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Funding for this research was provided in part by University of Northampton and Harvard Business School. All errors are our own.

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August 9, 2021

Abstract

Major U.S. credit rating agencies are criticized for failing to understand developments in other economies and thereby impeding capital access by assigning lower ratings. Consistent with this, we find that Moody's and S&P credit ratings are more favorable after the agencies establish a local presence in the rated issuer's country of domicile. The results appear to be driven by a decrease in negative adjustments applied to model-predicted ratings, indicating that rating analysts become more confident with their quantitative model outputs after a local presence. Positive adjustments also increase, suggesting that analysts become more willing to assign higher than model-predicted ratings. Subsequent evidence suggests that, after the local presence, rating increases are not merely catering to local economies but become more informative as evidenced by their negative association with future credit risk premium and probability of default. Our findings inform the debate on the regulation of credit rating agency markets around the world.

Keywords: credit rating agencies; credit ratings; rating adjustments; rating disagreement; geographic proximity; soft information

Declarations of interest: none.

*We are grateful for helpful comments from Michael Chin, Lauren Cohen, Susanna Gallani, Shane Greenstein, David Harris, Eddie Riedl, Maria (Wieczynska) Rykaczewski, Suraj Srinivasan, and workshop participants at Arizona State University, Boston University, Harvard Business School, Syracuse University, University of Chicago, University of North Carolina at Chapel Hill, University of Nottingham, University of Technology Sydney, and Syracuse University. We are grateful to Zhuoran Dai and Carolyn Liu for research support. We acknowledge financial support from the University of Northampton and Harvard Business School. All errors are our own.

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1 Introduction

Credit ratings are an integral part of capital markets. Investors use ratings to mitigate their disadvantage of informational asymmetry relative to borrowers (Ferri, 2004). A rating aggregates public and private information about a borrower's credit quality, and reduces the need for individual investors to conduct detailed due diligence (Badoer et al., 2019). For borrowers, a rating unlocks access to capital by facilitating public and private debt pricing and contracting (Graham and Harvey, 2001; Faulkender and Petersen, 2006; Kisgen, 2006; Partnoy, 2009; Kisgen and Strahan, 2010; Roychowdhurry and Srinivasan, 2019). Ratings also broaden a firm's investor base beyond sophisticated investors that can perform complex credit analyses (Faulkender and Petersen, 2006; Petersen, 2009; Badoer et al., 2019).

Given this importance of ratings, global stakeholders care about how the ratings are assigned and many are critical of the dominance of U.S. rating agencies, namely S&P Global Ratings (S&P) and Moody's Investors Service (Moody's) (Ferri and Liu, 2003; Ferri, 2004; Attig et al., 2020). A long-standing claim is that these agencies do not fully understand developments in other economies and thereby impede access to capital by assigning lower ratings. To solve these impediments, for example, some members of BRICS (Brazil, Russia, India, China, South Africa) want their own rating agency (Economist, 2017). Some European Union (EU) members also want a European agency, especially after the 2010 debt crisis that many accuse U.S. agencies of exacerbating.[1] The EU now mandates that ratings usable for regulatory purposes be issued or endorsed by a EU-located agency (ESMA, 2011).

Motivated by the claim that U.S. agencies assign lower ratings because they fail to understand developments in other economies, we test the proposition that agencies assign more favorable ratings after they establish a local presence in the rated issuer's country of domicile. Ferri et al. (1999) highlight that rating agencies exacerbated the 1990s East Asian crisis by downgrading ratings more than the worsening in economic fundamentals justified. They suggest that, when in doubt, analysts tend to be more stringent and assign lower ratings.

[1] see https://www.cfr.org/backgrounder/credit-rating-controversy, last accessed March 25, 2021.

Such stringency is consistent with the notion that in the face of uncertainty, market participants take action to protect themselves (Duffie and Lando, 2001); such uncertainty may increase with a lack of a local presence. This is akin to the lemons problem (Akerlof, 1970), which suggests that a whole group may be perceived negatively if it is difficult to distinguish between the group's high and low quality members. That is, analysts that do not fully understand international markets are likely to discount outcomes of their risk analyses and assign lower average ratings. Thus, if a local presence enables analysts to better understand local markets and become more confident in their analyses, we expect them to become less stringent and assign more favorable ratings to local firms after establishing a local presence.

Yet, it is not obvious that a local presence leads to more favorable ratings. Rating agencies maintain that their methodologies are multidisciplinary and universal (Moody's Investors Service, 2006). By implication, a local presence is inconsequential and ratings might not change after establishing a local presence. Moreover, existing evidence suggest that rating agencies have the incentives to assign ratings that accurately reflect an entity's credit risk to protect themselves from reputational harm (e.g., Bonsall et al., 2016). Reputational harm can lead to reduced reliance on credit ratings and greater regulatory scrutiny (Bolton et al., 2012; DeHaan, 2017). Also, by enabling access to information and enhancing credit analysis (Ganguin and Bilardello, 2005; Bonsall et al., 2017), a local presence can lead to lower ratings if analysts are better able to uncover adverse information previously missed. This discussion forms the basis for the tension in our research proposition.

To test our proposition that a local presence affects ratings, we employ a staggered difference-in-differences design to examine whether and how ratings change after Moody's and S&P open local offices in rated issuers' domicile countries. Using a sample of non-U.S. firms rated by Moody's and S&P, we find results consistent with the proposition that a local presence leads to more favorable credit ratings. The baseline results show that ratings assigned by both Moody's and S&P increase by nearly one-notch in the period after the agencies establish a local presence. The results are robust to including several firm characteristics found in prior literature to be determinants of issuer credit ratings. In addition to year fixed effects, we alternatively include industry and country fixed effects, and firm fixed effects. Our results are robust under these specifications.

The decision to establish a local presence raises endogeneity concerns. An agency may open an office to comply with residency requirements, access new issuers, or enhance credit insights. It may also do so because a country's economic conditions or institutions are improving. In turn, it is these improvements that warrant higher credit ratings and not the hypothesized effects of a local presence. To mitigate these concerns, we estimate difference-in-differences tests that benchmark a firm's rating assigned by the agency with a local presence to the same firm's rating assigned by the agency without a local presence. We document an increase in ratings deviations between Moody's and S&P and more favorable ratings for the agency that has a local presence. By comparing ratings assigned to the same firm in the same economic environment by the two different agencies before and after one of the agencies establishes a local presence, we mitigate the concerns that rating changes observed after a local presence are attributed to other factors, such as economic improvements.

To investigate the potential mechanism through which a local presence affects credit ratings, we examine the components of credit ratings. Credit ratings reflect quantitative and qualitative factors (Ashbaugh-Skaife et al., 2006; Baghai et al., 2014; Kraft, 2015a,b; S&P Global Ratings, 2019; Bonsall et al., 2016). Analysts use quantitative models to determine a baseline credit rating based on quantitative data (i.e., model-based rating) and then make adjustments to the baseline credit rating to arrive at the actual rating. A local presence may affect the use of soft information in making qualitative rating adjustments. Prior research highlights that geographic proximity increases the use and impact of soft information (e.g., Malloy, 2005; O'Brien and Tan, 2015; Jaggi and Tang, 2017). Thus, the portion of credit ratings attributed to adjustments can increase as analysts incorporate more local knowledge in the ratings. Alternatively, a local presence mitigates the use of subjective adjustments that persistently bias ratings downwards. Consistent with Ferri et al. (1999), when in doubt, analysts assign lower ratings than what the fundamentals would predict. Accordingly, if adjustments are more likely to be negative without a local presence because of limited understanding of local economies, then we would observe less negative adjustments as analysts assign ratings closer to or above model-predicted ratings.

We uncover interesting insights. Following Baghai et al. (2014), we use a firm's fundamentals to predict its credit rating and determine rating adjustments as the difference between the actual and predicted rating. We find that the component of ratings attributed to adjustments decreases after a local presence, suggesting that a local presence leads analysts to make less adjustments and assign ratings that are closer to the model-predicted ratings. The adjustment decrease is driven by a decrease in negative adjustments, suggesting that analysts are more likely to assign more favorable ratings by loosening rating stringency.

Next, we investigate whether our findings reflect increased ratings quality or catering. Rating agencies sometimes cater to issuer demands for favorable ratings (Kedia et al., 2014; Kraft, 2015a). Thus, they may assign higher ratings as a means to build market share upon establishing a local presence. Conversely, a local presence can facilitate higher quality ratings by enhancing credit risk insights. To tease out these possibilities, we examine whether ratings become more or less informative about issuer default risk (see Duffie et al., 2007; Kedia et al., 2014). We find some evidence that ratings assigned after a local presence are accompanied by lower default risk premium and lower likelihood of default.[2] Thus these findings provide some evidence that a local presence enhances credit risk analysis and lead to ratings that do not merely reflect catering behavior but that are informative of default risk.[3]

To provide further evidence on catering or credit quality, we explore explanations based on the "lemons discount" predicated on (Akerlof, 1970) that an analyst with insufficient information does not differentiate between good and bad firms. To test this, we investigate the types of firms that receive more favorable ratings. We find, for example, more favorable

[2]Default risk premium is the annualized premium needed to compensate for a firm's default risk (Source: National University of Singapore, CRI database. Available at: http://nuscri.org [Accessed March 8, 2021]).

[3]Additional tests on stock market reactions show that investors view downgrades as more credible after a local presence, but view upgrades more skeptically.

ratings for firms in the lowest tercile by profitability. We interpret this as evidence that a local presence enables analysts to better assess firms that would have been previously perceived as low credit quality based on historical accounting or financial metrics. This greater ratings differentiation indicates enhanced credit risk analyses.

We perform a battery of robustness tests to strengthen inferences from our findings. For example, we address limitations in our sample composition, where firm-years for some countries with a local presence are mostly in the period after a local presence is established. In particular, firm-years occurring after a local presence is established in Japan (United Kingdom) are 98.41% (99.23%) for S&P and 98.94% (99.75%) for Moody's. To mitigate concerns that our results could be driven by these extremely high occurrences of firm-years in the post period, we re-estimate our baseline rating analysis on a sample of more balanced firm-years. We restrict our analysis sample such that the percentage of firm-years after a local presence is between 10% - 90%. Our inferences remain unchanged.

Our findings contribute to the literature on geographic proximity, previously studied in other contexts. For example, the distance from a Securities and Exchange Commission division office affects a firm's disclosure quality (Kedia and Rajgopal, 2011), audit quality (Choi et al., 2012), and stock price crash risk (Kubick and Lockhart, 2016). Kubick et al. (2017) find that proximity to Internal Revenue Services office affects firm's tax aggressiveness and IRS examinations. Ayers et al. (2011) find that local monitoring institutional investors affect firms' disclosure behavior. Proximity also affects equity analysts' forecasting accuracy (Malloy, 2005) and coverage decisions (O'Brien and Tan, 2015). As credit ratings are important in global markets, it is worthwhile to extend this inquiry to ratings and in the global context.

In the credit ratings literature, Jaggi and Tang (2017) find that a firm's distance to rating agency New York headquarters leads to higher bond rating errors.[4] Our approach differs from Jaggi and Tang (2017) in that we focus on a sample of non-US firms. The rating agencies' global presence make other global cities important in the rating process and warrant

[4]While not the main part of the paper, Bonsall et al. (2017) also use proximity as a proxy for S&P's ease of performing qualitative analysis.

a closer look. Moreover, we uncover new insights on the use of qualitative information in credit ratings. We show that actual ratings move up and closer to the ratings predicted by quantitative models, suggesting that a local presence leads analysts to make less negative rating adjustments as they become more confident about their quantitative model outcomes.

