Where the Heart Is: Information Production and the Home Bias[*]

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Information Production and the Home Bias

Abstract

We examine credit ratings produced by municipal bond analysts to shed new light on competing hypotheses in the home bias literature. Controlling for economic conditions, issuer fundamentals, issue characteristics, and analyst traits, we find that analysts who grew up in the state of the issuer award higher ratings than analysts who grew up in outside states. This effect is increasing in credit risk, lowers new issue credit spreads, and expands affected municipalities' debt capacity. Because this effect is driven by where analysts grew up, not by where they reside while producing ratings, we conclude that our results reflect favoritism rather than superior information. Tests of timeliness and direction in rating updates by home and outside analysts further support this conclusion. We also find that analysts' early life experiences influence the magnitude of the home bias. Overall, this paper shows that home bias can exist among information producers, not just investors, and has real economic effects.

"Where we love is home – home that our feet may leave, but not our hearts."

-- Oliver Wendell Holmes

We test whether a home bias on the part of credit analysts influences their information production and, if so, whether their preference reflects superior information or favoritism, and whether the bias affects issuer cost of capital. Assertions of home bias in credit ratings of sovereign issuers are now common. However, testing for home bias in sovereign credit ratings is challenging due to limited and murky cross-sectional variation in the home country of credit rating agencies and credit rating analysts.[1] We therefore take this question to the U.S. municipal bond market where there is wider cross-sectional variation from 50 states and it is possible to identify the home state of credit analysts rating municipal bonds (munis). Specifically, we obtain the first three digits of social security numbers (SSNs) for lead and secondary analysts identified in rating reports produced by Moody's and Standard & Poor's (S&P). These digits indicate the state where the number was issued. Prior to the Tax Reform Act of 1986, SSNs were typically assigned when a person got his or her first job or a driver's license—usually around the age of 15. We are therefore able to identify the place the analyst lived at this age, and we assume that this is where he or she grew up.[2] We refer to analysts who grew up in the state of the municipality whose debt they rate as "home analysts". We refer to analysts who grew up in other states as "outside analysts". Our baseline tests compare these two groups' ratings on the same bonds at the same time.

We find that 17% of the bonds in our sample have a home analyst from at least one rating agency. Our main finding is that home analysts consistently award ratings that are more issuer-friendly than outside analysts. This home analyst effect increases in issuer credit risk. We

[1] Cross-sectional variation is limited because the two biggest CRAs, Moody's Investor Service (Moody's) and Standard and Poor's (S&P), are both headquartered in the U.S. Together, these raters comprise approximately 80% of the ratings market. Fitch Ratings (Fitch) is the third largest rating agency in terms of market share. Fitch has majority French ownership, but has dual headquarters in the U.S. and London. Cross-sectional variation is murky because the headquarter country does not precisely describe the home affiliation of the raters. Moody's, S&P, and Fitch are international organizations, with offices, employees, and shareholders located around the globe.

[2] We adopt this approach from Pool, Stoffman, and Yonker (2012) and Yonker (2013). We explain the data collection procedure in more detail in Section 2.

decompose our sample, using outside analysts' ratings as benchmarks. Among bonds rated double A (single A) by outside analysts, we find that home analysts award ratings that are an average of 0.07 (0.20) notches higher. For bonds rated triple B by outside analysts, the rating inflation by home analysts averages 0.63 notches. Among bonds with speculative grade ratings from outside analysts, the rating inflation by home analysts averages 1.34 notches. These effects are statistically significant for each rating category and are economically significant. For context, Cornaggia, et al. (2015b) show that a one-notch upgrade reduces spreads on municipal bonds by 17 basis points. For robustness, we replicate our results redefining "home" as the state where the analyst earns his or her first college degree. The results are similar both in economic and statistical significance.

We find the home analyst effect exists both when ratings are initially assigned and when ratings are updated. However, the effect is stronger among the updates. We limit the sample to observations with rating changes and find that the home analyst effect averages 0.24 notches for single A and double A bonds, 1.12 notches for triple B, and 2.21 notches for the bonds with speculative grade ratings from outside analysts. Overall, the magnitude of the home analyst effect is large relative to other documented influences on rating agency information production.[3] For comparison, the modal disagreement between rating agencies is zero notches and disagreements greater than two notches are rare.

Our main tests include bond-month fixed effects. This specification is important because it dictates that our results can only be driven by differences in ratings produced by Moody's and S&P on the same bonds at the same time. This means alternative explanations based on time-varying economic conditions and/or time-varying bond or issuer characteristics cannot explain our findings. Potential alternative explanations for the home analyst effect must therefore derive from differences in analyst characteristics. However, our results are robust to controlling for a host of analyst characteristics, including the rating agency where he/she works (Moody's or

[3] For example, the competitive effect documented by Becker and Milbourn (2011) averages 0.19 notches and the revolving door effect documented by Cornaggia, et al. (2014) averages 0.23 notches.

S&P), education, age, gender, and tenure with respect to the rated issuer as well as the rating agency. Our results are even robust to controlling for analyst fixed effects that capture his/her general sense of optimism. Our results are further robust to varying the dimension along which we cluster standard errors including bond, issuer, issuer-year, state, or state-year.

A long-standing debate in the home bias literature is whether economic agents exhibit favoritism for geographically proximate entities because the agents are biased or because they have superior information.[4] We disentangle these hypotheses with several tests. First, if home analysts are better informed, then they should be 'first movers' in the event of a ratings update. However, Granger causality tests do not indicate that rating changes of home analysts lead similar changes by outside analysts. Further, if home analysts are unbiased, then they should exhibit similar propensities to upgrade or downgrade ratings as benchmark analysts. However, we observe that home analysts are significantly more likely to upgrade and significantly less likely to downgrade than their outside analyst counterparts. These results indicate that our main finding is not driven by home analysts' superior information.

Existing research that shows informational advantages are a function of geographic proximity; e.g., Coval and Moskowitz (2001), Malloy (2005), and Butler (2008). We conduct an additional test of favoritism (versus better information) based on this stylized fact. Moody's and S&P have offices scattered across the U.S. Therefore, analysts who work in the same states as the municipalities whose bonds they rate should have superior information over analysts who work in outside states. We introduce an indicator variable to our regressions that captures whether the analyst works in the same state as the issuer. The home analyst effect survives the addition of this variable. We find that analysts who work in the same state as the municipality whose bonds he/she rates produce higher (more favorable) credit ratings, but the magnitude of

[4] We review both sides of this literature in Section 1.1. In our setting, municipal bond analysts likely know more about the issuers in their home states than outside analysts. This information advantage could play a role in how analysts are assigned to issuers. However, our conversations with muni rating analysts indicate at least an informal CRA policy against assigning home analysts, presumably to mitigate any conflicts of interest. In any case, we design tests to determine whether the home analyst effect we document is driven by favoritism or superior information.

this effect is half the size of the home analyst effect (where home is defined by state of origin rather than by the state in which an analyst is employed).

To our knowledge, there is no empirical research on the *origins* of home bias. An advantage of our setting is that we can shed light on whether analysts' early life experiences influence the magnitude of the home bias. We construct variables based on prevailing cultural and economic conditions in the state during analysts' formative years. Specifically, we find that the bias is greatest among analysts who grew up in relatively poor states and states characterized in the psychology literature as having highly collective communities. However, we find no evidence that home bias is a function of the political environment in which the analyst grew up. We find significant bias of similar magnitudes among analysts raised in both red and blue states. Overall, these tests provide the first evidence that "nurture" plays a role in the pronouncement of home bias.

Finally, we test the extent to which the documented home bias affects taxpayers and bondholders. Specifically, we test whether the presence of a home credit analyst lowers the yields on municipal bonds and/or expands municipal debt capacity. We find a significant positive effect of a home analyst on new debt issuance. Controlling for issuer-year fixed effects, municipalities issue 0.75 more bonds per month, on average, after a home analyst begins rating the issuer's bonds.[5] Similar tests employing par values indicate municipalities raise more capital, mainly by issuing additional general obligation (GO) bonds. Tests of new issue yields and credit spreads indicate lower borrowing costs for affected municipalities. We observe that bond yields (and spreads) vary significantly with assigned ratings and that municipal bond investors (largely retail investors) do not adjust bond prices to correct the documented home bias. Overall, we conclude that affected municipalities enjoy real economic benefits from the presence of biased home analysts.

