and 2011 the "Share of Non Rating Income to Total Income from Issuer" (SNRITII) and the "Share of Total Income from Issuer to Total Income of Group ICRA" (STIITIGI). For ICRA-rated firms, the variable *Ln(Non-rating Issuer Revenue)* is then Ln(1 + STIITIGI x SNRITII x total revenue of ICRA in million Rupees). We note that the variable *Ln(Non-rating Issuer Revenue)* uses some voluntarily disclosed information on fee payments by CRISIL and ICRA that are reported by the raters together with issuer-level fee revenue information mandated by the "Circular CIR/MIRSD/CRA/6/2010" (see Section 2.3 on the exact disclosure requirements of the law); conditional on being reported by a rater in a given year, this information covers all non-rating services clients. Total revenue of the raters is obtained from the consolidated financial statements available on the raters' websites.

Default in t+1: This variable is defined at the firm-year level and takes the value of one in year *t* if a given issuer has a debt instrument on which it defaults in year *t+1* (irrespective of which agency rates that instrument); the variable takes a value of zero otherwise. The variable is available for the period 2010-2014 (using default information until September 2015). We obtain the default information from CMIE's Prowess database.

Table A-2. Which firms purchase non-rating services?

This table sheds light on the characteristics of firms that pay for non-rating services. Panel A reports summary statistics for the variables used in the regressions. Panel B reports the coefficients for regression models estimating the association between the purchase of non-rating services by issuers and issuer characteristics. Column 1 reports results from a linear probability model while column 2 reports coefficients from a probit model. *Non-rating Services*, the dependent variable, is a dummy variable that takes the value of one if an issuer pays for non-rating services in a given year, zero otherwise. In these regressions, we collapse the variable *Non-rating Services* from the issuer-agency-year to the issuer-year level: it takes a value of one if the issuer pays any rating agency for non-rating services in a given year. *Finance* is a dummy variable for firms in the financial services sector; *Ln(Assets)* is the natural logarithm of firm assets; *Cash/Assets* is the sum of cash, bank balance, and short-term investments, all divided by assets; *Leverage* is long-term debt divided by assets; *CAPEX/Assets* is net cash outflow from investment activities divided by assets; *Profitability* is EBITDA divided by assets; *Volatility of Profitability* is computed using the current year's data as well as the four previous years'; *Interest Coverage* is EBITDA divided by interest expenses; and, finally, *Listed* is an indicator variable for whether a firm is listed (on the BSE or the NSE) or not. All explanatory variables (except for the dummy variables) are winsorized at the 1% and 99% levels. Each observation corresponds to an issuer-year. The sample period is 2010-2015. Data is from the CMIE's Prowess database. Heteroskedasticity-robust standard errors, clustered by issuer, are reported below coefficients. * denotes estimates that are significantly different from zero at the 10% level, ** at the 5% level, and *** at the 1% level.

Panel A: Summary statistics

	Obs.	Mean	Std. Dev.	Min.	Max.
Non-rating Services	9,119	0.063	0.243	0.000	1.000
Finance	9,119	0.067	0.249	0.000	1.000
Ln(Assets)	9,119	8.440	1.792	4.858	14.124
Cash/Assets	9,119	0.052	0.071	0.000	0.427
Leverage	9,119	0.172	0.178	0.000	0.824
CAPEX/Assets	9,119	0.061	0.092	-0.146	0.594
Volatility of Profitability	9,119	0.044	0.041	0.001	0.273
Profitability	9,119	0.118	0.073	-0.088	0.368
Interest Coverage	9,119	17.869	83.827	-3.905	916.537
Listed	9,119	0.540	0.498	0.000	1.000

Panel B: Regressions

	(1)	(2)
Model:	Linear Probability	Probit
Dependent variable:	Non-rating Services	
Finance	0.121***	0.666***
	(0.022)	(0.103)
Ln(Assets)	0.040***	0.332***
	(0.003)	(0.022)
Cash/Assets	0.075	0.090
	(0.059)	(0.442)
Leverage	-0.059***	-0.822***
	(0.021)	(0.230)
CAPEX/Assets	-0.048*	-0.042
	(0.027)	(0.320)
Volatility of Profitability	-0.087	-1.184
	(0.066)	(0.949)
Profitability	0.236***	2.636***
	(0.046)	(0.491)
Interest Coverage	-0.000	-0.000
	(0.000)	(0.000)
Listed	0.023***	0.205***
	(0.007)	(0.074)
Year F.E.	x	x
Observations	9,119	9,118
Adjusted R-squared	0.122	--
Pseudo R-squared	--	0.230