We also contribute more directly to the long-standing claim about inadequate rating behavior outside of the U.S. and the global dominance of U.S. credit rating agencies. Evidence suggests that non-US firms generally receive lower ratings (Attig et al., 2020) and that agencies largely rely on country information rather than firms' idiosyncratic information (Ferri and Liu, 2003). Ferri (2004) attributes these differences to the agencies' underinvestments in information gathering. Our findings contribute by exploring the use of qualitative and quantitative information in ratings as agencies invest in information gathering by establishing a local presence. With policymakers around the world continuing to institute regulations in the credit rating agency market or seek to curtail the dominance of U.S. agencies, it is important to shed light on the ratings impact of rating agencies' organizational decisions. Moreover, the agencies should consider publishing reports documenting ratings performance by local presence akin to their annual transition and default reports.[5]

2 Background on credit rating agencies and ratings

Credit rating agencies are publishing and information companies that specialize in analyzing the credit risk of issuers (e.g., privately held and publicly traded corporations, non-profits, governments) and individual debt issues (e.g., corporate bonds, municipal bonds, bank loans) (S&P Global Ratings, 2019). Credit ratings reflect the opinions of the agencies on the credit risk of these issuers or issues.

In formulating these opinions, major rating agencies like Moody's and S&P use a combination of analysts and mathematical models (Moody's Investors Service, 2006; S&P Global

[5] e.g., https://www.spglobal.com/ratings/en/research/articles/210407-default-transition-and-recovery-2020-annual-global-corporate-default-and-rating-transition-study-11900573, as accessed May 22, 2021.

Ratings, 2019). Mathematical or quantitative models output a baseline rating based on quantitative data (i.e., model-based rating) that predicts the ability of an issuer to satisfy future liquidity needs. However, there is always uncertainty associated with expectations of future performance or cash flows based on historical or current quantitative data. Accordingly, analyst models use qualitative or soft information collected from publicly available disclosures as well as interviews and discussions with the issuer's management to make adjustments to the baseline rating to arrive at the actual rating. Thus, ratings do not reflect a defined set of financial ratios or rigid computer models alone, but reflect a comprehensive analysis of each individual issue and issuer using both quantitative and qualitative information.

The so-called big three agencies (S&P, Moody's, and Fitch) dominate the credit rating agency market. The European Securities and Markets Authority (ESMA) reports that the big three earned over 93% of the ratings-related revenues in the European Union in 2017 (ESMA, 2018): S&P earned about 46%, Moody's about 32%, and Fitch approximately 15%. These numbers are consistent in the U.S. and other regions. Although these agencies have long been rating non-U.S. issuers, they have not always had a physical presence outside of the United States.

Over the years, however, they have opened offices outside the U.S. in different countries at different times. Among other reasons, they open the offices to comply with residency requirements, for access to new issuers, or to enhance their credit insights. The agencies say opening local offices enhances the credit ratings process. For instance, when Moody's opened its South Africa office in 2003 or expanded into the Nordics, it expected that a local presence would enhance "insight into credit risk".[6]

The opening of these offices raises an important empirical research question of whether a local presence affects credit ratings. As credit rating analysts combine analyses of ratios and models with subjective qualitative information gathered from interacting with management and employees and from experiencing a firm's business environment (Ashbaugh-Skaife

[6]Moody's Press Releases: "Moody's Formally Opens Office in Johannesburg, South Africa," 19 November 2003; "Moody's expands its Nordic presence with opening of Stockholm office," 1 March 2016.

et al., 2006; Kraft, 2015a,b; S&P Global Ratings, 2019), there is strong reason to believe that credit ratings are affected by the existence of a local presence. A local presence can enable an in-depth and high-quality credit analysis. Ganguin and Bilardello (2005) highlight that proximity can ease direct contact between credit rating analysts and the issuers or increase the ability of the analysts to conduct issuer site visits. Bonsall et al. (2017) add that proximity enhances the ability of analysts to collect information and develop a more meaningful awareness and knowledge of local companies, business practices, and regulations in the local environment.

3 Research design and sample description

In this section, we discuss our sample selection and data sources, key variable measurement, and sample description.

3.1 Sample selection and data sources

We employ two samples of firms with a credit rating history from S&P and Moody's for the period covering fiscal years 1981 to 2018. The initial S&P sample consists of the full universe of foreign currency long-term issuer ratings from S&P CapitalIQ platform. We limit the sample to non-U.S. companies with a headquarters outside of the U.S. and are not government institutions, educational institutions, trade associations, foundations, or charitable institutions. The initial Moody's sample consists of ratings from Moody's Default and Recovery Database (DRD) as of May 7, 2019. For each firm, we keep the long-term issuer rating. If a long-term issuer rating does not exist, we use a long-term senior unsecured issue rating on the premise that a long-term unsecured issue rating is representative of a firm's long-term issuer rating. We limit the sample to non-U.S. companies headquartered outside of the U.S. and exclude entities identified as Sovereign, Sub-Sovereign, or Supranational.

For both S&P and Moody's, we use the start and end dates for each rating to transform the data into monthly observations and merge with financial information. Using equity ISIN (i.e., International Security Identification Number), the financial information for each fiscal year is matched to the credit rating that is active at the sixth month after the fiscal year end. This ensures that the issuer's annual reports have been published, and that the rating agencies have sufficient time to update their ratings based on the annual reports.

We obtain financial information from Thomson Reuters Worldscope (Worldscope). Except for selected key data items (e.g. total assets), the data items in Worldscope are typically in the the companies' financial statements original currency. To facilitate comparison across countries or currencies, we transform financial variables to ratios as needed. To reduce noise, we eliminate observations from countries with fewer than 25 total observations and observations from tax haven countries (Bermuda and the Cayman Islands).

Table 1 reports the sample selection. The final sample of rated non-U.S. firms in countries with or without a sovereign rating consists of 24,458 firm-years of S&P ratings (representing 2,556 unique firms) and 12,736 firm-years of Moody's ratings (representing 1,425 unique firms). These firm-years reflect the maximum number of observations with a credit rating and non-missing values for control variables, but the number of observations in the subsequent analyses varies based on empirical specifications. For example, we allow some specifications with multiple levels of fixed effects to drop singletons, which are groups with only one observation as a result of the multiple levels of fixed effects (Correia, 2015).

3.2 Identifying credit rating agency offices

We received the office location and opening dates via email from Moody's and S&P. To corroborate and/or supplement the locations and dates, we use each agency's annual reports, form 10-Ks, investor factbooks and presentations, press releases accompanying office openings, and transparency reports. These data sources are publicly available on web sites for S&P (http://investor.spglobal.com/) and Moody's (https://ir.moodys.com/). We also obtained press releases from Factiva and additional office information from Sinclair (2005).

To create a more complete data set, we use a combination of dates representing the earlier of: (i) the opening of a local office by the rating agency itself (whether a full office or a representative office), (ii) the acquisition of a majority stake in a local rating agency.

Table 2 presents Moody's and S&P office locations and the date the office locations opened. The first overseas offices were in the United Kingdom and Japan. S&P opened the United Kingdom office in 1984 and Moody's in 1986. Both opened offices in Japan in 1985. With some exceptions, Moody's and S&P generally open offices within a few years of each other in the same countries. These countries may be selected for their strategic locations within a region or for the size of the market of current and potential rated issuers.

3.3 Measuring corporate credit ratings

Our primary outcome variable of interest is the level of credit ratings (*Ratings*) at the individual firm level available from historical credit ratings data from Moody's and S&P. Credit ratings are assigned as letter ratings, which we capture as a numerical value for actual issuer ratings coded from 1 (SD/D) to 22 (Aaa), with higher values indicating higher credit quality.

3.4 Sample description

Table 3 shows the sample distribution by country, for the set of firms in the countries with and without a rating agency office.[7] Japan has the most number of firm-years with a rating from both S&P (11.82% of the sample of S&P ratings) and Moody's (15.58% of the sample of Moody's ratings). Consistent with Japan having one of the oldest offices, substantially all of the firm-years in Japan occur in the period after the rating agencies opened offices (98.41% of firm-years for S&P and 98.94% for Moody's). As would be expected, the other older office locations, Canada and the United Kingdom (UK) also have significant data coverage.

[7] In untabulated results, we also examine the sample distribution by year and find that the number of rated issuers increases over time.

Canada makes up 11.35% of S&P firm-years and 11.88% of Moody's, with 93.70% and 87.97% falling in the period after office openings for S&P and Moody's, respectively. Similarly, the UK makes up about 8.51% of S&P firm-years and 9.31% of Moody's, with nearly all firm-years falling in the period after office openings for S&P (99.23%) and Moody's (99.75%). Other significant data coverage come from France (6.93% - S&P, 5.81% - Moody's), Australia (5.06% - S&P, 4.63% - Moody's), and other countries with over 1% of the sample for S&P and Moody's. These include a number of Asian countries (e.g., Hong Kong, China, India, South Korea, and Indonesia) and other emerging markets (e.g., Brazil, Chile, Mexico, Russia).

On average, about 74.50% and 71.50% of S&P and Moody's firm-years, respectively, occur in the period after office opening. As previously noted, the older offices have the vast majority to nearly all firm-years after the office opening. Other countries have fewer, such as India with 83.59% of S&P firm-years and 75.85% of Moody's firm-years after office opening. While all of S&P firm-years (100%) in Sweden are after S&P opened an office there in 1988, only 9.42% of Moody's firm-years occur after Moody's opened an office there in 2016. Finally, several rated firms are in countries without an office yet. Overall, there is considerable variation across different countries to facilitate reasonably meaningful analyses of rating changes before and after office openings.

Table 4 presents summary statistics for the credit ratings and firm characteristics included in the primary analyses. As previously noted, the mean on *Local* indicate that 74.5% and 71.5% of firm-years occur after S&P and Moody's, respectively, open an office. The average firm rating for S&P is 14.111 and for Moody's is 14.865, with standard deviation of 3.743 and 3.772, respectively. The average firm rating is roughly equivalent to a BBB rating for S&P and Baa1 rating for Moody's.

With respect to the firm characteristics, the statistics reveal significant similarities between the characteristics of firms rated by S&P and Moody's. The rating agencies tend to assign ratings to many of the same firms, but they also have some non-overlapping firms. Respectively, the average firm size for S&P and Moody's is 23.181 and 23.631 in the natural log of total assets in billions of US dollars. The average return on sales ($EB/Sales$) is nearly identical (0.261 for S&P and 0.245 for Moody's), and cash-to-total asset ratio is 8.8% for both S&P and Moody's.

4 Empirical analyses and results

This section presents the methodology and results of our proposition that a local presence leads to higher ratings, along with associated additional tests for the mechanism and implications.

