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Going Local: The Effects of a Local Presence by Global Rating Agencies*

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Abstract

This paper examines whether and how corporate credit ratings change when global credit rating agencies establish a local presence in countries outside the United States. We show that a local presence is associated with higher credit ratings for local firms. Subsequent results reveal that the rating increase appears to be driven by a decrease in negative rating adjustments and an increase in positive adjustments. We interpret these findings as evidence that after a local presence rating analysts are more likely to assign higher ratings through rating adjustments and are less likely to make negative rating adjustments. Subsequent analyses suggest that, akin to the market for lemons, credit ratings increase rather than decrease because of general downward bias for ratings when analysts are unable or lack confidence to distinguish between good and bad credit quality firms.

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

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1 Introduction

Credit ratings are an integral part of global financial markets. Representing the estimated probability that a borrower will be able to meet its debt obligations, credit ratings provide investors with a mechanism to mitigate their disadvantage of informational asymmetry relative to borrowers (Ferri, 2004). For borrowers, a credit rating unlocks access to capital markets and facilitates contracting in both private and public markets. Regulatory requirements around the world allow many categories of market participants to invest only in entities and securities that have high credit ratings, and references to credit ratings form the basis for bond indices, investment guidelines, loan agreements, collateral triggers, and other important contracting provisions (Partnoy, 2009).

Given the importance of credit ratings, stakeholders around the world care deeply about how credit ratings are assigned, and many are especially critical of the dominance of U.S.-based credit rating agencies. Nearly all credit ratings in the global market are from the so-called "big three" credit rating agencies, S&P Global Ratings (S&P), Moody's Investors Service (Moody's), and FitchRatings (Fitch). Critics argue that these agencies do not fully understand developments in other economies and thereby impede firms' access to capital. To solve these impediments, for example, BRICS countries proposed creating an independent rating agency that would curtail the dominance of U.S.-based agencies.[1] There were also calls for the creation of an independent European ratings agency in the wake of the debt crisis in Europe that many accused U.S.-based agencies of exacerbating.[2] Additionally, until 2016, Chinese regulators mandated that bonds be rated by local rating agencies. However, the ratings did not provide "the same level of credit differentiation that investors have come to expect from ratings in major international markets" (Manulife Asset Management, 2016).

In this paper, we explore an alternative to solving the perceived impediments in international markets. Given investors' familiarity with and continued reliance on global rating

[1]BRICS = Brazil, Russia, India, China, South Africa; https://www.economist.com/finance-and-economics/2017/06/29/developing-countries-rebel-against-the-credit-rating-agencies

[2]see https://www.cfr.org/backgrounder/credit-rating-controversy

agencies, the impediments can alternatively be solved by having global agencies enhance their understanding of other economies through establishing a local presence. Thus, we examine whether and how establishment of a local presence by global credit rating agencies affects credit ratings for firms in the countries with the local presence. We test the proposition that a local presence leads to higher average credit ratings. Ferri, Liu, and Stiglitz (1999) highlight that rating agencies exacerbated the 1990s East Asian crisis by downgrading ratings more than the worsening in economic fundamentals would justify. Particularly, Ferri, Liu, and Stiglitz (1999) suggest that, when in doubt, rating analysts tend to be conservative and assign lower credit ratings in order to protect their reputation. Moreover, consistent with the concepts of the lemons problem (Akerlof, 1970),[3] if rating analysts do not fully understand international markets they are likely to discount information from these markets and assign lower ratings, on average. Thus, to the extent that a local presence enables analysts to better understand local markets and become more confident in their credit analyses, average credit ratings can increase with a local presence.

However, it is not obvious that a local presence would lead to higher credit ratings for local firms. Credit rating agencies maintain that their methodologies are multidisciplinary and universal (Moody's Investors Service, 2006). By implication, a local presence does not play a critical role in the ratings process and credit ratings might not change at all after a local presence is established. Additionally, as a local presence enhances credit analyses by enabling access to information and enhancing credit analysis (Ganguin and Bilardello, 2005; Bonsall et al., 2017) it can lead to lower ratings if analysts are better able to uncover adverse information previously missed. Thus, it is an open empirical research question whether and how a local presence affects credit ratings.

To shed light on this question of whether a local presence affects credit ratings, we exploit staggered opening of S&P and Moody's local offices around the world. S&P and Moody's have been expanding their global presence by establishing local offices around the world.

[3]Akerlof (1970) suggests that a group may be perceived negatively as a whole because it is difficult to distinguish good members of the group from the bad members of the group.

These offices are opened in different countries at different times, and this enables us to employ a difference-in-differences design to examine whether and how credit ratings change following the office openings.[4] We focus our analyses on credit ratings on debt obligations denominated in foreign currency (i.e., foreign currency credit ratings); these remain more prevalent and influential in the international bond markets for the majority of non-US issuers (Cantor and Packer, 1996).

We find results consistent with the proposition that a local presence leads to higher average credit ratings for firms. Our results show that credit ratings increase for firms in the countries where rating agencies establish a local presence. In the baseline analyses, results show that S&P ratings increase by nearly one-notch in the period after S&P establishes a local presence. The results are similar for Moody's ratings and are robust to including several firm characteristics found in prior literature to be determinants of credit ratings. We also include a variety of fixed effects specifications and find consistent results.