[5] These tests omit new bonds issued during the month when the home analyst appears in the data. This is because bonds receive initial credit ratings at issuance, so the time of issuance is a natural opportunity for a new (home) analyst to appear in the data. By applying this filter we prevent the results from arising mechanically. Indeed, the effect is stronger when we include these bonds.

This paper makes three main contributions. First, we employ the municipal bond market as a laboratory for studying home bias. This market provides a large and diverse cross-section of rated issuers and clean identification of "home". Second, because we can identify analysts' states of origin *and* the states in which analysts are employed, we have a unique opportunity to disentangle the competing hypotheses of favoritism and superior information. Third, we document a novel non-fundamental determinant of credit ratings and find that it has real effects for affected issuers.

1. Institutional Background and Literature Review

This paper connects three expanding literatures: economic effects of home bias, non-fundamental determinants of credit ratings, and municipal finance. We review these largely separate strands of literature in detail below, but first we motivate their intersection. In the wake of the recent financial crisis, the major credit rating agencies (CRAs) downgraded several sovereign issuers of debt, including the United States. Several finance ministers, in turn, charged the CRAs with home bias. Turkish Finance Minister Mehmet Şimşek states that "*Turkey would have attracted an additional $32 billion in portfolio and foreign direct investments if Turkey had been granted the rating it deserves.*"[6] Greek Foreign Minister Stavros Lambridinis suggests that downgrade by U.S. raters *"shows there may be some bias in the markets when it comes to the evaluation of specific issues of Europe."*[7] In the developed market, German Finance Minister Wolfgang Schabule suggests verification is needed *"… to check if there is abusive behavior"* by U.S.-based CRAs.[8]

Unfortunately, the industrial makeup of the ratings industry complicates empirical study of ratings bias among sovereign issuers. The first challenge is defining the home of the CRA. For example, Fuchs and Gehring (2013) and Dalsgaard, et al. (2014) identify Fitch Rating Company as U.S.-based although the firm was founded in France, is now dual-headquartered in London,

[6] "Unfair ratings by international agencies cost Turkey a fortune", Hurriyet Daily News, Ankara, Sept. 27, 2012.

[7] "Ratings agencies criticised by European Commission", BBC News, July 6, 2011.

[8] "EU moves towards partial gag on rating agencies", EUbusiness, Brussels, July 11, 2011

and retains majority French (FIMALAC) ownership. The second obstacle in sovereign ratings is identifying the home of the credit analysts responsible for producing the ratings. Major CRAs have offices in multiple countries and credit analysts may be domiciled in countries other than the country with CRA headquarters. The analyst may indeed be raised and/or domiciled in the country he/she rates. Third, the cross sectional variation in the "home" variable is quite limited, by definition, as is the sample of ratings updates. We overcome these challenges with a clean identification of home and wide cross-sectional variation in municipal bond ratings.

1.1 Home bias

Prior literature examining home bias in financial economics focuses almost exclusively on investor behavior, starting with early work by French and Poterba (1991) and Tesar and Werner (1995). Kang and Stulz (1997) and Coval and Moskowitz (1999) later introduce the alternative hypothesis that investor preference for home reflects an informational advantage rather than a behavioral bias. Supporting the information channel, Ivković and Weisbenner (2005) document positive excess returns to investing locally in smaller firms for which information asymmetries between local and nonlocal investors are greatest. However, a comparable analysis by Seasholes and Zhu (2010) finds no such advantage to local investing.

Many other studies indicate a familiarity bias, rather than an information advantage to local investing.[9] Cao, Han, Hirshleifer, and Zhang (2011) provide a model of familiarity bias that explains undiversified portfolios and find that equity prices reflect an unfamiliarity premium. Huberman (2001) finds that investors prefer the Regional Bell Operating Company (RBOC) that serves their local area to other RBOCs. Grinblatt and Keloharju (2001) find a cultural bias strongest among the least sophisticated investors. Bhattacharya and Groznik (2008) find a country-of-origin investment bias among foreign-origin persons living in the U.S. and Cohen

[9] Other papers examine other rational determinants of investor preference such as transaction costs, currency risk, and corporate governance; Bekaert and Wang (2009) review this literature.

(2009) documents significant overinvestment by employees in their employer's stock (resulting in a nearly 20% loss in retirement income).

Chan, Covrig, and Ng (2005) expand the home bias analysis to mutual fund managers and find evidence to support both rational and behavioral components of the bias. Pool, Stoffman, and Yonker (2012) find that fund managers overweight securities issued by firms in their home states. Because home-state investments do not outperform, their results suggest familiarity bias. Like Parwada (2008), their results are strongest for inexperienced (possibly less-sophisticated) fund managers.[10] Yonker (2013) expands the home bias analysis beyond investor behavior and examines bias in CEO decision-making. He finds that local CEOs are less likely to fire employees, and concludes that the favoritism is suboptimal. Our contribution to this strand of literature is evidence of a home bias among information intermediaries and a clean test of favoritism versus superior information. In contrast to the corporate bond and equity markets, where individual firms tend to have operations and customers in multiple states and countries, the geography of the muni market is concentrated and precisely defined.

1.2 Non-fundamental determinants of credit ratings

We also contribute to an expanding literature documenting factors exogenous to issuer credit quality that influence credit ratings. These non-fundamental determinants include changes in industrial organization (Becker and Milbourn, 2011; Flynn and Ghent, 2015), analyst career concerns (Cornaggia, et al., 2014), SEC certification (Kisgen and Strahan, 2010; Opp, et al., 2013; Behr, et al., 2014; Bruno, et al., 2014) and conflicts of interest inherent in CRA compensation structure.[11]

[10] Hong, et al. (2005) and Cohen, et al. (2008) also study fund managers, documenting the influence of education and social networks. Because this herding is not contained to local or home investments, these word-of-mouth effects are distinct from home bias. Hong and Kostovetsky (2012) find a behavioral bias of another flavor: mutual fund and hedge fund managers are driven by their political values.

[11] Regarding CRA compensation, see Sangiorgi, et al. (2009), Skreta and Veldkamp (2009), Jiang, et al. (2012), Strobl and Xia (2012), Bongaerts (2013), Xia (2014), Ghent, et al. (2014), and Cornaggia, et al. (2015a).

Models of CRA behavior predict subjectivity at the CRA level (Bar-Isaac and Shapiro, 2012; Bolton, et al., 2012; Manso, 2013) and empirical evidence indicates that CRA subjectivity reduces ratings quality (Griffin and Tang, 2012; He, et al., 2012; Cornaggia and Cornaggia, 2013; Griffin, et al., 2013).[12] In addition to subjectivity at the CRA level, Fracassi, et al. (2014) document significant subjectivity at the analyst level. These authors do not explore the source of bias, but find that it has real economic effects on corporate issuers. Cornaggia, et al. (2014) find one source of analyst-level bias stemming from the revolving door between the CRAs and rated firms. We document another specific source of analyst-level bias. Our contribution to this literature is evidence of subjectivity on the part of municipal bond rating analysts favoring their home states – which significantly impacts their home states' debt capacity and cost of capital.

1.3 Municipal finance

Finally, we contribute to municipal finance literature. Early work focuses primarily on muni tax exemption to test theories of debt and taxes and on solving the "muni puzzle"; e.g., Trzcinka (1982), Green (1993), and Chalmers (1998).[13] Despite the size of this market, additional empirical work has been limited by the relative lack of available data.[14] Lacking access to trade prices, Ingram, et al. (1983) employ offer yields as proxies. These authors discuss the relatively poor information environment of the muni market that makes CRAs important information intermediaries for muni investors. Unlike corporations regulated by the SEC, municipalities are not subject to reporting requirements. Cuny (2014) reports that nearly three in ten municipalities fail to file annual financial statements. This dearth of information is often compounded by corruption resulting in greater credit risk (Butler, et al., 2009) and additional costs to taxpayers (Ang, et al., 2014).

[12] In contrast to the evidence of ratings inflation among the more lucrative structured finance products, Alp (2013) and Baghai, et al. (2014) find a tightening of standards for corporate bonds.