4.1 Baseline regressions

To test the proposition that a local presence leads to higher ratings, we estimate a regression of credit ratings on local offices, while controlling for firm characteristics and various fixed effects. We specify the following model:

$$\begin{aligned} Ratings_{i,t+\tau} = {} & \beta_0 + \beta_1 Local_{it} + \beta_2 Size_{it} + \beta_3 IntCov_{it} \\ & + \beta_4 EB/Sales_{it} + \beta_5 Lev_{it} + \beta_6 Debt/EB_{it} \\ & + \beta_7 NegDebt/EB_{it} + \beta_8 Cash_{it} + \beta_9 PPE_{it} \\ & + \beta_{10} CAPEX_{it} + \beta_{11} EA\_Vol_{it} + \beta_{12} ROA_{it} + \varepsilon_{it} \end{aligned} \tag{1}$$

The dependent variable (*Ratings*) is the level of credit ratings at the firm level. We run separate regressions for ratings from S&P and Moody's. The explanatory variable of interest is *Local*, which is an indicator variable equal to one if S&P or Moody's has an office in the issuers' country of domicile.[8] We expect a positive coefficient on *Local* (i.e., $\beta_1 > 0$) if local presence increases the level of credit ratings after a local presence.

Equation (1) is a staggered difference-in-differences design (see, Bertrand and Mullainathan, 2003; Armstrong et al., 2012; Gormley and Matsa, 2016). The specification allows for control

[8] We focus on office openings and not specific local analysts because it is less costly to identify office openings. We believe the local office is meaningful because it forms a basis for information collection. Even if local analysts do not participate in committees that determine final ratings, they share their views on the business environment and local entities.

variables and for firms from different countries that have office openings at different times. The staggered office openings means that our treatment group includes firms from countries that have an office opening and the control group includes firms from countries that never have an office opening and firms from countries that had in the past or will in the future have an office opening.

We include a vector of control variables found in prior literature (specifically, Baghai et al., 2014) to be determinants of credit ratings. The control variables include: $Size$ is the natural logarithm of total assets; $IntCov$ is earnings before interest, taxes, depreciation, and amortization divided by interest expense; $EB/Sales$ is earnings before interest, taxes, depreciation, and amortization divided by sales; Lev is the sum of long- and short-term debt divided by total assets; $Debt/EB$ is the sum of long- and short-term debt divided by earnings before interest, taxes, depreciation, and amortization, and is set equal to zero if the value is negative; $NegDebt/EB$ is an indicator variable equal to one if $Debt/EB < 0$, and zero otherwise; $Cash$ is cash and short-term investments divided by total assets; PPE is net property, plant, and equipment divided by total assets; $CAPEX$ is capital expenditures divided by total assets; EA_Vol is the volatility of earnings measured over the previous 5 years; and ROA is return on assets, measured as net income divided by total assets. We provide detailed variable descriptions and data sources in Appendix A.

We run different specifications with and without fixed effects. The firm (country) fixed effects control for unobserved, time-invariant differences across firms (countries). The standard errors are adjusted for clustering at the firm and year level to account for residual correlation across years for a given firm (time-series dependence) and across different firms in a given year (cross-sectional dependence) (Petersen, 2009).

Table 5 presents the results for S&P in columns (1) to (3) and Moody's in columns (4) to (6). The specification in column (1) and (4) includes country fixed effects, column (2) and (5) includes firm-fixed effects, and column (3) and (6) add a sovereign rating to the firm-fixed effects. The findings support the proposition that a local presence is positively associated with the level of credit ratings. The coefficients on *Local* are positive and significant across all the specifications and rating agencies, indicating that a local presence improves the level of credit ratings both within-country and within-firm.

Using the coefficient in column (1) for S&P with country fixed effects (coeff. =0.801, t-stat = 4.078), the results indicate that a local presence is associated with nearly a one notch increase in the issuer credit rating. Subsequent results (untabulated) show that the coefficient continues to be positive and statistically significant after controlling for sovereign credit rating (coeff. =0.481, t-stat = 2.603). An increase in credit ratings can have significant impact on the cost of borrowing (Kisgen and Strahan, 2010). In particular, even a one-half notch increase in the credit ratings can make a difference between an issuer being assigned investment grade rating (BBB-) or speculative grade rating (BB+), which can subject an issuer's bonds to exclusion from indices based only on investment grade ratings.

We document consistent magnitudes for Moody's ratings in columns (4) with country fixed effects (coeff. =0.933, t-stat = 3.395) and in columns (5) with firm fixed effects (coeff. =0.921, t-stat = 4.112). The coefficient in column (5) reflects within-firm changes, indicating economically significant changes in the ratings.

Overall, the results indicate that a local presence is associated with higher credit ratings across firms in a given country and within firms. The results are also robust to controlling for a sovereign rating, which captures country-level factors that are reflected in the sovereign rating and can also impact a firm-level rating.

A potential explanation for our findings of higher ratings is that credit ratings can improve because analysts become less conservative with a local presence; Ferri et al. (1999) suggest that rating agencies tend to be conservative and assign lower credit ratings when they are in doubt, something that can happen if the rating agencies are not close to the firms they rate. Higher ratings can also be explained by the ease with which a local presence allows companies to influence their ratings. In latter sections, we explore the potential mechanism, through which ratings change. We also explore whether rating changes reflect catering behavior as rating agencies cater to issuer demands for more favorable ratings.

4.2 Rating differences

The decision to open a local office is not random and raises endogeneity concerns. A local office can be strategically located to facilitate access to countries within a given region rather than to capitalize on expected growth in a given country. For example, an office in South Africa may have nothing to do with expected growth in South Africa but is opened to take advantage of the infrastructure in South Africa to reach other countries in Africa. Similarly, an office in Dubai provides a hub for a rating agency to easily reach countries in the Middle east, Asia, or Africa. Yet, endogeneity may arise if an office is opened because a country's economic conditions are improving and it is that improvement in economic conditions that also warrants higher credit ratings rather than the benefit of a local presence.

To mitigate these concerns, we not only control for a country's economic environment through the inclusion of sovereign credit ratings,[9] but we also perform tests on the differences in ratings for a given firm rated by both agencies, with only one agency having a local presence. In the event that only one rating agency has a local presence and that agency has the benefit of a local presence, we would expect changes in the rating differences between the agencies (i.e., $|R^1_{i,t+1} - R^2_{i,t+1}| > 0$). To determine whether differences exist, we re-estimate our baseline regression with rating disagreement as the dependent variable:

$$
\begin{aligned}
RatingsDiff_{i,t+\tau} = {} & \beta_0 + \beta_1 Local_{it} + \beta_2 Size_{it} + \beta_3 IntCov_{it} \\
& + \beta_4 EB/Sales_{it} + \beta_5 Lev_{it} + \beta_6 Debt/EB_{it} \\
& + \beta_7 NegDebt/EB_{it} + \beta_8 Cash_{it} + \beta_9 PPE_{it} \\
& + \beta_{10} CAPEX_{it} + \beta_{11} EA\_Vol_{it} + \beta_{12} ROA_{it} + \varepsilon_{it} \qquad (2)
\end{aligned}
$$

where $RatingsDiff$ is the absolute value of the difference between the values for $Ratings$ assigned by S&P (R^1) and Moody's (R^2) for a given firm at a given time (i.e., $|R^1_{i,t+1} - R^2_{i,t+1}|$).

[9]The sovereign credit ratings captures a country's economic conditions and other institutional factors relevant to a firm's credit risk.

All other variables are as described in equation (1) above.

Table 6 reports the findings and shows positive and significant coefficients on local presence. These findings show that a local presence is positively associated with differences in ratings between Moody's and S&P. The results in column (1) and (2) include country fixed effects without controlling for sovereign rating (coeff. = 0.314, t-stat = 3.016) and with control for sovereign rating (coeff. = 0.320, t-stat = 3.037). We document similar results in column (3) and (4) including firm fixed effects.[10]

Overall, we find evidence that a local presence by one agency increases the differences in ratings (split ratings) between the rating agencies for a given firm. This supports our baseline results that a local presence impacts credit ratings. This analysis on the differences in ratings between rating agencies strengthens our identification as we examine differences in the ratings of the same firm that is rated by Moody's and S&P before and after one of the rating agencies opens an office in the firm's country of domicile.

We note, however, that our data have some limitations: Moody's and S&P generally open offices in the same places within a year or two of each other, leaving very limited time window when there is only one rating agency with a local office in a country. Nonetheless, our findings provide some assurance that endogeneity concerns do not necessarily explain our primary inferences.

4.3 Mechanism: Subjective and qualitative rating adjustments

To investigate the mechanism through which a local presence affects credit ratings, we explore the adjustments in the ratings. Credit ratings not only reflect quantitative information, but also reflect qualitative factors (Ashbaugh-Skaife et al., 2006; Kraft, 2015a,b). Analysts begin with a baseline quantitative-based rating and then make adjustments to the baseline credit rating to arrive at the actual rating that incorporates qualitative factors.

Existing evidence suggests that a local presence increases the use of qualitative factors

[10] We also find that the ratings are more favorable for the rating agency that has a local presence (i.e., $R^1_{i,t+1} > R^2_{i,t+1}$). These results are not tabulated.

(Malloy, 2005; O'Brien and Tan, 2015; Jaggi and Tang, 2017). It increases analysts' ability to collect information and develop a more meaningful awareness and knowledge of local companies, business practices, and local regulatory environment (Ganguin and Bilardello, 2005; Bonsall et al., 2017). Thus, the portion of credit ratings attributed to adjustments can increase as analysts incorporate more local knowledge after a rating agency establishes a local presence.

There is also another possibility of how rating adjustments are used in ratings. Specifically, analysts may deviate from the model-based ratings for other reasons not related to acquisition of qualitative factors. It is possible that, prior to a local presence, analysts lack confidence in their credit analyses tend to be stringent and assign lower credit ratings (Ferri et al., 1999), and this may be driven by subjective deviations from the model-based rating. If rating adjustments are more likely to be negative without a local presence because of limited understanding of local economies, then we expect less negative adjustments as analysts assign ratings closer to or above the model-based ratings.

To test these possibilities, we examine whether and how establishing a local presence affects the portion of credit ratings attributed to rating adjustments. We employ a two-step process. In step 1, we compute the component of credit ratings attributed to rating adjustments ($RatingsAdjust$) as the difference between $Ratings$ (i.e., actual rating) and predicted rating (i.e., model-based rating). That is, $RatingsAdjust$ = $Ratings$ - $RatingsPredict$. We describe the prediction model and associated results in Appendix B. In step 2, we re-estimate equation (1) with rating adjustments ($RatingsAdjust$) as the dependent variable. We present the results from step 2 in Table 7.[11]

Our findings uncover interesting insights. If the prevailing evidence, that geographic proximity increases the use of soft information into decision making (e.g., Malloy, 2005; O'Brien and Tan, 2015; Jaggi and Tang, 2017), holds in our setting we would expect a local

[11]We exclude the control variables when estimating the regression for $RatingsAdjust$ because the same control variables are used to derive $RatingsAdjust$. However, the results are consistent with all the control variables included.

presence to increase the rating adjustments (i.e., soft information). However, we document that the value of total rating adjustments decreases after a local presence. Specifically, in the S&P sample, our findings show a negative and significant coefficients in column (1) with industry fixed effects (coeff. = -0.232, t-stat = -2.615) and column (2) with firm fixed effects (coeff. = -0.334, t-stat = -3.825). The dependent variable for these results is the absolute value of the difference between actual rating and predicted ratings (i.e., unsigned rating adjustment). We also document negative, but insignificant coefficients for the Moody's sample in column (5) and (6) for the same dependent variable. These findings show that the portion of ratings attributed to soft information decreases with a local presence, a departure from inferences drawn in existing evidence (Ganguin and Bilardello, 2005; Bonsall et al., 2017; Jaggi and Tang, 2017).