Table A-3. Ratings and the provision of non-rating services – OLS regressions for the sub-sample of observations used in ordered probit tests

This table reports the coefficients for linear regression models estimating the association between ratings and the provision of non-rating services. Each observation corresponds to an issuer-agency-year. The variables are defined in Table 1 of the draft. The sample period is 2010-2015. This sub-sample only consists of observations in which issuers have multiple raters in a given year. Panel A presents specifications with the indicator *Non-rating Services* as the explanatory variable, while Panel B reports specifications that employ *Ln(Non-rating Issuer Revenue)*. Heteroskedasticity-robust standard errors, clustered by issuer, are reported below coefficients. * denotes estimates that are significantly different from zero at the 10% level, ** at the 5% level, and *** at the 1% level.

Panel A: Specifications analogous to Table 3 in the main text

	(1)	(2)	(3)
		Issuer Rating	
Non-rating Services	-0.378***	-0.326***	-0.299***
	(0.076)	(0.068)	(0.068)
Issuer F.E.	x		
Year F.E.	x		
Agency F.E.	x	x	
Issuer x Year F.E.		x	x
Agency x Year F.E.			x
Observations	5,141	5,141	5,141
Adjusted R-squared	0.955	0.955	0.956

Panel B: Specifications analogous to Table 4 in the main text

	(1)	(2)	(3)
		Issuer Rating	
Ln(Non-rating Issuer Revenue)	-0.419***	-0.404***	-0.362***
	(0.065)	(0.063)	(0.065)
Issuer F.E.	x		
Year F.E.	x		
Agency F.E.	x	x	
Issuer x Year F.E.		x	x
Agency x Year F.E.			x
Observations	4,979	4,979	4,979
Adjusted R-squared	0.953	0.953	0.954

Table A-4. Ratings and past payments for non-rating services – ordered probit regressions *(based on Table 5 in the main text)*

This table reports the coefficients for ordered probit regression models estimating the association between ratings and non-rating revenue from issuers. Each observation corresponds to an issuer-agency-year. *Lag[·]* is the lag operator and denotes one-year lags of the relevant variable. In these tests, the dependent variable *Issuer Rating* is rounded to whole numbers. The variables are defined in Table 1 of the draft. The sample period is 2010-2015. This sub-sample only consists of observations in which issuers have multiple raters in a given year. Heteroskedasticity-robust standard errors, clustered by issuer, are reported below coefficients. * denotes estimates that are significantly different from zero at the 10% level, ** at the 5% level, and *** at the 1% level.

	(1)	(2)
	Issuer Rating	
Ln(Non-rating Issuer Revenue)	-0.447	-0.231
	(0.328)	(0.350)
Lag[Ln(Non-rating Issuer Revenue)]	-0.771**	-0.979***
	(0.330)	(0.316)
Agency F.E.	x	
Issuer x Year F.E.	x	x
Agency x Year F.E.		x
Observations	3,076	3,076
Pseudo R-squared	0.759	0.765

Table A-5. Ratings and non-rating services: sub-samples for issuers close to important thresholds in the ratings spectrum—ordered probit regressions *(based on Table 6 in the main text*)

This table reports the coefficients for ordered probit regression models estimating the association between ratings and the purchase of non-rating services by issuers. Each observation corresponds to an issuer-agency-year. In these tests, the dependent variable *Issuer Rating* is rounded to whole numbers. The variables are defined in Table 1. The sample period is 2010-2015. These tests focus on issuers that are close to an important "threshold" on the rating scale, such as AA- and BBB-, which is used for contracting and regulatory purposes (see Section 2.2). Specifically, in Panel A, the sample contains issuers that in a given year obtain at least one of the following "close" ratings from a rating agency that they do not pay for consulting: A+, A, A-, BB+, BB, or BB-. In Panel B, the tests focus on issuers that that (i) in a given year obtain at least one "close" rating (A+, A, A-, BB+, BB, or BB-) from a rating agency that they do not pay for consulting, and that (ii) have at least two ratings in that year that are different from each other. Heteroskedasticity-robust standard errors, clustered by issuer, are reported below coefficients. * denotes estimates that are significantly different from zero at the 10% level, ** at the 5% level, and *** at the 1% level.