To investigate potential mechanisms through which a local presence affects credit ratings, we explore changes in the components of credit ratings, namely model-based ratings and rating adjustments. Credit ratings reflect quantitative and qualitative factors (Ashbaugh-Skaife, Collins, and LaFond, 2006; Kraft, 2015a,b; S&P Global Ratings, 2019). 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. Following existing literature (e.g., Baghai, Servaes, and Tamayo, 2014), we use firm fundamentals to predict a firm's credit rating and determine rating adjustments as the difference between the actual rating and predicted rating.

A local presence may affect the use of soft information in making qualitative rating

[4] Alternatively, we could focus on the dates that rating reports are authored by local analysts. We make a design choice to focus on office openings. Practically, it is less costly to identify office openings than it is to identify actual analysts located in each office. Moreover, many offices do not have enough analysts to author reports for local firms such that foreign analysts continue to rate local firms. A focus on the local office is meaningful because it provides a basis for information collection. A local analysts noted that even if he did not participate in rating committee meetings to determine ratings for local entities, "we will share our views regarding the business environment and the specific entity with Moody's."

adjustments. A substantial body of research highlights that the use and impact of soft information increases with geographic proximity (e.g., Malloy, 2005; O'Brien and Tan, 2015; Jaggi and Tang, 2017). Accordingly, the portion of credit ratings attributed to adjustments can increase as analysts incorporate more local knowledge in the ratings. There is also another possibility, that a local presence mitigates the use of subjective adjustments that persistently bias ratings downwards. Consistent with evidence in (Ferri, Liu, and Stiglitz, 1999), rating agencies may assign lower credit ratings than what the fundamentals would predict prior to a local presence. That is, 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 model-based ratings.

We uncover interesting insights. Our results show that the proportion of credit ratings attributed to adjustments decreases after an agency establishes a local presence (i.e., a decrease in the absolute value of the difference between actual rating and predicted rating). That is, in total, when a rating agency establishes a local presence it is more likely to assign higher credit ratings that are closer to the model-based ratings. But this change is asymmetrical for positive and negative adjustments. We find that there are more positive adjustments (i.e., actual credit ratings become higher than the predicted ratings) than there are negative adjustments after a local presence. We interpret these findings as evidence that after a local presence rating analysts are more likely to assign higher ratings through ratings adjustments and are less likely to make negative rating adjustments.

To provide further evidence, we explore potential explanations for why ratings increase rather than decrease with a local presence. We explore the implications based on the market for lemons (Akerlof, 1970), when an evaluator with insufficient information does not differentiate between good and bad firms. For example, we find that firms in the lowest tercile by profitability exhibit the highest increase in ratings after a local presence, suggesting that analysts may have previously penalized high quality firms based on where they ranked on some backward looking quantitative metrics. Overall, our findings suggest that a local presence enables rating agencies to distinguish between high and low quality firms, thereby raising the ratings of firms that would have been previously perceived as low credit quality on historical accounting or financial metrics.

Having established that a local presence affects ratings, we investigate the quality of the ratings by examining how market participants perceive changes in credit ratings following the establishment of a local presence. Employing the same difference-in-differences design on the staggered office opening dates, we document a negative relationship between a local presence and stock returns on both rating downgrades and rating upgrades. With respect to the downgrades, these findings suggests that investors view rating downgrades as more credible when the rating agency has a local presence. However, investors view upgrades more skeptically as the market reaction to rating upgrades is lower after a local presence. These findings are consistent with prior evidence (e.g., Holthausen and Leftwich, 1986) that rating upgrades typically provide less information to capital markets.

We perform a battery of robustness tests to strengthen inferences from our findings. Notably, why rating agencies open local can engender endogeneity concerns. The issue is that rating agencies may open an office between 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 being local. Our main research design addresses this concern by controlling for a country's economic environment through the inclusion of sovereign credit ratings. Nonetheless, in robustness tests, we provide additional evidence with a different identification strategy. For a given firm rated by both S&P and Moody's, we examine the rating differences between when one of the agencies establishes a local presence and the other does not. We find some evidence that differences between Moody's and S&P ratings increase after one agency opens a local office, suggesting that a local presence changes the level of credit ratings assigned after a local presence. This approach, 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, mitigates the concerns that higher ratings observed after a local presence are attributed to other factors such as overall economic improvements.

Additionally, our sample composition is subject to some significant limitations. 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, 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. Specifically, for the countries with a local presence, we limit the analysis to those countries, in which the percentage of firm-years after a local presence is between 10% - 90%. Our inferences remain unchanged. Overall we find that a local presence has a discernible impact on credit ratings.