[13] The stylized fact that muni yields appear too high relative to the after-tax yield on Treasury bonds is commonly referred to as the 'muni puzzle'.

[14] Federal Reserve 2014 Q1 Flow of Funds data indicate \$3.8 trillion float. Average daily trading volume in 2013 was \$11.2 billion according to SIFMA.

The lack of transparency in this market results in large transactions costs (Harris and Piwowar, 2006) and price segmentation (Green, et al., 2007).[15] Small investors pay more, although similarly-sized transactions also execute at different prices. Schultz (2012) finds that real time reporting required by the Municipal Securities Rulemaking Board (MSRB) in January 2005 reduces price dispersion, but not dealer markups. Indeed, the data indicate that dealers exploit local market power; Green, et al. (2010).

Improvements in price disclosure by the MSRB facilitate academic research and inform secondary markets.[16] However, there still exists relatively little non-price information (of variable quality) available in primary markets for municipal securities; Cornaggia, et al. (2015b). Perhaps it is not surprising that muni markets (dominated by retail investors) continue to rely on CRAs for information to price risk.[17] Our contribution to this strand of literature is evidence of a previously undocumented influence on municipal bond ratings – and thus on the information environment of this OTC market – and its impact on municipal debt capacity.

2. Data and Sample

We obtain credit ratings for uninsured munis from Moody's website and Standard and Poor's Ratings Direct for the 2000-2012 time period.[18] We translate these 21-point alphanumeric ratings into numeric scales increasing in credit quality, such that triple A ratings take the value of 21. We then identify 1,354 unique names of lead analysts from the analyst reports (571 from Moody's and 783 from S&P).[19] For each name, we collect information from LinkedIn.com and Intelius.com on analyst age, gender, job history and location, and educational history including undergraduate and graduate degrees, degree granting institutions, and the number of years

[15] Pirinsky and Wang (2009) study the segmentation resulting from asymmetric tax-exemption.

[16] Sirri (2014) describes secondary market trading and studies the impact of price transparency on trade pricing.

[17] In addition to the mechanistic reliance on CRAs documented by Cornaggia, et al. (2015b), Butler (2008) reports that unrated municipal bonds are difficult to place – particularly for non-local underwriters.

[18] Munis are more commonly wrapped with third party insurance than other securities in part to protect the tax-exempt cash flows (Nanda and Singh, 2004). Because market perception of insured bonds reflects the credit quality of the monolines, we focus on uninsured bonds in our empirical analyses.

[19] For the vast majority of ratings actions/reports, the secondary analysts fill the role of an additional contact and have less input in the report than lead analysts. We examine secondary analysts' influence later in the paper.

enrolled in each institution. If we cannot identify analyst age, we estimate age by subtracting 18 years from the first year the analyst attended college, or, if not available, 22 years from college graduation date.

Next, we manually identify the home state and (as verification) the age of each analyst using the LexisNexis Public Records database. Specifically, we search the LexisNexis database to obtain SSNs for the subset of credit rating analysts for whom we have demographic data. If we find multiple matches by name, we restrict the search to a four-year window around the age data obtained from LinkedIn. If this restriction does not identify a unique individual, we further filter search results to individuals with address histories in one of the states indicated on the job and education history from LinkedIn. Employing this series of steps, we identify 646 unique analysts of the 1,354 candidates; 247 are Moody's analysts and 399 are from S&P. We collect the first three digits of these 646 analysts' SSNs from the LexisNexis database. These digits indicate the state in which the SSN was obtained (the analysts' home states).[20] We are grateful to Scott Yonker for helping us gather and understand SSNs.

To analyze the impact of home analysts on municipality debt issuance and cost of debt, we obtain new issue characteristics from the Ipreo i-Deal database. Specifically, we collect the following data for new issues by municipalities rated by our sample of analysts over the sample period 2000-2012: issue size, offer yield, maturity date, coupon rate, bond type (GO or revenue), call features, and whether the new issue is negotiated or competitive, insured, and/or classified as a Build America Bond (BAB). We also obtain data indicating the number of other bonds outstanding for each issuer. We estimate credit spreads with Treasury bond yields, available from the U.S. Department of the Treasury.

3. Empirical Results

[20] Prior to 2011, the first three digits of SSNs were unique to specific states; http://www.socialsecurity.gov/employer/stateweb.htm.
Subsequent digits five through seven were issued sequentially (i.e., in order and increasing with time); http://www.socialsecurity.gov/employer/ssns/HGJune2411_final.txt.

3.1 Descriptive statistics

Figure 1 displays distributions of home states of lead muni rating analysts employed by Moody's and S&P. Distributions by states where analysts grew up are found in Panels A and B. We observe that high population states issuing more bonds, New York and California in particular, also produce the most lead muni analysts.[21] However, some large western cities, such as Seattle, Las Vegas, Denver, and Omaha, produce none in our sample. Distributions in panels C and D indicate where these credit analysts earned their first college degrees. These panels contain more observations than Panels A and B because we are better able to verify education records than social security numbers. Panels C and D indicate an even higher disproportion of analysts with ties to New York and Pennsylvania and greater representation by Texas, relative to California and other western states.

[Insert Figure 1]

Table 1 reports summary statistics. Panels A and B characterize credit analysts and credit ratings for 443,349 bond-month observations with matched analyst pairs employed in tests of home bias (reported in Tables 2 and 3). These tests require matched pairs of home and outside analysts rating the same bond at the same time.[22] According to our primary definition of "home", an analyst is a home (outside) analyst if he/she received his/her social security number in the same state as the issuer (a different state than the issuer). Panel A shows that 45% of bond-month observations have a home analyst from Moody's, implying that 55% of home analysts are employed by S&P.

Panel A (Panel B) summarizes the characteristics of, and the ratings produced by, home (outside) analysts in the matched-pair sample. Firstly, we note from the rating levels that the average rating produced by the home analysts is comparable to that produced by outside

[21] Our baseline results in Table 2 are robust if we exclude bonds issued by the states of, and municipalities within, New York, California, Texas, and Massachusetts.

[22] To the extent that a home bias affects credit ratings, bonds rated by only one CRA could have the greatest potential for bias to manifest. Bonds rated *only* by a home analysts lack any disciplinary effect provided by a benchmark analyst. Such bias is difficult to detect, however, without the benchmark for comparison.

analysts; these ratings are identical at the median, 10th, and 90th percentiles. This finding is important because it is inconsistent with a general conservatism on the part of the outside analysts, aware of an informational disadvantage vis-à-vis their home analyst counterparts.

Advanced degree is an indicator variable taking a value of one if the analyst has an advanced degree and zero if the analyst has a terminal bachelor's degree or lower education level. *Issuer tenure* measures the number of years an analyst has rated the issuer. *Agency tenure* is the number of years the analyst has worked at his/her employing CRA. *In-state rating* is an indicator variable taking a value of one if the analyst currently works in an office in the same state as the issuer whose bonds the analyst is rating and zero if the analyst works in a different state than the issuer. Most analysts in both panels have advanced degrees and over half (57% and 58%) are female. Their average age is similar (38 and 36 years at the median, respectively) and they have been employed by their respective CRAs an average 6.57 and 6.09 years, respectively. On average, analysts cover municipalities from their state of origin longer than municipalities from other states (3.24 years versus 2.44 years, respectively). Perhaps most interesting is the similarity between the panels in the proportion of analysts who reside currently (i.e. contemporaneous to the rating) in the state of issuance. Among home analysts in Panel A, 55% continue to reside in their home state. In Panel B, 54% of analysts currently work in the states they rate, though they grew up elsewhere. This finding is important because it is inconsistent with an informational advantage of home analysts based on proximity to the issuer.

[Insert Table 1]

In order to disentangle home-state favoritism from potentially superior information available to residents, we later employ a larger sample of analyst pairs including observations where both or neither analyst is from the state of issuance. These observations are excluded from baseline tests of home bias, as they contribute no variation in the key variable *Home analyst*, but are useful for additional tests of proximity effects (reported in Table 5). For example, an observation where both Moody's and S&P's analysts are from states other than the state of issuance adds no information to tests of home bias, but is useful in testing proximity if one of the analysts currently works in the same state as the issuer. Likewise, an observation where both Moody's and S&P employ home analysts may contribute variation in their current state of residence. Including each type of analyst pair (home-home, home-outside, outside-outside) allows us to test competing effects of favoritism and proximity advantage. Panel C of Table 1 displays the rating and analyst statistics for this set of analyst pairs (N = 6,329,304 bond-month-analyst observations).