Panel A: Issuers close to AA- and BBB- thresholds

	(1)	(2)	(3)	(4)	(5)	(6)
			Issuer Rating			
Non-rating Services	-0.909***	-1.251***	-1.194***			
	(0.247)	(0.311)	(0.310)			
Ln(Non-rating Issuer Revenue)				-1.364***	-1.566***	-1.407***
				(0.153)	(0.218)	(0.263)
Issuer F.E.	x			x		
Year F.E.	x			x		
Agency F.E.	x	x		x	x	
Issuer x Year F.E.		x	x		x	x
Agency x Year F.E.			x			x
Observations	2,424	2,424	2,424	2,403	2,403	2,403
Pseudo R-squared	0.496	0.556	0.565	0.497	0.557	0.565

Panel B: Issuers with split ratings close to AA- or BBB- thresholds

	(1)	(2)	(3)	(4)	(5)	(6)
			Issuer Rating			
Non-rating Services	-1.156***	-1.365***	-1.222***			
	(0.262)	(0.312)	(0.326)			
Ln(Non-rating Issuer Revenue)				-1.348***	-1.492***	-1.242***
				(0.145)	(0.189)	(0.268)
Issuer F.E.	x			x		
Year F.E.	x			x		
Agency F.E.	x	x		x	x	
Issuer x Year F.E.		x	x		x	x
Agency x Year F.E.			x			x
Observations	1,765	1,765	1,765	1,752	1,752	1,752
Pseudo R-squared	0.462	0.499	0.511	0.462	0.499	0.511

Table A-6. Ratings and non-rating services: issuers in the financial services sector versus issuers in other sectors—ordered probit regressions *(based on Table 7 in the main text*)

This table reports the coefficients for ordered probit regression models estimating the association between ratings and the purchase of non-rating services by issuers. Each observation corresponds to an issuer-agency-year. In these tests, the dependent variable *Issuer Rating* is rounded to whole numbers. The variables are defined in Table 1 of the draft. The sample period is 2010-2015. This sub-sample only consists of observations in which issuers have multiple raters in a given year. The sample in Panel A excludes financial services firms, while the sample in Panel B focusses on a sample of only financial services firms. Heteroskedasticity-robust standard errors, clustered by issuer, are reported below coefficients. * denotes estimates that are significantly different from zero at the 10% level, ** at the 5% level, and *** at the 1% level.

Panel A: Excluding issuers in financial services

	(1)	(2)	(3)	(4)	(5)	(6)
			Issuer Rating			
Non-rating Services	-0.365**	-0.386	-0.416*			
	(0.180)	(0.240)	(0.240)			
Ln(Non-rating Issuer Revenue)				-0.567*	-0.837	-0.879*
				(0.331)	(0.544)	(0.515)
Issuer F.E.	x			x		
Year F.E.	x			x		
Agency F.E.	x	x		x	x	
Issuer x Year F.E.		x	x		x	x
Agency x Year F.E.			x			x
Observations	3,677	3,677	3,677	3,632	3,632	3,632
Pseudo R-squared	0.583	0.649	0.655	0.580	0.647	0.653

Panel B: Only issuers in financial services

	(1)	(2)	(3)	(4)	(5)	(6)
				Issuer Rating		
Non-rating Services	-0.356**	-0.184	-0.176			
	(0.147)	(0.211)	(0.215)			
Ln(Non-rating Issuer Revenue)				-0.562***	-0.653***	-0.642***
				(0.128)	(0.201)	(0.211)
Issuer F.E.	x			x		
Year F.E.	x			x		
Agency F.E.	x	x		x	x	
Issuer x Year F.E.		x	x		x	x
Agency x Year F.E.			x			x
Observations	1,464	1,464	1,464	1,347	1,347	1,347
Pseudo R-squared	0.529	0.621	0.635	0.529	0.624	0.638

Table A-7. Ratings, defaults, and the provision of non-rating services—probit regressions