We contribute to the broad literature on geographic proximity. The effects of geographic proximity have been studied in other contexts and have been shown to have important consequences to governance and corporate outcomes. The distance from a Securities and Exchange Commission division office is found to affect the quality of a firm's accounting disclosures (Kedia and Rajgopal, 2011), audit quality (Choi, Kim, Qiu, and Zang, 2012), and stock price crash risk (Kubick and Lockhart, 2016). Similarly, Kubick, Lockhart, Mills, and Robinson (2017) find that proximity to Internal Revenue Services office affects firm's tax aggressiveness and the likelihood and productivity of IRS examinations. Ayers, Ramalingegowda, and Yeung (2011) find that local, as opposed to distant, monitoring institutional investors affect firm disclosure behavior. Proximity also affects equity analysts' forecasting accuracy (Malloy, 2005) and coverage decisions (O'Brien and Tan, 2015). Given the importance of credit ratings in the global credit markets, it is important to extend this inquiry into proximity to rating agencies and in the global context. The effects of geographic proximity on credit ratings cannot be readily inferred from the equity market outcomes because of differences between equity and credit ratings arising from the asymmetric payoff between equity investors (served by equity analysts) and debt holders (served by credit rating analysts).

We also contribute to the credit ratings literature. Notably, our study is closely related to Jaggi and Tang (2017), which examine effects of proximity of the firm to credit rating agency headquarters in New York. They find that longer distance between the firm and the rating agency headquarters leads to higher errors in bond ratings.[5] Our findings complement Jaggi and Tang (2017), but our approach differs in significant ways. We propose that a local presence, as opposed to the distance from the New York headquarters, can also explain variations in credit ratings. Accordingly, we focus on a sample of non-US firms. The significant global presence by the credit rating agencies has made other cities around the world, aside from New York City, important in the credit rating process and warrant a closer look. Moreover, we also provide direct evidence of the effects on the type of information (quantitative and qualitative) and uncover new insights on the asymmetric changes in the components of ratings after a local presence. Additionally, we explore various scenarios to explain why ratings increase rather than decrease with a local presence.

Overall our findings contribute more directly to the ongoing debate about the dominance of the U.S.-based rating agencies in the global markets. As policymakers around the world continue to institute regulations in the credit rating agency market or seek to curtail activities of foreign-based agencies, it is important to shed light on the ratings impact of rating agencies' organizational decisions.

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

[5]While not the main part of the paper, but an additional test for robustness, Bonsall, Koharki, and Neamtiu (2017) also use geographic proximity as a proxy for S&P's ease of performing qualitative analysis.

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 (S&P Global Ratings, 2019). Mathematical or quantitative models are used to determine a baseline credit rating for an issuer based on quantitative data (i.e., model-based rating). Analyst models involve credit rating analysts using 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 credit rating to arrive at the actual rating. That is, the actual credit ratings are generally "not based on a defined set of financial ratios or rigid computer models. Rather, they are a product of comprehensive analysis of each individual issue and issuer" (Moody's Investors Service, 2006).

The big three credit rating agencies (S&P, Moody's and Fitch) dominate the credit rating agency market. According to a report by the European Securities and Markets Authority (ESMA), the big three earned over 93% of the ratings-related revenues in the European Union in 2017 (ESMA, 2018). Specifically, S&P earned about 46%, Moody's about 32%, and Fitch approximately 15%. These numbers are consistent in the U.S. and all other markets around the world. Yet, although these credit rating agencies have been rating issuers around the world for decades, they have not always had a physical presence outside of the United States. Over the years, however, the rating agencies have indeed established offices around the world, but there are still many countries in which they continue to issue credit ratings without having a local presence.

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, its executives expected that a local presence would enhance "insight into credit risk".[6] This narrative, which stands in contrast to the position that credit rating methodologies are universal, raises an important empirical research question of whether a local presence in countries around the world by rating agencies would affect credit ratings.

[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.

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, Collins, and LaFond, 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. Moreover, Bonsall, Koharki, and Neamtiu (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. As a result, we expect a local presence to affect credit ratings.

3 Research design and sample description

In this section, we discuss our sample selection and data sources, present our research methodology, and discuss sample descriptive statistics.

3.1 Data

3.1.1 Sample selection and data sources

Our analyses are based on two samples of firms with a credit rating history from S&P and Moody's for the period covering fiscal years 1981 to 2018. Issuers can seek credit ratings on their debt obligations denominated in domestic and foreign currency. We focus our analyses on foreign currency credit ratings which remain more prevalent and influential in the international bond markets for the majority of non-US issuers (Cantor and Packer, 1996).

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 companies with a headquarters outside of the U.S. and are not government institutions, educational institutions, trade associations, foundations, or charitable institutions. Using the start and end dates for each rating, we transform the ratings data into firm-year observations and match these firm-years observations to an equity ISIN (i.e., International Security Identification Number) that exists on Worldscope. The ratings data from S&P generally contain an ISIN and where it is missing we use different approaches to identify ISIN associated with the ratings. First, we use the CapitalIQ Excel Plug-in, which uses CapitalIQ unique identifiers to look up ISIN. Second, we use Bureau Van Dijk matching algorithm to identify ISIN based on the following parameters: Company Name, LEI, Ticker, SIC Code, Website Address, full Physical Address, Phone/Fax Number. Third, we manually match the ratings data with the Worldscope financial data based on the company (issuer) name and the headquarters. We drop firm-years still missing ISIN.

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 senior unsecured rating on an outstanding debt issue with the longest maturity. We assume that an unsecured issue rating is representative of a firm's long-term issuer rating. Similar to S&P sample, we limit the sample to companies headquartered outside of the U.S. and exclude observations for entities identified as Sovereign, Sub-Sovereign, or Supranational.