Panel D characterizes our sample of 60,685 new muni issues employed in tests of real economic effects. Most (72%) new issues are general obligation (*GO*) bonds with an average maturity of 9.4 years. These are small issues, averaging $1.2 million par value and paying approximately 4.2% coupons. Roughly half are negotiated issues and 86% are callable. The average issuer in this sample has 5.8 other issues outstanding on the date of the new issuance. Most importantly for our tests, at least one CRA employs a lead rating analyst from the issuing state in 17% of 60,685 new issues; Moody's (S&P) employs a home analyst to rate 10% (11%) of these bonds. We report rating level statistics for both raters across the full sample of new issues, irrespective of analyst state of origin. S&P is more issuer-friendly in this sample; 0.4 notches higher on average and a full notch higher than Moody's at the median.

Offer yield is the raw offer yield on the bond, averaging 3.64%. We estimate *Spread to Treasury* as the difference between a bond's offer yield and the yield of the U.S. Treasury bond (T-bond) with the closest maturity on the day the muni was issued. Because T-bonds are taxable, spreads are negative on average and at the median. Our sample contains Build America Bonds (*BAB*), which are taxable, and we estimate after-tax spreads accordingly.[23] *After-tax spread to Treasury* is the difference between a bond's offer yield and the after-tax yield of the T-bond with the closest maturity, assuming a 35% marginal tax rate. If the bond is a *BAB*, then *After-tax*

[23] Cestau, et al., (2013) detail the BAB program; BABs were issued for 20 months as part of the 2009 fiscal package. Unlike traditional munis, BABs are taxable to the holder and the Treasury rebates 35% of the coupon to the issuer.

spread to Treasury is the difference between its after-tax offer yield (assuming a 35% rate) and the after-tax yield of the T-bond with the closest maturity.

3.2 Tests of home bias

Table 2 reports parameter estimates from OLS regressions testing the home bias hypothesis.[24] Results from model (1) are reported for the complete sample of 443,349 bond-month observations in column (1). By construction, each bond-month will have one home and one outside lead analyst, resulting in 886,698 bond-month-analyst observations. Column (2) reports results for model (1) for the subsample excluding triple A benchmarks and columns (3) through (6) report results after dividing the sample by benchmark rating categories.

$$\textit{Rating Level} = \alpha + \beta_1 \textit{ Home analyst} + \beta_2 \textit{ Moody's} + \beta_3 \textit{ Moody's} \times \textit{Post recalibration} + \text{bond-month fixed effects} \tag{1}$$

Rating level is the numeric translation of S&P and Moody's 21-point alphanumeric scales and is increasing in credit quality such that triple A ratings take the value 21. In Panel A, *Home analyst* is an indicator taking value of one (zero) if the bond was issued by a municipality in the lead rating analyst's home state (for the outside analyst who did not grow up in this state). The *Moody's* indicator takes that value of one (zero) for ratings from Moody's (S&P) and controls for systematic differences in ratings practices between the agencies. Issue characteristics, issuer fundamentals, and prevailing economic conditions should affect both home and outside analysts' ratings and thus bond-month fixed effects prevent these factors from affecting our results.

We interact the *Moody's* indicator with a *Post recalibration* indicator to control for the structural shift in Moody's municipal rating scale in April 2010. Moody's (2010) clarifies that this revision in rating scale was intended to enhance the comparability of ratings across asset classes; it did not indicate any change in fundamental credit quality of the rated municipalities. Cornaggia, et al. (2015b) report that this recalibration event resulted in a one-notch modal

[24] We use OLS instead of an ordered probit because our regressions include bond-month fixed effects. Ordered probit models are difficult to estimate when there are fixed effects and only a small number of observations within each group. In our case, because each bond-month has two observations, applying an ordered probit would be similar to fitting a traditional probit with two observations.

change-in-scale with a zero-to-four notch range. Coefficients on the control variables generally indicate that Moody's was the harsher CRA prior to its recalibration in 2010 after which it became the more issuer-favorable of the two agencies. However, both of these average effects are driven by the higher credit quality issuers and reverse in the lower quality issuers.

[Insert Table 2]

The results in column (1) indicate no home analyst effect in the full sample. However, 168,875 of these bond-month observations (337,750 bond-month-analyst observations) are associated with matched pairs of analysts for which the outside analyst rates the issue triple A. Because bonds rated triple A by outside analysts have no opportunity for observable rating inflation by home analysts, we exclude them in column (2) and a home analyst effect emerges. Among observations with the potential for a home bias effect to manifest, the average effect is 0.12 notches. The magnitude of this effect (equivalent to 12 of 100 ratings inflated by one notch) is statistically significant at 1%.[25] However, we observe that the effect is increasing in the credit risk of the issuer.

Higher credit quality issuers, for which the benefit of ratings inflation is relatively low, exhibit lower than average inflation (0.07 notches among the largest double A category) although the effect remains significant at 1%. Single A issuers exhibit roughly the average effect (0.20 notches). Bonds rated at the lower end of investment grade (triple B) by outside analysts exhibit an average 0.63 notch effect and those rated as junk by the outside analyst exhibit 1.34 notch inflation by the home analyst, on average. These results support the home bias hypothesis. Issuers at or near speculative grade face liquidity premiums in addition to increased credit risk premiums (Chen, et al., 2007; Ellul, et al., 2011). As such, the potential benefit of inflated ratings is greater for these issuers.

[25] We test (but do not tabulate) the robustness of this result to alternative standard error clusters. The home analyst effect remains significant at 5% (at 10%) when we cluster standard errors at the state or state-year level (at the issuer or issuer-year level) rather than clustering standard errors at the bond level as tabulated.

In untabulated results, we test whether the home analyst effect varies by where outside analysts grew up. On one hand, outside analysts might be neighborly and thus share home analysts' positive perspectives on states that border their own home state. In this case, outside analysts would award issuer-friendly ratings, and the home analyst effect would weaken. On the other hand, state rivalries could lead outside analysts to give low ratings to municipalities in the home analyst's state, thus driving up the home analyst effect. For example, Michigan and Ohio share a border but the two are bitter rivals.[26]

We test these competing hypotheses several ways. First, we restrict our baseline sample to observations where the outside analyst is from a state which shares a border with the home analyst's state. We revisit the regression in model (1) in Table 2 Panel A using this sample. We find the coefficient on *Home analyst* is 0.15 and is significant at 1%. This effect is similar in magnitude and significance to the result in Table 2 Panel A. Second, we restrict our baseline sample to observations where the outside analyst is from a state that does *not* share a border with home analyst's state. We repeat the regression in model (1) in Table 2 Panel A using this sample and find the coefficient on *Home analyst* is 0.11 and significant at 1%. Comparing these two coefficients, it appears the home analyst effect is slightly stronger if the outside analyst is from a neighboring state. This comparison would appear to give credence to the "state rivalry" hypothesis. However, when we pool the two subsamples and interact *Home analyst* with an indicator variable taking a value of one if the outside analyst is from a neighboring state (and zero if the outside analyst is from a hinterland state), the coefficient on the interaction term is economically and statistically insignificant. In short, it does not appear that the home analyst effect is related to where outside analysts grew up.

Motivated in part by the results of Cohen, et al. (2008), we revisit our baseline tests defining analysts' homes as the states in which they obtain their college degrees. We revisit

[26] Today, this rivalry is most fervent when the University of Michigan and the Ohio State University compete in college football. However, the rivalry runs much deeper, dating back to the "Toledo War" of 1835-1836, when the two states laid claim to the strip of land where the city of Toledo resides.

model (1) in Panel B, redefining *Home analyst* as an indicator taking value of one (zero) if the bond was issued by a municipality in the state where the lead rating analyst earned her first college degree (for the outside analyst who did not earn a college degree in this state). As seen in Figure 1, the sample of bonds for which we identify lead analyst education is larger than the sample for which we identify lead analyst states of origin. Results in Panel B are similar in magnitude and significance to those in Panel A. The average home analyst effect in column (2) is 0.14 notches, significant at 1%.[27] As in Panel A, the effect increases in credit risk, significant at 1% in each ratings category in columns (3) through (6).