More interestingly, we find asymmetric effects on negative and positive adjustments. The results in column (3) and (4) for the S&P sample and (7) and (8) for the Moody's sample show positive and significant coefficients when the dependent variable is the signed rating adjustments. We find that there are more positive adjustments, indicating that the average actual credit ratings become higher than the average predicted ratings. Therefore, these findings suggests that the decrease in the total rating adjustments above is driven by a decrease in the use of negative adjustments. That is, following a local presence, rating adjustments are less likely to be negative relative to the period before a local presence.

5 Implications: ratings quality or catering?

Our evidence thus far establishes that a local presence has a discernible and significant impact on credit ratings. In this section, we provide evidence on the implications of a local presence on the quality of ratings. Specifically, we examine whether the changes in credit ratings after a local presence reflect an increase in the informative of the ratings or catering.

Existing evidence suggest that rating agencies cater to issuer demands for more favorable ratings (Kedia et al., 2014; Kraft, 2015a). Accordingly, upon establishing a local presence a rating agency may assign higher ratings as a means to build relationships and increase its market share. On the other hand, rating agencies open local offices on the premise that a local presence can facilitate higher quality ratings by enhancing insight into credit risk. We perform three tests to provide evidence on the quality of ratings.

5.1 Informativeness of credit ratings for future default risk

First, if a local presence improves the quality of credit ratings, the credit ratings should become more informative of issuer default risk. To test this, we follow prior studies (e.g., Duffie et al., 2007; Kedia et al., 2014) and examine whether ratings become more or less informative about issuer default risk by regressing proxies for default risk on the interaction between a local presence and credit ratings. We specify the following regression:

$$\begin{aligned} DefaultRisk_{i,t+\tau} = {} & \beta_0 + \beta_1 Local_{it} + \beta_2 Ratings_{it} + \beta_3 Local * Ratings_{it} \\ & + \beta_4 Size_{it} + \beta_5 IntCov_{it} + \beta_6 EB/Sales_{it} + \beta_7 Lev_{it} \\ & + \beta_8 Debt/EB_{it} + \beta_9 NegDebt/EB_{it} + \beta_{10} Cash_{it} + \beta_{11} PPE_{it} \\ & + \beta_{12} CAPEX_{it} + \beta_{13} EA\_Vol_{it} + \beta_{14} ROA_{it} + \varepsilon_{it} \end{aligned} \tag{3}$$

We capture the dependent variable ($DefaultRisk$) using two proxies, Actuarial Spread (AS) and Probability of Default (PD) obtained from National University of Singapore, CRI database (Available at: http://nuscri.org [Accessed March 8, 2021]). AS is built on the design of conventional Credit Default Swaps (CDS) without involving an upfront fee and reflects the credit risk of corporate obligors. CDS spreads have been widely used as a credit risk indicator, with higher spreads associated with higher credit risk. PD measures the likelihood of an obligor being unable to honor its financial obligations, with higher values indicating a greater likelihood of default. The CRI PD estimates the default risk of publicly listed firms by quantitatively analyzing their financial statements, stock market data and macro-financial factors retrieved from various international data sources and is a more granular gauge for credit risk.[12] The coefficients of interests are on the interaction between a local presence and credit ratings ($Local * Ratings$), indicating the informativeness of ratings on future default risk after a local presence. All other variables are as described in equation (1) above.

Table 8 presents the results. Columns (1) to (3) show the results for the dependent variables Actuarial Spread (AS) and columns (4) to (6) for Probability of Default (PD) for years t+2, t+3, and t+5. All the specifications include firm-fixed effects and are based on Moody's credit ratings. We document negative coefficients across all the columns for AS and PD, with stronger results for PD years t+2 (coeff. = -0.001, t-stat = -1.719) and t+3 (coeff. = -0.001, t-stat = -1.796). Other coefficients indicate, for example, that higher credit ratings are associated with lower default risk as expected. The coefficients on *Ratings* are negative and significant across all specifications.

Overall, our findings show that ratings assigned after establishing a local presence are accompanied by lower default risk premium and lower likelihood of defaults. We interpret these findings as providing some evidence that a local presence enhances credit risk analysis and lead to ratings that do not merely reflect catering behavior but that are informative of default risk, at least in the sample of Moody's ratings and within-firm.[13]

Alternatively, we could examine changes in the rate at which credit ratings predict actual defaults by looking at Type I errors (i.e., a firm that is rated high quality ends up in defaults; missed default) and type II errors (i.e., a default predicted to occur does not occur; false default prediction). However, data on defaults outside of the United States are limited.

5.2 Stock market reactions

Second, we explore how a local presence impacts the stock market relevance of credit rating changes. To test this, we examine the abnormal stock returns in the stock market around credit rating changes before and after a local presence. We estimate the following model:

[12] This is similar to expected default frequencies (EDF) (Duffie et al., 2007; Kedia et al., 2014; Bonsall et al., 2016). We use PD as it is similar and is readily available.

[13] The results for S&P ratings are inconclusive.

$$
\begin{aligned}
AbnRet_{i,t+\tau} = {} & \beta_0 + \beta_1 Local_{i,t} + \beta_2 \mathit{\Delta Rating}_{it} \\
& + \beta_3 Price/Book_{it} + \beta_4 Size_{it} + \beta_5 IntCov_{it} \\
& + \beta_6 EB/Sales_{it} + \beta_7 Lev_{it} + \beta_8 Debt/EB_{it} \\
& + \beta_9 NegDebt/EB_{it} + \beta_{10} Cash_{it} + \beta_{11} PPE_{it} + \beta_{12} CAPEX_{it} \\
& + \beta_{13} EA\_Vol_{it} + \beta_{14} ROA_{it} + f_i + \omega_{lt} + \lambda_{jt} + \varepsilon_{it} \qquad (4)
\end{aligned}
$$

The dependent variable is the three-day abnormal stock return (*AbnRet*) around credit rating changes. We perform the analyses separately for market reaction to negative rating changes and positive rating changes. As defined above, *Local* is an indicator variable equal to one if S&P/Moody's has a local office, and zero otherwise. Because the reaction to a rating change is likely a function of the magnitude of the rating change, we include in the set of control variable a measure of the magnitude of the rating change (*ΔRating*). All other control variables are as described above for equation (1).

We present the results in Table 9 for negative rating changes (i.e., downgrades) and positive rating changes (i.e., upgrades). This follows prior evidence that investors respond differently to negative and positive news (Lopez and Rees, 2002). The results for rating downgrades are in column (1) with country fixed effects and column (2) with firm fixed effects. The coefficient in column (1) for the analysis within country is negative and significant (coeff. = -0.020, t-stat = -2.341), but the coefficient in column (2) is not statistically significant (coeff. = 0.006, t-stat = 0.387). These findings suggests that for firms within a given country, investors view rating downgrades as more credible when the rating agency has a local presence in a country. However, these current results show no changes in market reaction within firm.

The results for rating upgrades are in column (3) with country fixed effects and column (4) with firm fixed effects. In column (3) and (4), we also document negative and significant coefficient within-country (coeff. = -0.015, t-stat = -2.895) and within-firm (coeff. = -0.030, t-stat = -2.481). These findings indicate a decrease in the market reaction to rating upgrades both within-country and within-firm, and are consistent with prior evidence (e.g., Holthausen and Leftwich, 1986) that rating upgrades typically provide less information to capital markets.

5.3 Differentiation between types of firms

Third, we examine the differentiation in credit ratings between different types of firms. Our expectation is that credit ratings are more informative and relevant if they are better able to differentiate firms as well as incorporate all available information. Akerlof (1970) postulates that an evaluator with insufficient information does not differentiate between good and bad firms. In our setting, rating analysts that lack deep insights into individual firm's credit risk are likely to assign ratings to these firms based on observable group characteristics. For example, analysts could rely on the profitability of a firm and all firms with similar profitability could be evaluated the same, with poor performing firms by profitability metrics being assigned lower ratings. Conversely, as rating agencies establish a local presence and enhance credit risk analysis, analysts are likely to assign higher ratings to the firms that were previously discounted. To test for this possibility, we group firms into terciles by operating performance and stock market performance. If analysts routinely judge firms by given metrics, then potentially high quality firms in the bottom terciles of these performance metrics would exhibit increases in the credit ratings.

We present our findings in Table 10. In Panel A, we group firms into terciles by operating performance, as measured by EBITDA divided by sales ($EB/Sales$). If profit margin is the only thing that matters, then all firms with low profitability will be evaluated similarly. Generally, these firms would receive a lower credit rating. Converserly, in the event that a local presence does enhance credit risk analysis, firms with low profitability are more likely to exhibit greater increases in the credit rating as analysts incorporate other information and are better able to separate out quality firms. Results in Panel A provide some support for this proposition. We document positive coefficients on the interaction between a local presence and the bottom tercile and negative coefficients on the interaction between a local presence and the top tercile, relative to the middle tercile. The positive coefficients are statistically significant for the S&P ratings in columns (1) to (3). We interpret these findings as evidence that, relative to other tercile firms, firms in the bottom tercile of operating profitability are associated with higher ratings after an agency establishes a local presence.

We draw similar conclusions in Panel B when we group firms by stock market performance as captured by the price-to-book ratio (P/B). Our findings are consistent with those for operating and debt performance. We find that low performance on an observable firm characteristic exhibits higher ratings after a local presence which enhances credit risk analyses. The coefficient on the interaction between a local presence and the bottom tercile for price-to-book ratio is positive and statistically significant for S&P ratings and positive for Moody's ratings, indicating that ratings increase for these set of firms.

Overall, our evidence suggests that analysts may have previously penalized high quality firms based on where they ranked on some backward looking quantitative metrics. This lends some support to a situation akin to the market for lemons as a potential explanation for the overall increase in ratings. That is, a local presence enables rating agencies to distinguish between high and low quality firms, thereby raising the ratings of high quality firms that were previously discounted. We caution, however, that there are potentially several ways to measure operating or market performance and results may be sensitive to these measures. We perform analyses with additional proxies for operating performance, such as return on assets, ebitda growth, or asset growth. Our results with these proxies are similar with respect to the sign of the coefficients. However, not all the same coefficients are statistically significant. Moreover, as shown in Table 10, the results for Moody's are not statistically significant. This potentially speaks to some differences in the ratings approach between S&P and Moody's.

6 Robustness tests

6.1 Balanced sample

Our sample description shows that substantially all firm-years for a number of countries with a local presence are in the period after a local presence is established. For example, as shown earlier, firm-years occurring after a local presence is established in Japan are 98.41% for S&P and 98.94% for Moody's. Similarly, the UK has nearly all firm-years falling in the period after office openings for S&P (99.23%) and Moody's (99.75%). To mitigate concerns that our results could be driven by these extremely high occurrences of firm-years in the post period, we re-estimate our baseline rating analysis on a sample of more balanced countries. Specifically, for the countries with a local presence, we limit the analysis to those countries, in which the percentage of firm-years after an office opening is between 10% - 90%.

Using the more balanced sample, we re-estimate equation (1) with issuer ratings (*Ratings*) as the dependent variable. Table 11 presents the results. We document consistent results, finding that credit ratings increases after a rating agency establishes a local presence. Coefficients on *Local* are positive and significant across all the specifications and rating agencies.