Similar to the S&P sample, we use the start and end dates for each rating to transform the ratings data into firm-year observations and match these firm-years observations to an equity ISIN (i.e., International Security Identification Number) that exists on Worldscope. Moody's DRD does not contain an ISIN for a company. Instead, among others, DRD includes the following identifiers for some of the observations: Debt ISIN, nine-digit Debt CUSIP and six-digit Issuer CUSIP. We run each of these identifiers as well as the company name through the Capital IQ Excel Plug-in to look up Equity (company) ISIN. We also received a list of some company ISIN from Moodyâs Analytics. Additionally, we run the Bureau Van Dijk matching algorithm based on company name, LEI (i.e., Legal Entity Identification) extracted from moodys.com, ticker, SIC Code, and country. Finally, we manually match any remaining ratings data to Worldscope financial data based on the issuer name and country of domicile. We drop firm-years still missing ISIN.

For both S&P and Moody's, we merge the credit ratings information with financial information such that financial information for each fiscal year is matched to the credit rating assigned or active at six months after the fiscal year end. This ensures that the issuer's annual reports have been published, and that the rating agencies have had sufficient time to update their ratings based on the annual reports.[7] Financial information for all the firms (i.e., issuers) in our sample comes from Thomson Reuters Worldscope (Worldscope). Except for selected key data items (e.g. total assets), the data items in Worldscope are typically not translated into a common currency, but rather given in the original currency of the companies' financial statements. To facilitate comparison across countries or currencies, we transform most of the financial variables in our empirical to ratios. To reduce noise, we eliminate observations from countries with fewer than 25 total observations as well as observations from tax haven countries (Bermuda and the Cayman Islands), which typically don't have genuine headquarters.

Table 1 reports the sample selection. The final sample of rated firms domiciled outside of the U.S. 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. In particular, we allow 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).

[7] For robustness, we also use different time horizons, including ratings at three and twelve months after the fiscal year end.

3.1.2 Identifying credit rating agency offices

A key aspect of our study is the identification of a credit rating agency's global office locations and the dates the offices opened. The major rating agencies, Moody's and S&P, are US-based investor services firms with significant rating activities across the world and with increasing physical presence in major global cities.

We obtain and cross-reference location and date information from several sources, starting with data supplied by the rating agencies via email. S&P supplied the office opening dates, and Moody's supplied the incorporation dates of the local entities. The incorporation dates sometimes differ from the office opening dates, as obtained from other sources. We corroborate and/or supplement the dates using each agency's annual reports, form 10-Ks, investor factbooks and presentations, press releases accompanying office openings, and transparency reports. Annual reports, Form 10-ks and investor information are publicly available through the investor web sites for S&P (http://investor.spglobal.com/) and Moody's (https://ir.moodys.com/). We obtain press releases from the investor web sites and a search on FACTIVA. Transparency reports are mandated by regulatory authorities in the European Union, and the reports are available on the respective web sites for S&P and Moody's.[8] We also obtain office information, primarily data for older offices, from Sinclair (2005).

While we focus on a rating agency's office locations, we note that rating agencies often operate in some selected markets through local affiliated credit rating agencies. They also establish some offices through acquisitions of or joint ventures with local rating agencies. To create a more complete data set, we use a combination of office opening dates. The year of an office opening represents 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. We exclude minority acquisitions or other affiliations, as well as offices that opened for a period of less than two years.

[8] see S&P at https://www.standardandpoors.com/en_US/web/guest/regulatory/disclosures; Moody's at https://www.moodys.com/Pages/reg001007.aspx

Table 2 presents Moody's and S&P office locations and the date the office locations opened. The first recorded overseas offices were in the United Kingdom and Japan in the early 1980s. 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 and have offices in virtually all the same cities in a country. A number of these cities are selected for their strategic locations within a region and/or the size of the credit ratings market (i.e., number of current and potential rated local issuers). Our primary analyses focus on the firms domiciled in the country where the office is located.

3.1.3 Measuring corporate credit ratings

Our primary outcome variable of interest is the level of credit ratings at the individual firm level. We obtain *Ratings* from available historical credit ratings data as described above. Credit ratings are assigned as letter ratings, so in our empirical analyses we capture *Ratings* as a numerical value for actual issuer ratings coded from 1 (SD/D) to 22 (Aaa), with higher values indicating higher credit quality.

3.2 Baseline empirical model

Our proposition is that a local presence leads to higher credit ratings for local firms. To test this proposition, we employ a difference-in-differences design to determine whether and how credit ratings change as rating agencies establish local presence. We capture a local using the dates an agency opens an office in a non-U.S. country. These offices are opened in different countries and at different times. Using the staggered office openings, we specify the following model:

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

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. 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. The equation 1 is essentially a difference-in-differences design Bertrand and Mullainathan (see, 2003); Armstrong et al. (see, 2012); Gormley and Matsa (see, 2016). The specification allows for control variables and for firms from different countries that have office openings at different times. The staggered office opening dates means that our treatment group includes the firms from countries that have an office opening and the control group is not restricted to firms from countries that never have an office opening. Instead, the control group includes all 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, Servaes, and Tamayo, 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. [9] 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).