We explore next whether the home analyst effect is manifested in initial ratings or through abnormal rating updates. Biased home analysts may award inflated ratings (relative to benchmark) to new issues, upgrade issues unexpectedly, or forbear when outside analysts downgrade. In Table 3 Panel A, we restrict the sample of bond-months to initial ratings. Panel B restricts the sample to bond-months exhibiting ratings changes by either the home or outside analyst, or both.

Table 3 employs model (1) defining "home" by analyst state of origin. In Panel A, results are consistent with those observed in Table 2, however the results are statistically weaker than before when split by rating categories in columns (2) through (4).[28] In contrast, the results in Panel B are stronger in every rating category. Among the sample of ratings changes, we observe a significant (at 1%) average home analyst effect of 0.34 notches in column (1). As before, the effect increases in credit risk. Bonds rated single or double A by outside analysts exhibit a home analyst bias of 0.24 notches – approximately one in four ratings inflated by one notch, on average. Among issues rated triple B by outside analysts, the effect is 1.12 notches on average. Among speculative grade munis, the average bias is 2.21 notches. Although the effect is

[27] The home analyst effect remains significant at 1% (at 10%) when we cluster standard errors at the state or state-year level (at the issuer or issuer-year level) rather than at the bond level as tabulated.

[28] No munis in our sample are *issued* with ratings below BBB/Baa. The bond-month observations below this level in Table 2 Panel B reflect subsequent downgrades.

significant (at 5%) in the full sample of initial ratings, we conclude that the bias is primarily manifested through home analyst forbearance in the face of deteriorating credit quality.

[Insert Table 3]

3.2.1 Are home analysts better informed?

Next, we consider potentially competing information effects. That is, home analysts may be better informed than analysts from outside the state. A common test of ratings quality is the accuracy ratio (Moody's, 2003). However, the infrequency of municipal defaults makes the accuracy ratio less useful for this purpose. We employ instead tests of ratings timeliness and direction of updating. If home analysts are better informed, then we should observe that they are first movers in subsequent rating actions (i.e., upgrades and downgrades). We test this conjecture with Granger causality regressions following Bruno, et al. (2014). However, we find that home analysts' upgrades and downgrades neither lead nor lag those of outside analysts.[29]

We also test for differences in directional updating. If home analysts ratings exhibit superior information, rather than favoritism, then with a large sample and long time series (such as ours), we should observe upgrade and downgrade propensities that are comparable to benchmark analysts. We find instead that home analysts are significantly more likely to upgrade (at 1%) and significantly less likely to downgrade (at 1%) than outside analysts, consistent with behavioral bias rather than superior information. These results are tabulated in Table 4. We test for potentially competing information effects in a multivariate setting in Table 5.

[Insert Table 4]

In Table 5, we include each type of analyst pair in the sample (home-home, home-outside, outside-outside), control for analyst fixed effects, and add a measure of analyst proximity to the issuer.[30] The *Home analyst* indicator is defined by analysts' state of origin as in Table 2. All other variables are defined in Table 1. We include analyst fixed effects in model (2)

[29] Tabulated results are available from the authors. We omit these insignificant coefficients to conserve space.

[30] Adding each type of analyst pair allows us to test competing effects of favoritism and proximity advantage (as explained in Section 3.1 above).

to control for variation in analysts' general sense of optimism and report the results in column (1).[31]

$$\textit{Rating Level} = \alpha + \beta_1\, \textit{Home analyst} + \beta_2\, \textit{Moody's} + \beta_3\, \textit{Moody's} \times \textit{Post recalibration} + \text{bond-month fixed effects} + \text{analyst fixed effects} \quad (2)$$

This addition to the baseline model (1) does not diminish the significance of the home analyst effect. The coefficient on *Home analyst* reported in column (1) remains positive, significant at 1%, and similar in magnitude to Table 2. Controlling for analyst fixed effects effectively compares ratings by the same analyst across issuers in different states. We conclude that home analysts are not only biased relative to benchmark analysts (Table 2) but also relative to themselves (in ratings of issuers from other states).

[Insert Table 5]

In lieu of analyst fixed effects, we control for observable analyst characteristics in models (3) and (4) and include an indicator variable identifying analysts residing in the state of issuance at the time of the rating (*In-state rating*). Model (4) also incorporates an interaction term in order to test the extent to which local residence amplifies or mitigates the home bias. We report results from models (3) and (4) in columns (2) and (3) of Table 5, respectively.

$$\begin{aligned}\textit{Rating Level} = \alpha &+ \beta_1\, \textit{Home analyst} + \beta_2\, \textit{In-state rating} + \beta_3\, \textit{Female} + \beta_4\, \textit{Advanced degree} \\ &+ \beta_5\, \textit{Age} + \beta_6\, \textit{Issuer tenure} + \beta_7\, \textit{Agency tenure} + \beta_8\, \textit{Moody's} \quad (3) \\ &+ \beta_9\, \textit{Moody's} \times \textit{Post recalibration} + \text{bond-month fixed effects}\end{aligned}$$

$$\begin{aligned}\textit{Rating Level} = \alpha &+ \beta_1\, \textit{Home analyst} + \beta_2\, \textit{In-state rating} + \beta_3\, \textit{Home analyst} \times \textit{In-state rating} \\ &+ \beta_4\, \textit{Female} + \beta_5\, \textit{Advanced degree} + \beta_6\, \textit{Age} + \beta_7\, \textit{Issuer tenure} + \beta_8\, \textit{Agency tenure} \quad (4) \\ &+ \beta_9\, \textit{Moody's} + \mathrm{B}_{10}\, \textit{Moody's} \times \textit{Post recalibration} + \text{bond-month fixed effects}\end{aligned}$$

In columns (2) and (3), we observe a significant (at 1%) positive coefficient on *In-state rating*. This variable identifies analysts residing in the state of issuance at the time of the rating and serves as our measure of analyst proximity. Prior evidence provided by Coval and

[31] We are motivated by the evidence from Fracassi, et al. (2014) indicating significant variation in analyst optimism.

Moskowitz (2001), Malloy (2005), and Butler (2008) indicate that proximate economic agents benefit from superior information relative to distant agents. As such, the significant coefficient on the *In-state rating* indicator suggests that superior information results in more favorable ratings, on average. This result is consistent with the notion that less informed analysts are more conservative.

More importantly for our primary hypothesis, the home bias effect is not diminished by the inclusion of the proximity variable. Controlling for information effects associated with proximity and a host of analyst characteristics, the coefficient on *Home analyst* remains positive, significant at 1%, and similar in magnitude to Table 2.[32] We conclude that the significant home bias is not merely driven by proximity and reflects favoritism on the part of home analysts.

3.2.2 Analysts' early life experiences

Next, we examine the potential influence of home analysts' early life experiences. We hypothesize that behavioral home bias depends in part on the type of community in which the analyst grew up. We rely on state-level measures of community available from the psychology literature. We also consider the economic and political environment prevalent in the state during the analysts' formative years. We revisit model (1), introducing new interaction terms to gauge cross-sectional variation in home bias and report the results in Table 6.

Vandello and Cohen (1999) create an eight-item index, ranking states in terms of collectivist versus individualist tendencies.[33] They find that collectivist tendencies are strongest in the Deep South and individualist tendencies are strongest in the Mountain West and Great Plains. The authors attribute the collective nature of the South to its "tragic" history as a defeated region, social structure resulting from planation farming (as opposed to independent farmers of

[32] We have no hypotheses regarding the age, experience, or gender of the analysts, but the data indicate the home analyst effect is stronger among female analysts and analysts with longer tenure with their employers. The effect appears weaker among analysts with advanced degrees and those covering bonds for a longer time period.