6.2 Additional sample screening

Our primary analyses are based on a sample that excludes firms headquartered in countries that are traditionally considered tax havens (Bahamas, Cayman Islands, Bermuda). In general, most companies with a headquarters in these countries are not necessarily assessed for credit risk based on these countries' sovereign risk; these are companies that are often operating from different locations. The primary sample also eliminates firms from a country with fewer than 25 total observations over our sample period. For robustness, we relax these sample restrictions and our inferences from our baseline results do not change.

7 Conclusion

Credit rating agencies are important information intermediaries and gatekeepers in the financial system (Partnoy, 2002; Bonsall et al., 2017; Roychowdhurry and Srinivasan, 2019). Their credit ratings affect access and cost of borrowing for various entities around the world (Ferri et al., 1999; Kisgen, 2006; Kim and Wu, 2008; Kisgen and Strahan, 2010; Cornaggia et al., 2018). Yet the dominant rating agencies are continually under scrutiny for failing to fairly represent various economic and business environments around the world. While the rating agencies defend the rigor and universality of their rating processes, the rating agencies have expanded their global presence by establishing local offices in various parts of the world. These offices are intended to enhance the credit ratings process by enabling in-depth and high-quality credit risk analysis.

In this paper, we shed light on the credit rating process by investigating whether and how the rating agencies establishment of a local presence in countries outside of the U.S. influences credit ratings. Our empirical findings support the proposition that a local presence has positive and significant association with the level of credit ratings. A local presence is associated with greater rating splits between Moody's and S&P ratings, and the ratings tend to be more favorable for the rating agency with a local presence. Our subsequent analyses attribute the change in ratings to qualitative rating adjustments. We find that rating analysts are less likely to make negative adjustments, thereby reducing the discounting of their model predicted ratings. They are also more likely to make positive qualitative adjustments.

An important question is whether the observed rating changes are indicative of better quality or catering. We document some evidence that credit ratings after a local presence are associated with lower default risk premium and lower likelihood of default. We also show that the increase is more pronounced for in firm that were likely to experience downward bias in ratings prior to a local presence, potentially because analysts are better able to distinguish between high and low credit quality firms after a local presence. Overall, we interpret our findings as providing some reasonable evidence that a local presence has a causal relation with and leads to higher credit ratings.

Notwithstanding certain data limitations, our research findings are timely. Several regulatory bodies around the world are continually debating and solving for perceived impediments from credit ratings. Our research findings inform these debate on the regulation of the credit rating agency markets around the world and contribute more directly to the specific ongoing debate about the dominance of the U.S.-based rating agencies in the global markets.

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Appendix A - Variable definitions

Variable	Definition and measurement
Local	An indicator variable equal to one if S&P (or Moody's) has an office location in the respective fiscal year and zero otherwise (Press releases; S&P Global Ratings, Inc.; Moody's Investor Services).
Rating	A numerical value for a firm's credit ratings, coded from 1 (SD/D) to 22 (AAA), for S&P and Moody's as indicated (CapitalIQ; Moody's web site/Default and Recovery Database).
$RatingsDiff$	The absolute value of the difference between *Ratings* for S&P and Moody's credit ratings.
$RatingsPredict$	The predicted rating estimated following Baghai et al. (2014) using the following regression model:

$$\begin{aligned} Ratings_{i,t+\tau} = {} & \beta_0 + \beta_1 Size_{it} + \beta_2 IntCov_{it} + \beta_3 EB/Sales_{it} \\ & + \beta_4 Lev_{it} + \beta_5 Debt/EB_{it} + \beta_6 NegDebt/EB_{it} \\ & + \beta_7 Cash_{it} + \beta_8 PPE_{it} + \beta_9 CAPEX_{it} \\ & + \beta_{10} EA\_Vol_{it} + \beta_{11} ROA_{it} + f_i + \omega_{lt} + \lambda_{jt} + \varepsilon_{it} \end{aligned} \tag{5}$$

$RatingsAdjust$	The difference between *Ratings* (i.e., actual rating) and $RatingsPredict$ (i.e., predicted rating).

Control variables	(Data from Worldscope, unless stated otherwise)
Size	Firm size measured as the natural logarithm of total assets in US dollars [ITEM7230].
$IntCov$	Earnings before interest, taxes, depreciation, and amortization (EBITDA) [ITEM1401 + ITEM1251 + ITEM1151 - ITEM1255] divided by interest expense on debt [ITEM1251].
$EB/Sales$	Earnings before interest, taxes, depreciation, and amortization (EBITDA) [ITEM1401 + ITEM1251 + ITEM1151 - ITEM1255] divided by net sales or revenues [ITEM1001].
Lev	Leverage measured as the sum of long-term debt [ITEM3255] and short-term debt [ITEM3051] divided by total assets [ITEM2999].
$Debt/EB$	The sum of long-term debt [ITEM3255] and short-term debt [ITEM3051] divided by Earnings before interest, taxes, depreciation, and amortization (EBITDA) [ITEM1401 + ITEM1251 + ITEM1151 - ITEM1255]
$NegDebt/EB$	An indicator variable equal to one if the ratio $Debt/EB < 0$, and zero otherwise.
Cash	Cash and cash equivalents [ITEM2005] divided by total assets [ITEM2999].

Appendix A (continued from previous page)

Variable	Definition and measurement
PPE	Net property, plant, and equipment [ITEM2501] divided by total assets [ITEM2999].
$CAPEX$	Capital expenditures for additions to fixed assets [ITEM4601] divided by total assets [ITEM2999].
EA_Vol	The standard deviation of EBITDA over the prior five fiscal years; a minimum of two years required.
ROA	Earnings before interest, taxes, depreciation, and amortization (EBITDA) [ITEM1401 + ITEM1251 + ITEM1151 - ITEM1255] divided by total assets [ITEM2999].
$SovRatg$	The sovereign credit rating from Moody's and S&P, respectively (CapitalIQ for S&P ratings; Moody's web site/Default and Recovery Database for Moody's).
$SovRatgDiff$	The difference between S&P and Moody's $SovRatg$.
Other variables	(for relevance and informativeness of ratings)
AS	The Actuarial Spread (AS) is the annualized premium that is needed to compensate the counterparty for the default risk, on an actuarial basis, of the reference company. (National University of Singapore, CRI database. Available at: http://nuscri.org [Accessed March 8, 2021]).
PD	The Probability of Default (PD) measures the likelihood of an obligor being unable to honor its financial obligations. (National University of Singapore, CRI database. Available at: http://nuscri.org [Accessed March 8, 2021]).
$AbnRet_{i,t+\tau}$	The two-day cumulative abnormal stock return following the announcement of a rating downgrade and upgrade. Daily abnormal returns are the daily returns of the issuer minus the market returns on that day. The market returns are calculated as the average daily returns of all firms in the sample that are in the same country as the issuer, excluding the issuer (Datastream).
P/B	Stock market performance measured as the ratio of market valuation to book-value of assets (Datastream and Worldscope).

Appendix B - Ratings Prediction Model

We estimate the predicted rating ($RatingsPredict$) in line with Baghai et al. (2014) using the following regression model:

$$
\begin{aligned}
Ratings_{i,t+\tau} = {} & \beta_0 + \beta_1 Size_{it} + \beta_2 IntCov_{it} + \beta_3 EB/Sales_{it} \\
& + \beta_4 Lev_{it} + \beta_5 Debt/EB_{it} + \beta_6 NegDebt/EB_{it} \\
& + \beta_7 Cash_{it} + \beta_8 PPE_{it} + \beta_9 CAPEX_{it} \\
& + \beta_{10} EA\_Vol_{it} + \beta_{11} ROA_{it} + f_i + \omega_{lt} + \lambda_{jt} + \varepsilon_{it}
\end{aligned} \tag{5}
$$

The dependent variable is the actual rating ($Ratings$) (i.e., a numerical value for actual issuer ratings, and is coded from 1 (SD/D) to 22 (Aaa)). We include a set of control variables found in prior literature to be key determinants of credit ratings. These controls variables, as described under equation (1), are: $Size$ is the natural logarithm of total assets; $IntCov$ is earnings before interest, taxes, depreciation, and amortization divided by interest expense; $EB/Sales$ is earnings before interest, taxes, depreciation, and amortization divided by sales; Lev is the sum of long- and short-term debt divided by total assets; $Debt/EB$ is the sum of long- and short-term debt divided by earnings before interest, taxes, depreciation, and amortization, and is set equal to zero if the value is negative; $NegDebt/EB$ is an indicator variable equal to one if $Debt/EB < 0$, and zero otherwise; $Cash$ is cash and short-term investments divided by total assets; PPE is net property, plant, and equipment divided by total assets; $CAPEX$ is capital expenditures divided by total assets; EA_Vol is the volatility of earnings measured over the previous 5 years; and ROA is return on assets, measured as net income divided by total assets. We provide detailed variable descriptions and data sources in Appendix A.

We also include country (ω_{it}) fixed effects to control for unobserved, time-invariant differences across countries. The standard errors are adjusted for clustering at the firm and year level to account for residual correlation across years for a given firm (time-series dependence) and across different firms in a given year (cross-sectional dependence) (Petersen, 2009).

The table below presents the results of the estimation. *RatingsAdjust* is computed as actual rating minus the predicted rating from this estimation.

Table B1: Ratings Prediction Model Results

This table reports prediction model for credit ratings to general predicted ratings, as specified in equation (5). The dependent variable is *Ratings*, which is a numerical value for issuer ratings, coded from 1 (SD/D) to 22 (AAA). *Local* is an indicator variable equal to one if S&P/Moody's has a local office, and zero otherwise. Standard errors are clustered by firm and year. Control variables included are described in Appendix A. ***, **, and * denotes two-tailed statistical significance for 1%, 5%, and 10% respectively.

	S&P (1)	Moody's (2)
Size	0.982***	1.051***
	(27.392)	(20.284)
IntCov	0.007***	0.009***
	(8.959)	(7.335)
EB/Sales	1.429***	1.362***
	(6.467)	(3.459)
Lev	−2.037***	−2.497***
	(−6.145)	(−5.274)
Debt/EB	0.006	0.003
	(1.605)	(0.735)
NegDebt/EB	−0.052	−0.367
	(−0.305)	(−1.174)
Cash	−0.087	−0.890
	(−0.172)	(−1.243)
PPE	0.824***	1.011**
	(2.797)	(2.265)
Capex	0.187	−1.861
	(0.209)	(−1.076)
EA_Vol	−1.741***	−2.202***
	(−7.184)	(−6.074)
ROA	11.360***	10.412***
	(13.121)	(7.220)
SovRatg	0.366***	0.357***
	(15.185)	(15.031)
Country FE	Y	Y
Industry FE	N	N
Firm FE	N	N
Year FE	N	N
Observations	24,392	12,732
Adjusted R^2	0.677	0.694

Table 1: Sample Selection

This table reports the sample selection criteria. The sample represents the period covering 1981 to 2018.