3.3 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.[10] 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. 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) and Australia (5.06% - S&P, 4.63% - Moody's), as well as several other countries with over 1% of the

[9] As noted for equation 3, Baghai, Servaes, and Tamayo (2014) include a few more variables that we exclude due to missing data for our sample of non-US firms. We include fixed effects to mitigate omitted variable bias. The difference-in-differences design also strengthens causal inferences in the paper.

[10] In untabulated results, we also examine the sample distribution by year and find that the number of rated issuers increases over time, with significant coverage starting in the early to mid-2000s.

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 73.69% of S&P and Moody's firm-years, respectively, occur in the period after office opening. As noted above, most of 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. Thus, while a significant portion of the firm-years occur in the period after the office opening, there is considerable variation across different countries to facilitate reasonably meaningful analyses of changes in ratings 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 so is cash-to-total asset ratio of 8.8% for S&P and Moody's.

4 Empirical results

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

4.1 The effects of a local presence on firms' credit ratings

To test our proposition, we examine whether and how the level of credit ratings by each rating agency changes after establishing a local presence. We estimate equation 1 with firms' credit ratings (*Ratings*) as the dependent variable.

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, Liu, and Stiglitz (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.

4.2 Mechanism: 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, Collins, and LaFond, 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. These adjustments and the application by different rating agencies can be influenced by a local presence.

Existing empirical evidence is clear about how geographic proximity increases the use of and the effects of soft information on decision making (e.g., Malloy, 2005; O'Brien and Tan, 2015; Jaggi and Tang, 2017). A local presence increases the ability of the analysts to conduct issuer site visits, facilitates the analysts ability to collect information and develop a more meaningful awareness and knowledge of local companies, business practices, and regulations in the local environment (Ganguin and Bilardello, 2005; Bonsall, Koharki, and Neamtiu, 2017). Thus ratings could change and differences between rating agencies arise as qualitative factors become prominent with a local presence. These rating impacts are in the form of qualitative rating adjustments. That is, the portion of credit ratings attributed to adjustments is likely to increase as analysts make more adjustments to the model-based ratings by incorporating more local knowledge after 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 conservative and assign lower credit ratings (Ferri, Liu, and Stiglitz, 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 6.[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 presence to increase the rating adjustments. However, we document that the value of total rating adjustments decreases after a local presence. Specifically, in the S&P sample,

[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.

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, Koharki, and Neamtiu, 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. That is, 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 adjustment. That is, following a local presence, rating adjustments are less likely to be negative relative to the period before a local presence.

Overall our evidence suggests that prior to a local presence rating analysts deviate more from model-based ratings for negative adjustments. After a local presence, the size of total adjustment decreases but analysts incorporate more positive soft information thereby increasing average credit ratings via positive adjustments.

4.3 Why do the ratings increase?

To provide further evidence, we explore potential explanations for why the ratings increase rather than decrease with a local presence. There are potentially several explanations for why ratings increase rather than decrease. We propose that one such explanation relates to the market for lemons as postulated in Akerlof (1970), when an evaluator with insufficient information does not differentiate between good and bad firms. In our setting, we postulate that prior to a local presence, rating analysts lack deep insight into credit risk of individual firms and 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. As rating agencies establish a local presence and enhance credit risk analysis, analysts then assign higher ratings to 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 7.

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 C 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 7, 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.

4.4 Relevance of credit rating changes

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 the ratings changes in the wake of a local presence. Specifically, we examine whether the local presence impacts the relevance of credit rating changes. To test for this, we examine the relationship between the stock market reaction to credit rating changes and local presence as follows:

$$
\begin{aligned}
AbnRet_{i,t+\tau} = {} & \beta_0 + \beta_1 Local_{i,t} + \beta_2 \Delta Rating_{it} \\
& + \beta_3 Price/Book_{it} + \beta_4 Size_{it} + \beta_5 IntCov_{it} \\
& + \beta_6 EB/Sales_{it} + \beta_7 Lev_{it} + \beta_8 Debt/EB_{it} \\
& + \beta_9 NegDebt/EB_{it} + \beta_{10} Cash_{it} + \beta_{11} PPE_{it} + \beta_{12} CAPEX_{it} \\
& + \beta_{13} EA\_Vol_{it} + \beta_{14} ROA_{it} + f_i + \omega_{lt} + \lambda_{jt} + \varepsilon_{it}
\end{aligned}
\tag{2}
$$

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 ($\Delta Rating$). All other control variables are as described above for equation 1 and detailed descriptions are provided in Appendix A.

To do this, we estimate equation 2 and present the results in Table 8. We perform our analyses separately for negative rating changes (i.e., downgrades) and positive rating changes (i.e., upgrades), consistent with 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). show no reaction at all. 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.

In addition to examining the market reaction to credit rating changes, we could examine whether opening an office location improves the accuracy (i.e., quality) of ratings. To provide this evidence, we would examine changes in the rate at which credit ratings predict 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). Unfortunately, we do not have sufficient data to construct a sample of future defaults; the incidence of reported defaults is extremely small in our sample.

5 Robustness tests

5.1 Endogeneity concerns: why agencies open offices

There are many reasons why rating agencies establish a local presence, and the reasons can engender endogeneity concerns in our analyses. The issue is that rating agencies may open an office 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. We address this concern in various ways.