[33] The authors consider the percentage of people living alone, percentage of elderly people living alone, percentage of households with grandchildren living in them, divorce-to-marriage ratio, percentage of people with no religious affiliation, percentage of people voting libertarian, the ratio of people carpooling to work (scaled by people driving alone), and the percentage of self-employed workers.

the Great Plain states), and the church life that pervades southern culture (in contrast to the Northeast).[34] In stark contrast to the South, the West was the last remaining frontier of the U.S. and some parts remain largely uncultivated. Like the West, people of the Great Plains are characterized by self-reliance associated with sparse population, vast distances, and harsh unpredictable weather. An exception to the broad generalization of the West is the Southwest (New Mexico, Arizona, Nevada, and California) settled primarily by Mexican and Spanish populations in the 1840s -1860s. Utah is predicted and observed to be more individualistic than its Southwestern neighbors given the pervasive influence of Mormon culture (see footnote 28).

High collectivism is an indicator taking the value of one for home analysts growing up in states with above-median collectivism. The interaction term *Home analyst* × *High collectivism* reported in column (1) of Table 6 indicates that analysts from states ranking high on the "collectivism" index exhibit a significantly stronger home bias than analyst from states characterized by a high degree of individualism. In fact, this interaction term completely absorbs the direct effect of the *Home analyst*. We conclude that the home bias observed in Table 2 is driven entirely by analysts from "high collectivism" states.

[Insert Table 6]

Harrington and Gelfand (2014) create an index ranking states from "tight" (with many strongly enforced rules and little tolerance for deviance) to "loose" (with few strongly enforced rules and greater tolerance for deviance) with respect to social mores. Some states rank similarly on both this "tightness" index and the "collectivism" index; Mississippi, Louisiana, and South Carolina are both "tight" and "collective" (i.e., low numbers according to both indexes). However, many states rank very differently on one index than they do on the other. For example, Nebraska ranks #24 for "tightness" and #48 for "collectivism". Cornhuskers are marked by "individualism", but are still relatively "tight" with respect social mores. Conversely, Hawaii ranks #43 for "tightness" and #1 for "collectivism". Polynesians are the most collective group,

[34] The authors argue that the church as an institution promotes strong group ties through camps and other events.

but are very “loose” with respect to social mores. The interaction term in column (2) of Table 6 is insignificant. Although “collectivism” is highly significant in column (1), the relative “tightness” of the analysts’ home communities does not appear to affect future favoritism.

We use state-level income and GDP, per capita, to test for potential effects of the home economic environment. For each home analyst in our sample, we measure (in 2012 dollars) the average annual per capita income and per capita GDP in their home state from the year of their birth to twenty years later. According to the results of Vandello and Cohen (1999), poverty is a primary determinant of community “collectivism”. As such, we expect that the coefficients on the interaction term in columns (3) and (4) obtain the opposite sign as that in column (1). As predicted, we find that analysts who grew up in relatively poor states later exhibit a greater degree of home bias than those who grew up in relatively wealthy states. The coefficient on the interaction term *Home analyst* × *High per capita income* is significant at 1% and completely offsets the direct effect of *Home analyst* in column (3). Similar to column (1), we conclude that the home bias documented in Table 2 is driven by analysts from relatively poor states.

Finally, we consider the potential impact of the political environment prevailing during the analysts’ formative years in columns (5) through (7). Column (5) reports results from model (1) for the subset of home analysts that grew up in a *Red state* (where the majority of the population voted for a Republican candidate in at least half of the presidential elections from the year of their birth to twenty years later). Column (6) reports results from model (1) for the subset of home analysts that grew up in a blue state (where the majority of the population voted for a Democrat in at least half of the presidential elections from the year of their birth to twenty years later).[35] We observe a significant home bias in each group with magnitude similar to Table 2. The additional interaction term in the pooled regression reported in column (7) indicates no significant difference in the bias exhibited by home analysts who grew up in red and blue states.

[35] Red and blue states in column (7) do not sum to 100% of the sample in column (1) because some analysts grew up in swing states. Specifically, 46% (43%) of sample home analysts grew up in red (blue) states and 11% grew up in states not classified as either.

3.2.3 Secondary analyst influence

We consider the potential influence of secondary analysts in Table 7. Specifically, using our main sample of matched-pair bond-month observations employed in Table 2 column (2), we identify secondary analysts – supporting both lead analysts – as either home or outside analysts (using the methodology detailed in Section 2). We predict that the behavioral component to the home bias should be exacerbated in cases where home analysts are supported by secondary analysts who are from the same home state. The interaction term in column (1) of Table 7 confirms our prediction. The home bias documented in Table 2 (0.12 notches on average) is stronger by 0.22 notches when the secondary analyst supporting the home analyst is from the same home state. This difference is significant at 1%.

[Insert Table 7]

In column (2), we test the prediction that the difference between ratings produced by home analysts and benchmark analysts will be smaller in cases where the outside (benchmark) analyst is supported by a secondary analyst from the same state as the home analyst. The interaction term in column (2) confirms this prediction. The home bias in Table 2 (0.12 notches on average) is diminished by 0.08 notches when another home analyst serves as secondary to the outside analyst serving as the benchmark.

Overall, we conclude from Tables 2 through 7 that there exists a significant home bias among credit analysts rating municipal bonds that increases in the credit risk of issuers, manifests primarily in forbearance, increases in the "collectivism" of the home analysts' home states, and cannot be explained by a general sense of analyst optimism or superior information. In the next section, we test whether this analyst favoritism has real economic effects on their home states.

3.3 Real economic effects

We hypothesize that favorable ratings produced by biased home analysts reduce bond yields and expand municipal debt capacity. Table 8 reports results from OLS regressions with new issuance activity as dependent variables. Panel A reports results for the full sample of munis and Panel B reports results for GO bonds. We sum all issuance activity over six month windows prior to and following the arrival of a home analyst for each municipality. We drop the issuer-month during which a home analyst begins rating the issuer's bonds. (Not surprisingly, issuance activity jumps in the month a home analyst begins rating a municipality's bonds because new bond issues represent a natural opportunity for new analysts to appear in the data.) The dependent variable in model (5) is first measured as a monthly average issuance (i.e., the number of new bond issues in the six-month period, divided by six). We report the results in columns (1) through (3). In columns (4) through (6), *New issuance* is instead defined as the average monthly face value of new bond issues over the period (i.e., the total par value of new bond issues in the six-month period, divided by six).

$$\textit{New issuance} = \alpha + \beta_1 \textit{ Home analyst} + \text{issuer-year fixed effects} \tag{5}$$

The explanatory indicator variable in columns (1) and (4) turns on for the period after the arrival of at least one home analyst, from either or both raters. In columns (2) and (5), this explanatory variable takes the value of one if the S&P analyst is from the state of the issuer; columns (3) and (6) employ an indicator for home analysts at Moody's.

In the full sample of GO and revenue bonds included in Panel A, results indicate that municipalities issue significantly more bonds after the arrival of a home analyst in columns (1) through (3). However, results in columns (4) through (6) do not indicate a significant increase in total par value borrowed. Among the GO bonds in Panel B, the result in column (1) indicates a significant (at 5%) increase in GO bonds issued after the arrival of a home analyst. The result in column (4) further indicates a significant (at 10%) increase in total par value borrowed after the home analyst begins rating the bonds. However, the home analysts at S&P appear less influential than those at Moody's. Both results for home analysts at S&P are insignificant. The results for Moody's are significant at 1% in column (3) and at 5% in column (6).

Overall, results in Table 8 indicate that biased ratings from home analysts expand the debt capacity of affected municipalities, that the additional debt is more likely general obligation than revenue bonds, and that home analysts at Moody's are more influential than home analysts employed by S&P.

[Insert Table 8]

We consider next the impact of home analysts on the cost of municipal financing. Cornaggia, et al. (2015b) document a mechanistic reliance of muni investors on credit ratings for price-relevant information. As such, we expect to find a monotonically decreasing average yield (spread) as ratings levels increase. Of interest here is the question of whether the market observes the home analyst favoritism documented in Tables 2 through 7 and prices outside analysts' ratings differently. He, et al. (2012) document higher yields imposed on inflated ratings of mortgage-backed securities (MBS). The differences in our setting are twofold. First, municipal bond investors are largely retail investors whereas MBS investors are (presumably more sophisticated) institutional investors. Second, the conflict of interest in MBS ratings was at the CRA level and well recognized by regulators and in popular financial press. Conflicts at the analyst level are less well documented.[36] Ultimately, the extent to which muni investors observe and price the home analyst bias is an empirical question.