	S&P		Moody's	
	Firm-Year Observations	Unique Firms	Firm-Year Observations	Unique Firms
Initial Sample	77,628	8,053	31,085	3,484
Less observations that don't match to Worldscope	52,114	5,362	16,925	1,839
Less observations from countries with little coverage or tax havens	622	108	1,234	209
Less observations with missing financial data	434	27	190	11
Subsample before sovereign rating	24,458	2,556	12,736	1,425
Less observations without a sovereign rating	66	6	4	0
Final Sample with Country Ratings	24,392	2,550	12,732	1,425

Table 2: Dates of Office Locations

Table 2 reports the local offices for Moody's and S&P by country and year the office was opened. The year of an office opening represents the earlier of: 1. the opening of a local office by the rating agency itself (whether a full office or a representative office); 2. the acquisition of a majority stake in a local rating agency. Minority acqusitions or other affiliations, as well as offices that were opened for a period of less than two years, are not included. The dates were obtained and cross referenced from multiple sources, including (i) data supplied by the rating agency itself. S&P supplied the office opening dates, and Moody's supplied the incorporation dates of the local entities (which sometimes differ from the office opening dates); (ii) annual reports and Form 10-Ks; (iii) investor factbooks and presentations from http://investor.spglobal.com/Investor-Presentations and https://ir.moodys.com/news-and-financials/events-and-presentations/default.aspx; (iv) transparency reports, as required by regulatory authorities in the European Union as found on the agency web sites; (v) agency press releases, and (vi) Sinclair (2005), which includes data for the older offices.

Country	S&P Offices	Moody's Offices
United Kingdom	1984	1986
Japan	1985	1985
Australia	1990	1988
France	1990	1988
Sweden	1988	2016
Germany	1992	1991
Spain	1992	1993
Canada	1993	1994
Mexico	1993	2000
Hong Kong	1995	1994
Cyprus	-	1995
Singapore	1996	1995
Argentina	1997	2002
Brazil	1998	1997
Russia	1998	2004
Italy	1999	1999
South Korea	2000	2002
China	2004	2002
Taiwan	2006	2002
South Africa	2008	2003
India	2005	2005
Czech Republic	-	2006
Israel	2008	2007
United Arab Emirates	2008	2007
Turkey	2011	-
Poland	2014	2013
Colombia	2014	-
Panama	-	2015
Peru	-	2015
Chile	2016	-
Saudi Arabia	2017	2018
Ireland	2018	-

Table 3: Sample Distribution by Country

Table 3 presents the sample distribution by country for the issuers rated by Standard and Poor's Global Ratings, Inc. (S&P) and Moody's Investor Services (Moody's). The sample is limited to the final sample, after removing observations from countries with less than 25 firm-year observations, observations from Bermuda and the Cayman Islands, and observations with missing financial data that is necessary for the creation of the control variables.

	S&P			Moody's		
Country	Total N	% of Sample	Observations after office opening	Total N	% of Sample	Observations after office opening
Japan	2,892	11.82%	98.41%	1,984	15.58%	98.94%
Canada	2,776	11.35%	93.70%	1,513	11.88%	87.97%
United Kingdom	2,082	8.51%	99.23%	1,186	9.31%	99.75%
France	1,694	6.93%	95.57%	740	5.81%	94.46%
Australia	1,237	5.06%	98.71%	590	4.63%	99.49%
Germany	990	4.05%	98.59%	585	4.59%	97.95%
Brazil	874	3.57%	98.97%	274	2.15%	94.16%
Hong Kong	842	3.44%	98.10%	311	2.44%	98.07%
China	690	2.82%	96.81%	203	1.59%	93.10%
Russia	640	2.62%	99.06%	225	1.77%	92.44%
Italy	605	2.47%	89.42%	360	2.83%	84.72%
Netherlands	564	2.31%	0.00%	346	2.72%	0.00%
Sweden	559	2.29%	100.00%	329	2.58%	9.42%
Switzerland	542	2.22%	0.00%	164	1.29%	0.00%
Mexico	495	2.02%	99.80%	295	2.32%	81.36%
Spain	489	2.00%	99.39%	191	1.50%	100.00%
Chile	437	1.79%	11.44%	197	1.55%	0.00%
South Korea	437	1.79%	84.44%	469	3.68%	76.33%
Indonesia	402	1.64%	0.00%	94	0.74%	0.00%
India	384	1.57%	83.59%	236	1.85%	75.85%
Taiwan	336	1.37%	69.05%	0	0.00%	-
Thailand	290	1.19%	0.00%	111	0.87%	0.00%
Ireland	278	1.14%	0.00%	88	0.69%	0.00%
Singapore	250	1.02%	99.60%	145	1.14%	100.00%
New Zealand	245	1.00%	0.00%	63	0.49%	0.00%
Argentina	228	0.93%	94.30%	198	1.55%	61.62%
Belgium	197	0.81%	0.00%	40	0.31%	0.00%
Malaysia	192	0.79%	0.00%	126	0.99%	0.00%
Finland	187	0.76%	0.00%	188	1.48%	0.00%
Greece	186	0.76%	0.00%	0	0.00%	-
Luxembourg	184	0.75%	0.00%	120	0.94%	0.00%
Turkey	172	0.70%	51.16%	103	0.81%	0.00%
Portugal	162	0.66%	0.00%	77	0.60%	0.00%
Norway	144	0.59%	0.00%	240	1.88%	0.00%
Saudi Arabia	142	0.58%	7.75%	39	0.31%	0.00%
Kazakhstan	136	0.56%	0.00%	55	0.43%	0.00%
Austria	131	0.54%	0.00%	161	1.26%	0.00%
United Arab Emirates	120	0.49%	77.50%	168	1.32%	90.48%
Denmark	115	0.47%	0.00%	128	1.01%	0.00%
Philippines	111	0.45%	0.00%	73	0.57%	0.00%
Poland	108	0.44%	28.70%	53	0.42%	30.19%
Peru	105	0.43%	0.00%	53	0.42%	47.17%
South Africa	101	0.41%	80.20%	50	0.39%	98.00%

Table 3, Sample Distribution by Country (continued)

	S&P			Moody's		
Country	Total N	% of Sample	Observations after office opening	Total N	% of Sample	Observations after office opening
Colombia	79	0.32%	45.57%	62	0.49%	0.00%
Czech Republic	78	0.32%	0.00%	0	0.00%	-
Israel	77	0.31%	57.14%	0	0.00%	-
Kuwait	72	0.29%	0.00%	0	0.00%	-
Qatar	66	0.27%	0.00%	42	0.33%	0.00%
Nigeria	60	0.25%	0.00%	0	0.00%	-
Bahrain	48	0.20%	0.00%	0	0.00%	-
Vietnam	46	0.19%	0.00%	61	0.48%	0.00%
Hungary	36	0.15%	0.00%	0	0.00%	-
Sri Lanka	30	0.12%	0.00%	0	0.00%	-
Tunisia	30	0.12%	0.00%	0	0.00%	-
Morocco	29	0.12%	0.00%	0	0.00%	-
Lebanon	28	0.11%	0.00%	0	0.00%	-
Monaco	28	0.11%	0.00%	0	0.00%	-
Total(Average %)	24,458	-	74.50%	12,736	-	71.50%

Table 4: Summary Statistics

Table 4 reports the descriptive statistics for the final sample, after removing observations from countries with less than 25 firm-year observations, observations from Bermuda and the Cayman Islands, and observations with missing financial data that is necessary for the creation of the control variables. For firms with zero interest payments, the interest coverage ratio ($IntCov$) is set to equal the 99th percentile of the distribution. $Size$, $IntCov$, $EB/Sales$, EA_Vol and ROA are winsorized at the 1st percentile and the 99th percentile. Lev, $Debt/EB$, $Cash$, PPE and $Capex$ are winsorized only at the 99th percentile, as they are bounded by 0 from below. Variables are described in Appendix A.

	S&P				Moody's			
	N	Mean	SD	Median	N	Mean	SD	Median
$Local$	24,458	0.745	0.436	1.000	12,736	0.715	0.451	1.000
$FirmRatg$	24,458	14.111	3.743	14.000	12,736	14.865	3.772	15.000
$Size$	24,458	23.181	1.704	23.109	12,736	23.631	1.672	23.589
$IntCov$	24,458	34.823	90.042	6.589	12,736	29.215	72.518	6.436
$EB/Sales$	24,458	0.261	0.250	0.210	12,736	0.245	0.232	0.201
Lev	24,458	0.308	0.178	0.291	12,736	0.315	0.178	0.297
$Debt/EB$	24,458	7.427	13.605	3.061	12,736	9.036	18.493	3.250
$NegDebt/EB$	24,458	0.041	0.199	0.000	12,736	0.045	0.206	0.000
$Cash$	24,458	0.088	0.085	0.062	12,736	0.088	0.086	0.063
PPE	24,458	0.318	0.289	0.265	12,736	0.310	0.286	0.259
$Capex$	24,458	0.048	0.054	0.034	12,736	0.048	0.053	0.035
EA_Vol	24,458	0.106	0.221	0.044	12,736	0.094	0.175	0.043
ROA	24,458	0.032	0.057	0.025	12,736	0.029	0.055	0.021
$SovRatg$	24,392	18.997	3.890	21.000	12,732	19.551	3.673	22.000

Table 5: The Effect of Local Presence on the Level of Credit Ratings

Table 5 reports the effect of local office on the level of credit ratings assigned by S&P (Columns 1 - 3) and Moody's (Columns 4 - 6). The dependent variable is *Ratings*, which is a numerical value for issuer ratings, coded from 1 (SD/D) to 22 (AAA). *Local* is an indicator variable equal to one if S&P/Moody's has a local office, and zero otherwise. Standard errors are clustered by firm and year. Control variables included are described in Appendix A. ***, **, and * denotes two-tailed statistical significance for 1%, 5%, and 10% respectively.

	S&P Ratings			Moody's Ratings		
	(1)	(2)	(3)	(4)	(5)	(6)
Local	0.801***	0.620***	0.390***	0.933***	0.921***	0.682***
	(4.078)	(3.682)	(2.595)	(3.395)	(4.112)	(3.497)
Size	0.901***	0.877***	0.633***	0.989***	0.906***	0.635***
	(26.992)	(13.250)	(9.894)	(19.041)	(8.501)	(6.477)
IntCov	0.005***	0.001**	0.002***	0.008***	0.003***	0.003**
	(7.828)	(2.175)	(3.061)	(6.295)	(2.583)	(2.272)
EB/Sales	1.274***	0.018	-0.091	0.911***	0.033	-0.074
	(5.859)	(0.097)	(-0.542)	(2.965)	(0.119)	(-0.288)
Lev	-2.200***	-2.365***	-2.232***	-2.778***	-2.398***	-2.207***
	(-7.394)	(-6.871)	(-7.427)	(-6.912)	(-5.133)	(-5.325)
Debt/EB	0.002	-0.013***	-0.010***	0.001	-0.005	-0.004
	(0.530)	(-5.097)	(-4.818)	(0.428)	(-1.471)	(-0.952)
NegDebt/EB	-0.183	-0.865***	-0.677***	-0.641**	-0.818***	-0.740***
	(-1.025)	(-6.132)	(-5.917)	(-2.114)	(-3.972)	(-4.131)
Cash	-0.230	0.537	0.420	-2.583***	-0.120	-0.198
	(-0.526)	(1.380)	(1.082)	(-3.992)	(-0.256)	(-0.436)
PPE	0.922***	0.084	0.258	0.930**	0.865	0.997
	(3.737)	(0.294)	(1.021)	(2.406)	(1.266)	(1.604)
Capex	1.291	3.373***	2.655***	-0.716	3.144***	2.888***
	(1.518)	(5.746)	(5.528)	(-0.525)	(3.475)	(3.538)
EA_Vol	-1.610***	-1.303***	-1.077***	-1.810***	-1.332***	-1.220***
	(-7.019)	(-6.042)	(-6.302)	(-5.137)	(-4.252)	(-4.803)
ROA	11.443***	5.114***	5.285***	9.669***	4.259***	4.081***
	(14.176)	(6.752)	(7.831)	(8.836)	(4.305)	(4.585)
SovRatg			0.460***			0.441***
			(16.558)			(12.623)
Year FE	Y	Y	Y	Y	Y	Y
Industry FE	Y	N	N	Y	N	N
Country FE	Y	N	N	Y	N	N
Firm FE	N	Y	Y	N	Y	Y
N	24,458	24,458	24,392	12,736	12,736	12,732
Adj. R^2	0.676	0.898	0.915	0.686	0.900	0.914

Table 6: Differences in Credit Ratings when one Rating Agency has a Local Presence

Table 6 reports the effect of local office on the difference between the credit ratings assigned by S&P and Moody's. The dependent variable is $RatingsDiff$ which is the absolute value of the difference between S&P and Moody's credit ratings, where credit ratings (*Ratings*) is a numerical value for issuer ratings, coded from 1 (SD/D) to 22 (AAA). *Local* is an indicator variable equal to one if only S&P or only Moody's has a local office during the respective fiscal year, and zero otherwise. $SovRatgDiff$ is the difference between sovereign rating assigned by S&P and Moody's. Standard errors are clustered by firm and year. Control variables included are described in Appendix A. ***, **, and * denotes two-tailed statistical significance for 1%, 5%, and 10% respectively.