First, the setting of our sample mitigates endogeneity concerns related to economic improvements. In many cases a local office is 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. Nonetheless, the firms in the countries where the office is located will have the benefit of a local presence.

Second, our primary research design addresses endogeneity concerns relating to economic improvements by controlling for a country's economic environment through the inclusion of sovereign credit ratings. The sovereign credit ratings captures the country economic condition.

Third, in this section we perform robustness tests using 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. This is not obvious because when an agency with a local presence changes its ratings up or down, the other agency without a local presence can simply follow suit (i.e., herd). Thus a local presence may not result in differences between ratings assigned by an agency with a local presence and without a local presence. To determine whether differences exist, we estimate equation 1 with rating disagreement ($RatingsDiff$) as the dependent variable. $RatingsDiff$ is the difference between the values for *Ratings* as assigned by S&P and Moody's for a given firm at a given time.

Table 9 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 a sovereign rating (coeff. = 0.314, t-stat = 3.016) and with a sovereign rating control (coeff. = 0.320, t-stat = 3.037). We document similar results in column (3) and (4) including firm fixed effects.

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. These findings provide further support to the earlier findings that a local presence does impact the properties of credit ratings. In particular, 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.

However, there are some data 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 neccesarily explain our primary inferences.

5.2 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%. This ensures that firm-years are not substantially before or after a local presence is established.

Using this more balanced sample, we re-estimate equation 1 with issuer credit ratings (*Ratings*) as the dependent variable. Table 10 presents the results. We document consistent results, finding that credit ratings increases after a rating agency establishes a local presence. The coefficients on *Local* are positive and significant across all the specifications and rating agencies.

5.3 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.

6 Conclusion

Credit rating agencies are important information intermediaries and gatekeepers in the financial system (Partnoy, 2002; Bonsall, Koharki, and Neamtiu, 2017; Roychowdhurry and Srinivasan, 2019). Their credit ratings affect access and cost of borrowing for various entities around the world (Ferri, Liu, and Stiglitz, 1999; Kisgen, 2006; Kim and Wu, 2008; Kisgen and Strahan, 2010; Cornaggia, Cornaggia, and Israelsen, 2018). Yet the dominant rating agencies are continually coming under scrutiny for failing to fairly represent and exhibit a deeper understanding of different 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 analysis and ratings.

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, and that the increase in ratings can attributed to more positive rating adjustments (as opposed to ratings derived from quantitative information about the issuer). We find that the stock market participants view negative rating changes as more credible, but are somewhat skeptical of positive rating changes.

Having established that credit ratings increase after a local presence, we explore potential explanations for why the ratings increase rather than decrease. Grouping firms into terciles by operating performance and stock market valuation, we find evidence suggesting that analysts generally penalize firms based on where they ranked on some backward looking quantitative metrics. We interpret this as evidence in support of a situation akin to the market for lemons as a potential explanation for the overall increase in ratings. That is, analysts raise credit ratings of firms that were previously discounted, potentially because analysts are better able to distinguish between high and low credit quality firms after a local presence.

It is possible that the changes we document may be driven by economic trends rather than a local presence. That the properties of credit ratings in a given location are changing for other reasons could motivate rating agencies to establish a local presence, thus leading to reverse causality concerns. Our setting and research designs mitigate these concerns. In the setting, rating agencies may open offices for a variety of reasons, including for strategic purposes, that have nothing to do with economic trends in a given location. For instance, a location such as Dubai in the United Arab Emirates provides hub for international travel to Asia, Africa, Europe, and the United States. We also perform additional tests to rule the alternative explanation by examining rating differences for a firm rated by both S&P and Moody's and only one agency has a local presence. This, along with control variables for country credit risk as well as firm-fixed effects, mitigates the potential impacts of any omitted variables.

Overall, we interpret our findings as evidence that a local presence has a causal relation and leads to higher credit ratings.

References

Akerlof, G. (1970). The market for "lemons": Qualitative uncertainty and market mechanisms. *The Quarterly Journal of Economics 84*.

Armstrong, C. S., K. Balakrishnan, and D. Cohen (2012). Corporate governance and the information environment: Evidence from state antitakeover laws. *Journal of Accounting and Economics 53*(1), 185 – 204.

Ashbaugh-Skaife, H., D. Collins, and R. LaFond (2006). The effects of corporate governance on firms' credit ratings. *Journal of Accounting and Economics 41*(1-2), 203 – 243.

Ayers, B. C., S. Ramalingegowda, and E. P. Yeung (2011, June). Hometown advantage: The effects of monitoring institution location on financial reporting discretion. *Journal of Accounting and Economics 52*(1), 41–61.

Baghai, R. P., H. Servaes, and A. Tamayo (2014, October). Have Rating Agencies Become More Conservative? Implications for Capital Structure and Debt Pricing. *The Journal of Finance 69*(5), 1961–2005.

Bertrand, M. and S. Mullainathan (2003). Enjoying the quiet life? corporate governance and managerial preferences. *Journal of political Economy 111*(5), 1043–1075.

Bonsall, S. B., K. Koharki, and M. Neamtiu (2017). When do differences in credit rating methodologies matter? evidence from high information uncertainty borrowers. *The Accounting Review 92*(4), 53–79.