To answer this question, we specify OLS regression models with offer yields (or spreads) on new issues as dependent variables and credit ratings as explanatory variables. The dependent variable employed in models (6) and (7) is measured three ways in both panels of Table 9: *Offer yield* in column (1), *Spread to Treasury* in column (2), and *After-tax spread to Treasury* in column (3). Independent variables include dummy variables for each rating category. (The omitted group is bonds rated triple B or lower.) We interact each of these rating level indicators with a dummy variable taking the value of one if the muni is issued in the lead analyst's state of origin. We control for standard issue characteristics described in Table 1 Panel C and cluster

[36] To our knowledge, the only evidence of analyst-level conflicts of interest affecting credit ratings is reported recently by Cornaggia, et al. (2014).

standard errors at the issuer level. We suppress coefficients on control variables to conserve space. Given the differences in rating level distributions observed in Table 1 Panel C, we explore the price impact of each rater separately. We report results from model (6) in Panel A and results from model (7) in Panel B.

$$\begin{aligned}
\textit{Offer yield (or spread)} &= \alpha + \beta_1 (\textit{AAA}) + \beta_2 (\textit{AA+}) + \beta_3 (\textit{AA}) + \beta_4 (\textit{AA-}) + \beta_5 (\textit{A+}) \\
&+ \beta_6 (\textit{A}) + \beta_7 (\textit{A-}) + \beta_8 (\textit{AAA} \times \textit{S\&P home analyst}) + \beta_9 (\textit{AA+} \times \textit{S\&P home analyst}) \\
&+ \beta_{10} (\textit{AA} \times \textit{S\&P home analyst}) + \beta_{11} (\textit{AA-} \times \textit{S\&P home analyst}) + \beta_{12} \\
&(\textit{A+} \times \textit{S\&P home analyst}) + \beta_{13} (\textit{A} \times \textit{S\&P home analyst}) + \beta_{14} (\textit{A-} \times \textit{S\&P home analyst}) \\
&+ \textit{S\&P home analyst} + \textit{Moody's home analyst} + \text{bond controls} + \text{year fixed effects} \\
&+ \text{state of issuance fixed effects}
\end{aligned} \tag{6}$$

$$\begin{aligned}
\textit{Offer yield (or spread)} &= \alpha + \beta_1 (\textit{Aaa}) + \beta_2 (\textit{Aa1}) + \beta_3 (\textit{Aa2}) + \beta_4 (\textit{Aa3}) + \beta_5 (\textit{A1}) \\
&+ \beta_6 (\textit{A2}) + \beta_7 (\textit{A3}) + \beta_8 (\textit{Aaa} \times \textit{Moody's home analyst}) + \beta_9 (\textit{Aa1} \times \textit{Moody's home} \\
&\textit{analyst}) + \beta_{10} (\textit{Aa2} \times \textit{Moody's home analyst}) + \beta_{11} (\textit{Aa3} \times \textit{Moody's home analyst}) \\
&+ \beta_{12} (\textit{A1} \times \textit{Moody's home analyst}) + \beta_{13} (\textit{A2} \times \textit{Moody's home analyst}) + \beta_{14} \\
&(\textit{A3} \times \textit{Moody's home analyst}) + \textit{S\&P home analyst} + \textit{Moody's home analyst} \\
&+ \text{bond controls} + \text{year fixed effects} + \text{state of issuance fixed effects}
\end{aligned} \tag{7}$$

As expected, more favorable ratings are associated with lower yields. Relative to the benchmark rating category (bonds with triple B ratings and below), each higher rating category is associated with lower average offer yields (and spreads) in both panels. The differences are significant at 1% in all cases other than the level closest to the omitted benchmark (A- for S&P and A3 for Moody's). This significant reduction in average yields (spreads) is largely monotonic.

[Insert Table 9]

Next, we test the extent to which muni investors identify the home analyst favoritism and adjust yields accordingly. The difference in yields on like-rated bonds for which the rating is obtained from a home analyst versus an outside analyst is the sum of coefficients on the direct effect of the home analyst and the interaction term for the home analyst and the rating. We report F-tests for the significance of these summed regression coefficients in Panels A.2 and B.2. Both panels indicate insignificant differences in yields between bonds with inflated ratings from home analysts and like-rated bonds from outside analysts. The exception is the A+ rating category from S&P. Because muni investors do not penalize the documented ratings inflation, we conclude that affected municipalities enjoy lower costs of borrowing associated with the biased ratings awarded by home analysts.

4. Conclusion

We overcome identification challenges faced by prior studies of potential bias in sovereign credit ratings and document significant home bias among analysts rating municipal bonds. The home analyst bias is pervasive. We find that 17% of the issues in our sample are rated by at least one home analyst. Granger causality regressions and tests of directional updating do not indicate that home analysts act on superior information. Moreover, the home bias effect is robust to the inclusion of a control variable measuring analyst geographic proximity to the issuer. Overall, we conclude that our results reflect favoritism by home analysts.

The magnitude of the home bias increases in the credit risk of the issuer, but remains statistically significant across rating categories. Although the bias is significant in initial ratings, the magnitude is larger in ratings changes suggesting that our results primarily reflect home analyst forbearance when outside analysts downgrade. Additional tests indicate that the home bias is greatest among analysts who grew up in relatively poor states and states characterized in the psychology literature as highly collective in their communities. We find no difference in average bias among analysts raised in red or blue states.

Finally, we document real economic benefits (lower cost of debt and expanded debt capacity) of analyst favoritism toward their home states. Policy prescriptions are straight forward: regulators can note this additional conflict of interest in the credit rating process, require internal CRA controls to mitigate this effect, and require CRAs to disclose home analysts in rating reports.