(based on Table 9 in the main text)

This table reports the coefficients for probit regression models estimating the association between default rates and the provision of non-rating services. Each observation corresponds to an issuer-agency-year. The variables are defined in Tables 1 and 2 of the draft. In columns 5 to 8, *Issuer Rating* is rounded to whole numbers and one dummy variable per rating notch is included. The sample period is 2010-2014 (using default information until September 2015). Heteroskedasticity-robust standard errors, clustered by issuer, are reported below coefficients. * denotes estimates that are significantly different from zero at the 10% level, ** at the 5% level, and *** at the 1% level.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Default in t+1							
Non-rating Services	0.287**	0.371***	0.389***	0.524***	0.415***	0.411***	0.559***	0.582***
	(0.123)	(0.127)	(0.139)	(0.150)	(0.135)	(0.145)	(0.157)	(0.161)
Issuer Rating	0.162***	0.167***	0.184***	0.204***				
	(0.007)	(0.007)	(0.008)	(0.008)				
Constant	-3.514***							
	(0.084)							
Issuer Rating F.E.					x	x	x	
Agency F.E.		x	x		x	x		
Year F.E.			x			x		
Industry F.E.			x			x		
Industry x Year F.E.				x			x	x
Agency x Year F.E.				x			x	
Agency x Issuer Rating x Year F.E.								x
Observations	18,707	18,707	16,570	12,529	15,589	14,597	11,193	9,140
Pseudo R-squared	0.142	0.151	0.183	0.217	0.118	0.161	0.197	0.214

Table A-8. Ratings, defaults, and the provision of non-rating services: investment-grade versus high yield firms—probit regressions *(based on Table 10 in the main text)*

This table reports the coefficients for probit regression models estimating the association between default rates and the provision of non-rating services. Each observation corresponds to an issuer-agency-year. The variables are defined in Tables 1 and 2. Panel A shows results for the sample of investment-grade firms; Panel B reports results for high yield issuers. In columns 5 to 8, *Issuer Rating* is rounded to whole numbers and one dummy variable per rating notch is included. The sample period is 2010-2014. Heteroskedasticity-robust standard errors, clustered by issuer, are reported below coefficients. * denotes estimates that are significantly different from zero at the 10% level, ** at the 5% level, and *** at the 1% level.

Panel A: Investment grade

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Default in t+1							
Non-rating Services	0.100	0.224	0.309	0.470**	0.271	0.333	0.537**	0.523**
	(0.175)	(0.180)	(0.195)	(0.224)	(0.188)	(0.204)	(0.240)	(0.256)
Issuer Rating	0.164***	0.169***	0.177***	0.209***				
	(0.017)	(0.016)	(0.018)	(0.021)				
Constant	-3.517***							
	(0.149)							
Issuer Rating F.E.					x	x	x	
Agency F.E.		x	x		x	x		
Year F.E.			x			x		
Industry F.E.			x			x		
Industry x Year F.E.				x			x	x
Agency x Year F.E.				x			x	
Agency x Issuer Rating x Year F.E.								x
Observations	12,110	12,110	7,521	4,130	8,992	6,063	3,343	2,440
Pseudo R-squared	0.072	0.088	0.121	0.184	0.042	0.087	0.148	0.148

Panel B: High yield

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
				Default in t+1				
Non-rating Services	0.660***	0.693***	0.596**	0.877***	0.682***	0.588**	0.870***	0.826***
	(0.238)	(0.240)	(0.251)	(0.277)	(0.239)	(0.250)	(0.272)	(0.264)
Issuer Rating	0.163***	0.169***	0.176***	0.198***				
	(0.013)	(0.013)	(0.014)	(0.015)				
Constant	-3.527***							
	(0.176)							
Issuer Rating F.E.					x	x	x	
Agency F.E.		x	x		x	x		
Year F.E.			x			x		
Industry F.E.			x			x		
Industry x Year F.E.				x			x	x
Agency x Year F.E.				x			x	
Agency x Issuer Rating x Year F.E.								x
Observations	6,597	6,597	6,354	4,923	6,597	6,354	4,923	4,677
Pseudo R-squared	0.050	0.059	0.125	0.166	0.064	0.129	0.170	0.213