Cantor, R. and F. Packer (1996). Determinants and impact of sovereign credit ratings. *Economic policy review 2*(2).

Choi, J.-H., J.-B. Kim, A. A. Qiu, and Y. Zang (2012, February). Geographic Proximity between Auditor and Client: How Does It Impact Audit Quality? *AUDITING: A Journal of Practice & Theory 31*(2), 43–72.

Cornaggia, J., K. J. Cornaggia, and R. D. Israelsen (2018). Credit ratings and the cost of municipal financing. *The Review of Financial Studies 31*(6), 2038–2079.

Correia, S. (2015). Singletons, cluster-robust standard errors and fixed effects: A bad mix. *Technical Note, Duke University*.

ESMA (2018, November). Report on cra market share calculation. resreport, European Securities and Markets Authority.

Ferri, G. (2004). More analysts, better ratings: Do rating agencies invest enough in less developed countries? *Journal of Applied Economics 7*(1), 77–98.

Ferri, G., L.-G. Liu, and J. E. Stiglitz (1999). The procyclical role of rating agencies: Evidence from the east asian crisis. *Economic Notes 28*(3), 335–355.

Ganguin, B. and J. Bilardello (2005). *Fundamentals of Corporate Credit Analysis.* New York, NY: McGraw-Hill.

Gormley, T. A. and D. A. Matsa (2016). Playing it safe? Managerial preferences, risk, and agency conflicts. *Journal of Financial Economics 122*(3), 431 – 455.

Holthausen, R. and R. Leftwich (1986). The effect of bond rating changes on common stock prices. *Journal of Financial Economics 17*(1), 57 – 89.

Jaggi, B. and L. Tang (2017, April). Geographic location of the firm and credit rating accuracy. *Journal of Accounting, Auditing & Finance 32*(2), 155–181.

Kedia, S. and S. Rajgopal (2011, April). Do the SEC's enforcement preferences affect corporate misconduct? *Journal of Accounting and Economics 51*(3), 259–278.

Kim, S.-J. and E. Wu (2008). Sovereign credit ratings, capital flows and financial sector development in emerging markets. *Emerging Markets Review 9*(1), 17 – 39.

Kisgen, D. J. (2006). Credit ratings and capital structure. *Journal of Finance 61*(3), 1035–1072.

Kisgen, D. J. and P. E. Strahan (2010). Do regulations based on credit ratings affect a firm's cost of capital? *The Review of Financial Studies 23*(12), 4324–4347.

Kraft, P. (2015a). Do rating agencies cater? evidence from rating-based contracts. *Journal of Accounting and Economics 59*(2 - 3), 264 – 283.

Kraft, P. (2015b). Rating agency adjustments to GAAP financial statements and their effect on ratings and credit spreads. *The Accounting Review 90*(2), 641 – 674.

Kubick, T. R. and G. B. Lockhart (2016, May). Proximity to the SEC and Stock Price Crash Risk. *Financial Management 45*(2), 341–367.

Kubick, T. R., G. B. Lockhart, L. F. Mills, and J. R. Robinson (2017). IRS and corporate taxpayer effects of geographic proximity. *Journal of Accounting and Economics*.

Lopez, T. J. and L. Rees (2002). The effect of beating and missing analysts' forecasts on the information content of unexpected earnings. *Journal of Accounting, Auditing & Finance 17*(2), 155–184.

Malloy, C. J. (2005, April). The Geography of Equity Analysis. *The Journal of Finance 60*(2), 719–755.

Manulife Asset Management (2016, August). Navigating china's booming bond market: Marking over 5 years of expertise in china bond strategy.

Moody's Investors Service (2006). About Moody's ratings: Ratings policy and approach. https://www.moodys.com/Pages/amr002003.aspx.

O'Brien, P. C. and H. Tan (2015, February). Geographic proximity and analyst coverage decisions: Evidence from IPOs. *Journal of Accounting and Economics 59*(1), 41–59.

Partnoy, F. (2002). *Ratings, Rating Agencies and the Global Financial System. The New York University Salomon Center Series on Financial Markets and Institutions*, Volume 9 of *Ratings, Rating Agencies and the Global Financial System. The New York University Salomon Center Series on Financial Markets and Institutions*, Chapter The Paradox of Credit Ratings, pp. 65–84. Boston, MA: Springer.

Partnoy, F. (2009). Rethinking regulation of credit rating agencies: An institutional investor perspective. *Council of Institutional Investors, April 2009*.

Petersen, M. A. (2009). Estimating standard errors in finance panel data sets: Comparing approaches. *The Review of Financial Studies 22*(1), 435–480.

Roychowdhurry, S. and S. Srinivasan (2019). The Role of Gatekeepers in Capital Markets. *Journal of Accounting Research 57*(2), 295–322.

Sinclair, T. J. (2005). *The New Masters of Capital: American Bond Rating Agencies and the Politics of Creditworthiness.* Cornell University Press.

S&P Global Ratings (2019). Guide to credit rating essentials: What are credit ratings and how do they work? www.spglobal.com, last accessed February 2019.