	(1)	(2)	(3)	(4)
Local	0.314***	0.320***	0.248**	0.255***
	(3.016)	(3.037)	(2.544)	(2.596)
$SovRatgDiff$		0.048**		0.051**
		(2.074)		(2.173)
$Size$	−0.029*	−0.028*	0.063	0.068
	(−1.790)	(−1.738)	(1.298)	(1.422)
$IntCov$	0.0002	0.0002	−0.00002	−0.0001
	(0.775)	(0.515)	(−0.040)	(−0.264)
$EB/Sales$	0.271***	0.273***	0.061	0.063
	(2.579)	(2.579)	(0.549)	(0.560)
Lev	0.099	0.097	0.254	0.250
	(0.720)	(0.702)	(1.407)	(1.377)
$Debt/EB$	0.001	0.001	0.002	0.002
	(1.012)	(1.079)	(1.401)	(1.441)
$NegDebt/EB$	0.140	0.143	0.194***	0.197***
	(1.585)	(1.608)	(2.743)	(2.769)
$Cash$	0.010	0.030	−0.171	−0.158
	(0.050)	(0.145)	(−0.746)	(−0.678)
PPE	0.069	0.071	0.133	0.143
	(0.559)	(0.576)	(0.650)	(0.700)
$Capex$	−0.527	−0.507	−0.307	−0.295
	(−1.122)	(−1.074)	(−0.562)	(−0.539)
EA_Vol	0.133*	0.128	0.021	0.016
	(1.726)	(1.642)	(0.148)	(0.117)
ROA	−1.403***	−1.390***	−0.216	−0.189
	(−4.255)	(−4.203)	(−0.628)	(−0.544)
Year FE	Y	Y	Y	Y
Industry FE	Y	Y	N	N
Country FE	Y	Y	N	N
Firm FE	N	N	Y	Y
Observations	9,401	9,391	9,401	9,391
Adjusted R^2	0.145	0.145	0.468	0.469

Table 7: The Effect of Local Presence on Rating Adjustments

Table 7 reports the effect of local office on the component of credit ratings attributed to ratings adjustment. Columns (1) to (4) are for S&P ratings only and columns (5) to (8) are for Moody's ratings only. These results are for Step 2: tests the association between *Local* and *RatingsAdjust* (which is *Ratings* minus *RatingsPredicted*). In Step 1 (tabulated in Appendix B) we predict *Ratings* (a numerical value for issuer ratings, coded from 1 (SD/D) to 22 (AAA)) to generate *RatingsPredicted*. *Local* is an indicator variable equal to one if S&P or Moody's has a local office, and zero otherwise. Standard errors are clustered by firm and year. Control variables are not included because they are used in Step 1 to predict the rating. All variables are described in Appendix A. ***, **, and * denotes two-tailed statistical significance for 1%, 5%, and 10% respectively.

	S&P Rating Adjustments				Moody's Rating Adjustments			
	Unsigned		Signed		Unsigned		Signed	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Local	-0.232***	-0.334***	0.365**	0.336**	-0.040	-0.163	0.381*	0.561***
	(-2.615)	(-3.825)	(2.099)	(2.399)	(-0.424)	(-1.402)	(1.796)	(3.028)
Year FE	Y	Y	Y	Y	Y	Y	Y	Y
Industry FE	Y	N	Y	N	Y	N	Y	N
Country FE	N	N	N	N	N	N	N	N
Firm FE	N	Y	N	Y	N	Y	N	Y
N	23,392	23,392	23,392	23,392	12,732	12,732	12,732	12,732
Adj. R^2	0.050	0.516	0.108	0.690	0.071	0.525	0.120	0.683

Table 8: Informativeness of Ratings for Future Default Risk

Table 8 reports the results on credit ratings ability to predict future default risk. The dependent variables are the actuarial spread (AS) and probability of default (PD) at 2, 3, and 5 years after a given fiscal year end (Source: National University of Singapore, CRI database. Available at: http://nuscri.org [Accessed March 8, 2021]). *Ratings* is a numerical value for issuer ratings assigned by Moody's, coded from 1 (SD/D) to 22 (AAA). *Local* is an indicator variable equal to one if Moody's has a local office, and zero otherwise. Standard errors are clustered by firm and year. All other control variables included are described in Appendix A. ***, **, and * denotes two-tailed statistical significance for 1%, 5%, and 10% respectively.

	Actuarial Spread (AS)			Probability of Default (PD)		
VARIABLES	t+2 Years	t+3 Years	t+5 Years	t+2 Years	t+3 Years	t+5 Years
	(1)	(2)	(3)	(4)	(5)	(6)
Local	27.146**	26.695**	24.730**	0.009**	0.013**	0.018**
	(2.120)	(2.183)	(2.201)	(2.140)	(2.262)	(2.375)
Ratings	-3.911***	-3.693***	-3.245***	-0.001***	-0.002***	-0.002***
	(-4.007)	(-4.182)	(-4.264)	(-3.917)	(-4.134)	(-4.300)
*Local * Ratings*	-1.388	-1.323*	-1.167	-0.000	-0.001*	-0.001*
	(-1.597)	(-1.645)	(-1.617)	(-1.605)	(-1.719)	(-1.796)
Size	7.649***	7.827***	7.581***	0.002***	0.004***	0.006***
	(3.204)	(3.477)	(3.725)	(3.165)	(3.566)	(3.976)
IntCov	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***
	(-3.761)	(-3.877)	(-3.680)	(-3.736)	(-3.931)	(-3.875)
EB/Sales	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000
	(-1.511)	(-1.456)	(-1.476)	(-1.559)	(-1.539)	(-1.557)
Lev	46.109***	45.017***	41.315***	0.015***	0.021***	0.029***
	(5.224)	(5.495)	(5.701)	(5.105)	(5.395)	(5.539)
Debt/EB	0.201*	0.177*	0.143*	0.000*	0.000*	0.000*
	(2.013)	(1.978)	(1.925)	(2.022)	(1.991)	(1.950)
NegDebt/EB	9.438**	7.968**	5.594*	0.003**	0.004**	0.004
	(2.362)	(2.196)	(1.813)	(2.360)	(2.154)	(1.686)
Cash	-36.833***	-33.331***	-27.912***	-0.012***	-0.015***	-0.020***
	(-3.468)	(-3.563)	(-3.602)	(-3.433)	(-3.545)	(-3.585)
PPE	3.318	4.130	4.972	0.001	0.002	0.003
	(0.352)	(0.478)	(0.661)	(0.312)	(0.420)	(0.583)
Capex	7.774	5.566	3.762	0.003	0.003	0.005
	(0.297)	(0.244)	(0.196)	(0.317)	(0.296)	(0.343)
EA_Vol	19.770**	18.311**	15.929**	0.006**	0.008**	0.011***
	(2.560)	(2.650)	(2.618)	(2.576)	(2.757)	(2.825)
ROA	-73.062***	-68.810***	-60.675***	-0.023***	-0.031***	-0.043***
	(-3.846)	(-3.963)	(-4.005)	(-3.836)	(-4.016)	(-4.151)
SovRatg	-0.849	-0.757	-0.610	-0.000	-0.000	-0.000
	(-1.179)	(-1.183)	(-1.129)	(-1.216)	(-1.257)	(-1.256)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	No	No	No	No	No	No
Country FE	No	No	No	No	No	No
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	10,546	10,546	10,546	10,546	10,546	10,546
Adjusted R2	0.535	0.560	0.600	0.532	0.563	0.611

Table 9: Equity Market Reactions to Rating Changes

Table 9 reports the results on market reaction to rating changes. The dependent variable is the two-day abnormal stock return ($AbnRet_{i,t+\tau}$) following the announcement of a rating downgrade and upgrade. *ΔRatings* is the change in credit ratings (a numerical value for issuer ratings, coded from 1 (SD/D) to 22 (AAA)). *Local* is an indicator variable equal to one if S&P has a local office, and zero otherwise. Standard errors are clustered by firm and year. All other control variables included are described in Appendix A. ***, **, and * denotes two-tailed statistical significance for 1%, 5%, and 10% respectively.

	S&P Rating Downgrades		S&P Rating Upgrades	
	(1)	(2)	(3)	(4)
Local	-0.020**	0.006	-0.015***	-0.030**
	(-2.341)	(0.387)	(-2.895)	(-2.481)
ΔRatings	0.066***	0.020	-0.001	-0.001
	(3.129)	(0.639)	(-0.708)	(-0.175)
Size	0.001	0.001	-0.001	-0.005
	(0.663)	(0.126)	(-0.783)	(-0.736)
IntCov	0.00004	0.0001	-0.00001	-0.0001
	(1.048)	(1.148)	(-0.818)	(-1.230)
EB/Sales	-0.007	-0.010	-0.012***	0.004
	(-0.553)	(-0.388)	(-2.664)	(0.275)
Lev	-0.016	-0.022	-0.014**	-0.010
	(-1.209)	(-0.561)	(-2.006)	(-0.417)
Debt/EB	0.00001	-0.00003	0.00001	0.0002
	(0.037)	(-0.110)	(0.054)	(0.776)
NegDebt/EB	0.008	0.010	-0.009	0.0001
	(0.824)	(0.554)	(-1.047)	(0.005)
Cash	-0.008	0.052	0.002	0.020
	(-0.212)	(0.899)	(0.152)	(0.666)
PPE	0.030***	0.026	-0.002	-0.026
	(2.641)	(0.794)	(-0.247)	(-0.962)
Capex	0.002	0.037	0.008	-0.017
	(0.048)	(0.400)	(0.300)	(-0.207)
EA_Vol	-0.003	-0.010	0.001	-0.001
	(-0.223)	(-0.429)	(0.104)	(-0.126)
ROA	0.143***	0.114	-0.001	-0.031
	(3.493)	(1.443)	(-0.085)	(-0.724)
SovRatg	0.001	-0.0002	-0.0001	0.001
	(0.482)	(-0.138)	(-0.195)	(1.365)
Year FE	Y	Y	Y	Y
Industry FE	Y	N	Y	N
Country FE	Y	N	Y	N
Firm FE	N	Y	N	Y
N	3,507	3,507	2,569	2,569
Adj. R^2	0.115	0.420	0.100	0.497

Table 10: Credit Rating Changes by a Firm's Performance Grouping

Table 10 reports the results on potential explanations for why ratings increase rather than decrease. Firms are grouped into terciles by selected performance metrics, namely operating performance ($EB/Sales$) (Panel A) and stock market performance (P/B) (Panel B). The "Hi" and "Lo" indicate the top (Hi) and bottom (Lo) tercile for each variable. All other control variables included are described in Appendix A. ***, **, and * denotes two-tailed statistical significance for 1%, 5%, and 10% respectively.