Table A-9. Ratings, defaults, and payments for non-rating services—probit regressions
(based on Table 11 in the main text)

This table reports the coefficients for probit regression models estimating the association between default rates and payments for non-rating services. Each observation corresponds to an issuer-agency-year. The variables are defined in Tables 1 and 2 of the draft. In columns 5 to 8, *Issuer Rating* is rounded to whole numbers and one dummy variable per rating notch is included. The sample period is 2010-2014 (using default information until September 2015). Heteroskedasticity-robust standard errors, clustered by issuer, are reported below coefficients. * denotes estimates that are significantly different from zero at the 10% level, ** at the 5% level, and *** at the 1% level.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Default in t+1							
Ln(Non-rating Issuer Revenue)	0.133	0.256	0.273	0.404	0.447	0.316	0.481	0.438
	(0.192)	(0.180)	(0.288)	(0.339)	(0.297)	(0.344)	(0.381)	(0.388)
Issuer Rating	0.161***	0.166***	0.184***	0.203***				
	(0.007)	(0.007)	(0.008)	(0.009)				
Constant	-3.504***							
	(0.085)							
Issuer Rating F.E.					x	x	x	
Agency F.E.		x	x		x	x		
Year F.E.			x			x		
Industry F.E.			x			x		
Industry x Year F.E.				x			x	x
Agency x Year F.E.				x			x	
Agency x Issuer Rating x Year F.E.								x
Observations	18,508	18,508	16,458	12,436	15,514	14,539	11,145	9,051
Pseudo R-squared	0.141	0.150	0.183	0.217	0.118	0.162	0.198	0.213

Table A-10. Ratings, defaults, and payments for non-rating services: investment-grade versus high yield firms—probit regressions (*based on Table 12 in the main text*)

This table reports the coefficients for probit regression models estimating the association between default rates and payments for non-rating services. Each observation corresponds to an issuer-agency-year. Panel A shows results for investment-grade firms; Panel B reports results for high yield issuers. In columns 5 to 8, *Issuer Rating* is rounded to whole numbers and one dummy variable per rating notch is included. The sample period is 2010-2014. Heteroskedasticity-robust standard errors, clustered by issuer, are reported below coefficients. * denotes estimates that are significantly different from zero at the 10% level, ** at the 5% level, and *** at the 1% level.

Panel A: Investment grade

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
				Default in t+1				
Ln(Non-rating Issuer Revenue)	0.048	0.205	0.289	0.577	0.357	0.344	0.764	0.671
	(0.278)	(0.254)	(0.356)	(0.414)	(0.389)	(0.438)	(0.555)	(0.580)
Issuer Rating	0.164***	0.169***	0.179***	0.211***				
	(0.018)	(0.017)	(0.019)	(0.022)				
Constant	-3.525***							
	(0.156)							
Issuer Rating F.E.					x	x	x	
Agency F.E.		x	x		x	x		
Year F.E.			x			x		
Industry F.E.			x			x		
Industry x Year F.E.				x			x	x
Agency x Year F.E.				x			x	
Agency x Issuer Rating x Year F.E.								x

Observations	11,925	11,925	7,404	4,076	8,931	5,989	3,323	2,394
Pseudo R-squared	0.071	0.088	0.123	0.187	0.043	0.090	0.152	0.149

Panel B: High yield

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Default in t+1							
Ln(Non-rating Issuer Revenue)	0.799	0.928	0.549	1.408	0.947	0.591	1.560*	1.227
	(0.647)	(0.661)	(0.697)	(0.955)	(0.679)	(0.708)	(0.936)	(0.994)
Issuer Rating	0.163***	0.169***	0.176***	0.196***				
	(0.013)	(0.013)	(0.014)	(0.015)				
Constant	-3.524***							
	(0.176)							
Issuer Rating F.E.					x	x	x	
Agency F.E.		x	x		x	x		
Year F.E.			x			x		
Industry F.E.			x			x		
Industry x Year F.E.				x			x	x
Agency x Year F.E.				x			x	
Agency x Issuer Rating x Year F.E.								x
Observations	6,583	6,583	6,342	4,913	6,583	6,342	4,913	4,667
Pseudo R-squared	0.048	0.057	0.124	0.164	0.062	0.127	0.168	0.212