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: $$\begin{aligned} Ratings_{i,t+\tau} = {} & \beta_0 + \beta_1 Size_{it} + \beta_2 IntCov_{it} + \beta_3 EB/Sales_{it} \\ & + \beta_4 Lev_{it} + \beta_5 Debt/EB_{it} + \beta_6 NegDebt/EB_{it} \\ & + \beta_7 Cash_{it} + \beta_8 PPE_{it} + \beta_9 CAPEX_{it} \\ & + \beta_{10} EA\_Vol_{it} + \beta_{11} ROA_{it} + f_i + \omega_{lt} + \lambda_{jt} + \varepsilon_{it} \end{aligned}$$
$RatingsAdjust$	The difference between *Ratings* (i.e., actual rating) and $RatingsPredict$ (i.e., predicted rating).
Control variables	
$Size$	Firm size measured as the natural logarithm of total assets in US dollars (Worldscope).
$IntCov$	Earnings before interest, taxes, depreciation, and amortization divided by interest expense (Worldscope).
$EB/Sales$	Earnings before interest, taxes, depreciation, and amortization (EBITDA) divided by sales (Worldscope).
Lev	Leverage measured as the sum of long- and short-term debt divided by total assets (Worldscope).
$Debt/EB$	The sum of long- and short-term debt divided by earnings before interest, taxes, depreciation, and amortization, and is set equal to zero if value is negative (Worldscope).
$NegDebt/EB$	An indicator variable equal to one if $Debt/EB < 0$, and zero otherwise (Worldscope).
$Cash$	Cash and short-term investments divided by total assets (Worldscope).
PPE	Net property, plant, and equipment divided by total assets (Worldscope).
$CAPEX$	Capital expenditures divided by total assets (Worldscope).
EA_Vol	The standard deviation of EBITDA over the prior five fiscal years; a minimum of two years required (Worldscope).

Appendix A (continued from previous page)

Variable	Definition and measurement
ROA	Earnings before interest, taxes, depreciation, and amortization divided by total assets (Worldscope).
$SovRatg$	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 $SovRatg$.
Additional variables	
P/B	Stock market performance measured as the ratio of market valuation to book-value of assets (Datastream and Worldscope).
$AbnRet_{i,t+\tau}$	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).

Appendix B - Ratings Prediction Model

We estimate the predicted rating ($RatingsPredict$) following Baghai, Servaes, and Tamayo (2014) using the following regression model:

$$\begin{aligned} Ratings_{i,t+\tau} = {} & \beta_0 + \beta_1 Size_{it} + \beta_2 IntCov_{it} + \beta_3 EB/Sales_{it} \\ & + \beta_4 Lev_{it} + \beta_5 Debt/EB_{it} + \beta_6 NegDebt/EB_{it} \\ & + \beta_7 Cash_{it} + \beta_8 PPE_{it} + \beta_9 CAPEX_{it} \\ & + \beta_{10} EA\_Vol_{it} + \beta_{11} ROA_{it} + f_i + \omega_{lt} + \lambda_{jt} + \varepsilon_{it} \end{aligned} \tag{3}$$

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 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

	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

***, **, and * denotes two-tailed statistical significance for 1%, 5%, and 10% respectively.

This table reports prediction model for credit ratings to general predicted ratings, as specified in equation 3. 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.

Table 1: Sample Selection

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

Table 2: Dates of Office Locations

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 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, Timothy J. "The New Masters of Capital: American Bond Rating Agencies and the Politics of Creditworthiness" (2005), which includes data for the older offices.

Table 3: Sample Distribution by Country

Country	S&P Total N	S&P % of Sample	S&P Observations after office opening	Moody's Total N	Moody's % of Sample	Moody's 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	24,458	-	74.50%	12,736	-	73.69%

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.

Table 4: Summary Statistics

	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 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.

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

	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

***, **, and * denotes two-tailed statistical significance for 1%, 5%, and 10% respectively.

Table 5 reports the effect of local office on the level of credit ratings assigned by S&P (Panel A) and Moody's (Panel B), as specified in equation 1. 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.

Table 6: The Effect of Local Presence on Rating Adjustments

	S&P				Moody's			
	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

***, **, and * denotes two-tailed statistical significance for 1%, 5%, and 10% respectively.

Table 6 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 6) 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.

Table 7: Cross-sectional Analyses of Credit Rating Changes

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

***, **, and * denotes two-tailed statistical significance for 1%, 5%, and 10% respectively.

Table 7 (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

***, **, and * denotes two-tailed statistical significance for 1%, 5%, and 10% respectively.

Table 7 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.

Table 8: Local Presence and Market Reactions to Rating Changes

	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

***, **, and * denotes two-tailed statistical significance for 1%, 5%, and 10% respectively.

Table 8 reports the results on market reaction to rating changes, as specified in equation 2. 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.

Table 9: Differences in Credit Rating when one Credit Rating Agency has a Local Presence

	(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

***, **, and * denotes two-tailed statistical significance for 1%, 5%, and 10% respectively.

Table 9 reports the effect of local office on the difference between the credit ratings assigned by S&P and Moody's, as specified in equation (2). 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.

Table 10: Balanced Sample: the Effect of Local Presence on the Level of Credit Ratings

	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

***, **, and * denotes two-tailed statistical significance for 1%, 5%, and 10% respectively.

Table 10 reports the effect of local office on the level of credit ratings assigned by S&P (Panel A) and Moody's (Panel B), as specified in equation 1 and 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.