Panel A: Firms Grouped by Operating Performance ($EB/Sales$)

	S&P Ratings			Moody's Ratings		
	(1)	(2)	(3)	(4)	(5)	(6)
Local	0.811***	0.573***	0.365**	1.060***	0.909***	0.690***
	(3.946)	(3.360)	(2.458)	(3.684)	(4.044)	(3.420)
*Local*LoEB/Sales*	0.506***	0.466***	0.280**	0.097	0.063	0.046
	(3.064)	(3.058)	(2.308)	(0.421)	(0.349)	(0.269)
*Local*HiEB/Sales*	−0.453***	−0.159	−0.137	−0.404**	−0.007	−0.049
	(−2.891)	(−1.297)	(−1.372)	(−2.044)	(−0.047)	(−0.351)
LoEB/Sales	−0.929***	−0.523***	−0.370***	−0.285	−0.257	−0.218
	(−6.313)	(−3.854)	(−3.701)	(−1.410)	(−1.611)	(−1.492)
HiEB/Sales	0.746***	0.304***	0.213**	0.523***	0.208	0.164
	(5.311)	(2.761)	(2.352)	(2.984)	(1.370)	(1.143)
Size	0.894***	0.861***	0.622***	0.988***	0.889***	0.619***
	(26.817)	(12.990)	(9.747)	(18.937)	(8.376)	(6.364)
IntCov	0.005***	0.001**	0.002***	0.008***	0.003**	0.003***
	(7.543)	(2.205)	(3.038)	(6.374)	(2.126)	(2.679)
Lev	−2.349***	−2.458***	−2.316***	−2.788***	−2.558***	−2.341***
	(−7.890)	(−7.200)	(−7.764)	(−6.968)	(−5.592)	(−5.739)
Debt/EB	0.005	−0.010***	−0.007***	0.002	−0.003	−0.002
	(1.479)	(−3.982)	(−3.589)	(0.550)	(−0.776)	(−0.664)
NegDebt/EB	−0.348**	−0.740***	−0.539***	−0.850***	−0.694***	−0.604***
	(−1.969)	(−4.868)	(−4.363)	(−3.012)	(−3.564)	(−3.570)
Cash	−0.272	0.513	0.396	−2.572***	−0.149	−0.226
	(−0.623)	(1.310)	(1.017)	(−3.996)	(−0.320)	(−0.497)
PPE	0.980***	0.087	0.250	1.037***	0.796	0.933
	(3.926)	(0.307)	(0.990)	(2.736)	(1.137)	(1.455)
Capex	1.097	3.279***	2.623***	−0.859	3.176***	2.922***
	(1.230)	(5.523)	(5.442)	(−0.633)	(3.471)	(3.562)
EA_Vol	−1.463***	−1.278***	−1.068***	−1.749***	−1.346***	−1.236***
	(−6.844)	(−6.051)	(−6.240)	(−4.984)	(−4.291)	(−4.848)
ROA	11.095***	4.542***	4.710***	9.871***	3.401***	3.307***
	(14.558)	(6.244)	(7.392)	(9.113)	(3.643)	(4.047)
SovRatg			0.456***			0.439***
			(16.703)			(12.635)
Year FE	Y	Y	Y	Y	Y	Y
Industry FE	Y	N	N	Y	N	N
Country FE	Y	N	N	Y	N	N
Firm FE	N	Y	Y	N	Y	Y
N	24,392	24,392	24,392	12,732	12,732	12,732
Adj. R^2	0.678	0.898	0.915	0.686	0.901	0.914

Table 10 (continued)

Panel B: Firms Grouped by Stock Market Performance (P/B)

	S&P Ratings			Moody's Ratings		
	(1)	(2)	(3)	(4)	(5)	(6)
Local	0.514**	0.450***	0.295**	0.680**	0.758***	0.616***
	(2.447)	(2.743)	(2.097)	(2.162)	(3.743)	(3.242)
*Local*LoP/B*	0.490***	0.514***	0.328***	0.116	0.156	0.099
	(2.791)	(4.120)	(3.503)	(0.629)	(0.862)	(0.699)
*Local*HiP/B*	0.030	−0.180*	−0.145*	−0.015	0.071	−0.010
	(0.216)	(−1.821)	(−1.675)	(−0.088)	(0.506)	(−0.075)
LoP/B	−0.986***	−0.858***	−0.561***	−0.616***	−0.648***	−0.449***
	(−6.367)	(−7.469)	(−6.839)	(−3.980)	(−4.089)	(−3.598)
HiP/B	0.265**	0.439***	0.327***	0.236	0.193	0.212*
	(2.364)	(4.872)	(4.493)	(1.629)	(1.533)	(1.877)
Size	0.878***	0.941***	0.697***	0.983***	0.933***	0.673***
	(25.561)	(14.111)	(10.844)	(19.431)	(8.292)	(6.543)
IntCov	0.005***	0.001**	0.002***	0.007***	0.003**	0.003***
	(7.743)	(2.123)	(2.906)	(6.013)	(2.221)	(2.780)
EB/Sales	1.273***	0.008	−0.084	1.081***	0.039	−0.013
	(6.109)	(0.042)	(−0.503)	(4.062)	(0.148)	(−0.055)
Lev	−2.354***	−2.713***	−2.562***	−2.944***	−2.675***	−2.537***
	(−7.520)	(−7.336)	(−7.943)	(−6.728)	(−5.276)	(−5.746)
Debt/EB	0.004	−0.013***	−0.011***	0.002	−0.007*	−0.006*
	(1.307)	(−5.128)	(−4.952)	(0.512)	(−1.736)	(−1.846)
NegDebt/EB	−0.235	−0.876***	−0.700***	−0.614**	−0.891***	−0.805***
	(−1.313)	(−6.341)	(−6.008)	(−2.187)	(−4.383)	(−4.554)
Cash	−0.334	0.663*	0.528	−2.500***	−0.097	−0.184
	(−0.760)	(1.697)	(1.345)	(−3.983)	(−0.203)	(−0.402)
PPE	1.002***	0.180	0.299	1.099***	1.261**	1.362**
	(4.179)	(0.629)	(1.188)	(2.828)	(2.109)	(2.521)
Capex	0.984	3.159***	2.610***	−0.401	3.196***	2.889***
	(1.206)	(5.046)	(5.107)	(−0.323)	(3.491)	(3.469)
EA_Vol	−1.546***	−1.254***	−1.069***	−1.617***	−1.215***	−1.122***
	(−6.381)	(−6.044)	(−6.358)	(−4.561)	(−3.856)	(−4.296)
ROA	10.129***	4.159***	4.564***	8.246***	2.869***	2.914***
	(12.693)	(5.235)	(6.653)	(7.761)	(2.903)	(3.213)
SovRatg			0.431***			0.408***
			(16.007)			(11.770)
Year FE	Y	Y	Y	Y	Y	Y
Industry FE	Y	N	N	Y	N	N
Country FE	Y	N	N	Y	N	N
Firm FE	N	Y	Y	N	Y	Y
N	23,308	23,308	23,308	12,068	12,068	12,068
Adj. R^2	0.681	0.900	0.915	0.691	0.903	0.915

Table 11: Balanced Sample: the Effect of Local Presence on the Level of Credit Ratings

Table 11 reports the effect of local office on the level of credit ratings assigned by S&P (Panel A) and Moody's (Panel B) using a more balanced sample. For the set of firms with a local office, the sample is limited to countries, in which the percentage of observations after the opening of an office is between 10% and 90%. This exclude countries, in which substantially all firm-years are either before or after the office opening. The dependent variable is *Ratings*, which is a numerical value for issuer ratings, coded from 1 (SD/D) to 22 (AAA). *Local* is an indicator variable equal to one if S&P/Moody's has a local office, and zero otherwise. Standard errors are clustered by firm and year. Control variables included are described in Appendix A. ***, **, and * denotes two-tailed statistical significance for 1%, 5%, and 10% respectively.

	S&P Ratings			Moody's Ratings		
	(1)	(2)	(3)	(4)	(5)	(6)
Local	0.718***	0.537***	0.384**	1.204***	0.765**	0.558**
	(3.019)	(2.595)	(2.083)	(3.174)	(2.025)	(1.993)
Size	0.817***	1.145***	0.707***	1.324***	0.810***	0.462***
	(9.326)	(6.821)	(4.363)	(16.091)	(4.599)	(2.933)
IntCov	0.002**	−0.0003	−0.0001	−0.002*	−0.001	−0.001
	(1.972)	(−0.431)	(−0.268)	(−1.707)	(−0.777)	(−0.902)
EB/Sales	0.663	0.970*	0.901	0.187	0.415	0.280
	(1.184)	(1.653)	(1.491)	(0.363)	(0.835)	(0.703)
Lev	−1.128*	−2.645***	−2.154***	−3.955***	−3.277***	−2.951***
	(−1.666)	(−3.473)	(−3.356)	(−6.692)	(−4.534)	(−5.072)
Debt/EB	−0.020***	−0.013**	−0.007*	−0.013***	−0.007*	−0.003
	(−3.423)	(−2.300)	(−1.884)	(−3.165)	(−1.768)	(−1.541)
NegDebt/EB	−1.877***	−1.421***	−0.933***	−1.372***	−1.197***	−0.859***
	(−4.121)	(−3.551)	(−2.607)	(−3.251)	(−3.579)	(−3.780)
Cash	0.803	1.645	1.386	−1.654	−0.345	0.245
	(0.710)	(1.572)	(1.239)	(−1.470)	(−0.419)	(0.347)
PPE	0.619	−0.528	−0.810	0.326	−0.848	−0.590
	(0.879)	(−0.539)	(−1.327)	(0.511)	(−1.125)	(−0.876)
Capex	1.672	2.780	2.162	1.851	3.212**	3.681***
	(0.895)	(1.455)	(1.270)	(0.972)	(2.139)	(2.942)
EA_Vol	−1.689***	−2.261***	−1.681***	−1.099	−1.401**	−0.657
	(−2.919)	(−3.113)	(−2.727)	(−1.611)	(−2.243)	(−1.400)
ROA	11.639***	2.847	3.342**	7.254***	1.395	1.908
	(6.508)	(1.443)	(2.046)	(3.996)	(0.732)	(1.295)
SovRatg			0.487***			0.600***
			(10.721)			(11.448)
Year FE	Y	Y	Y	Y	Y	Y
Industry FE	Y	N	N	Y	N	N
Country FE	Y	N	N	Y	N	N
Firm FE	N	Y	Y	N	Y	Y
N	2,856	2,856	2,840	3,345	3,345	3,345
Adj. R^2	0.656	0.851	0.893	0.759	0.903	0.927