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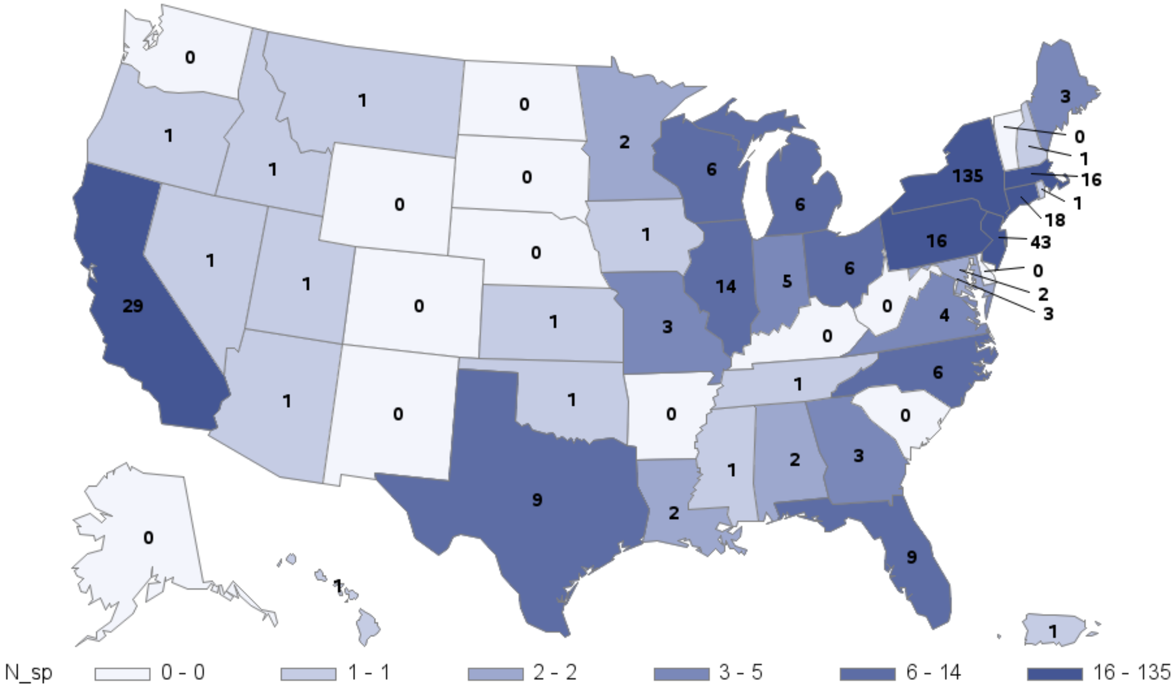
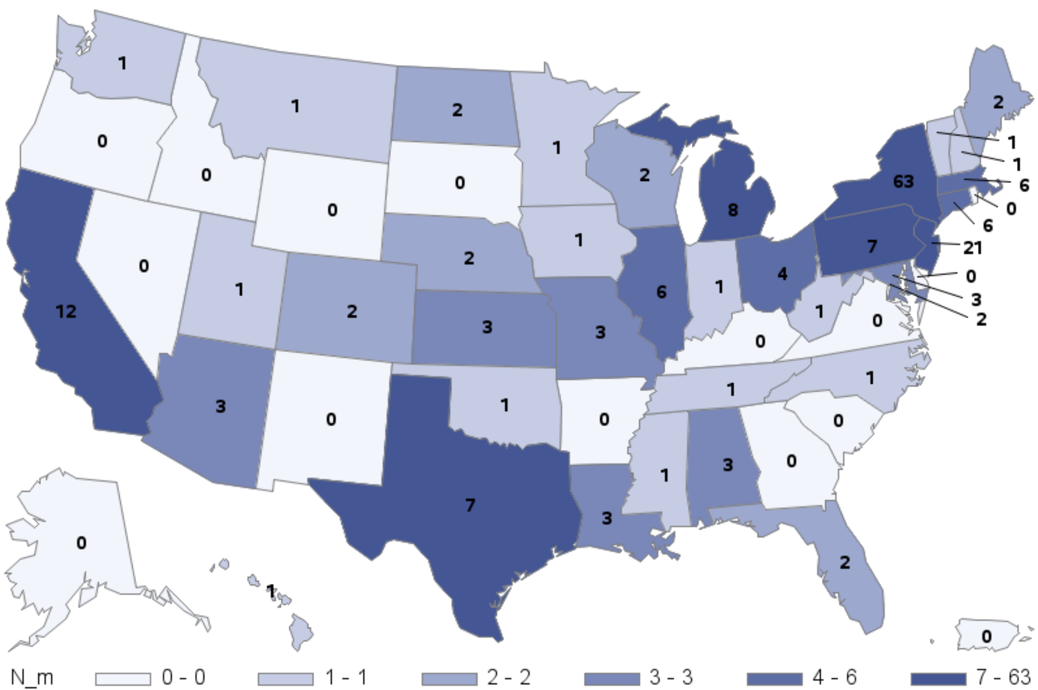
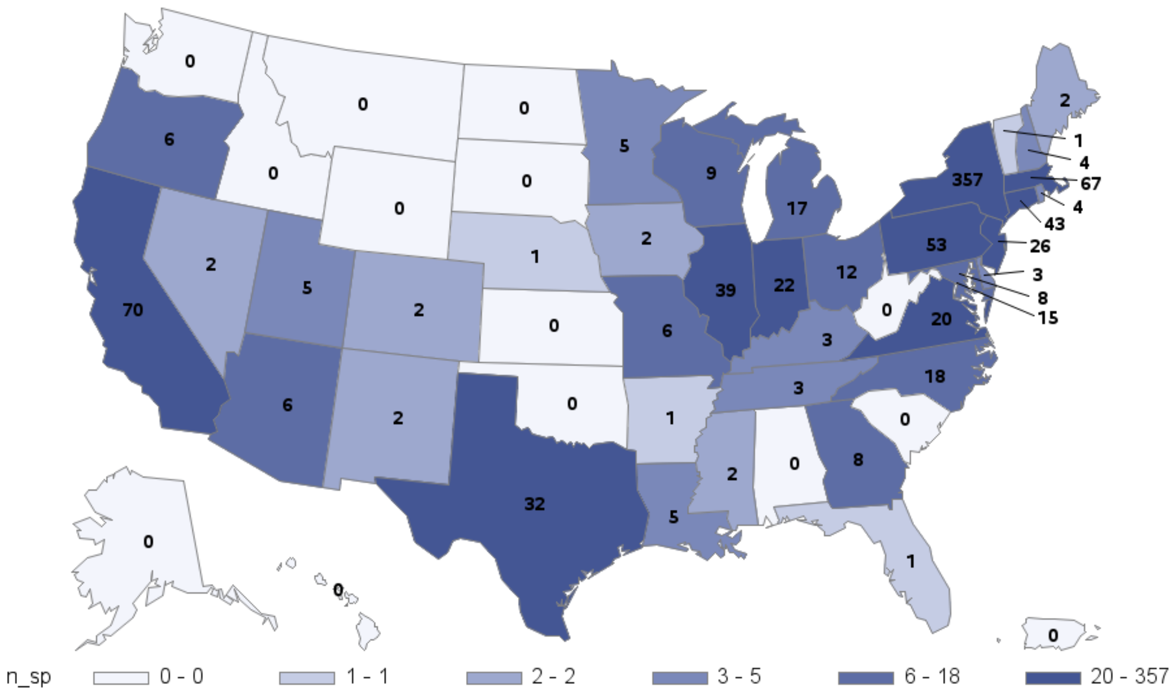


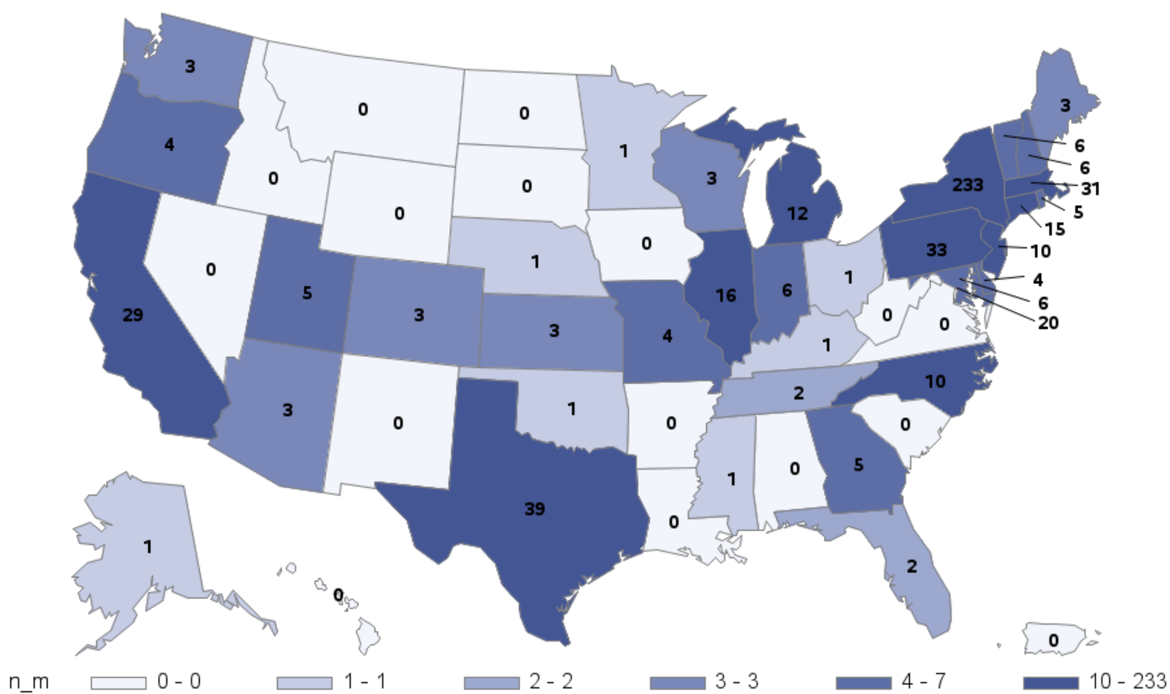
Panel A – Number of S&P Credit Analysts from Each State



Panel B – Number of Moody's Credit Analysts from Each State



Panel C – Number of S&P Credit Analysts' Degrees from Each State



Panel D – Number of Moody's Credit Analysts' Degrees from Each State

Figure 1. Distributions of home analysts. This figure displays counts of the number of analysts by their home states. Panels A and B define an analyst's home by where he/she received his/her social security number. Panels C and D define an analyst's home by where he/she earned his/her first college degree.

Table 1
Summary Statistics

Panels A and B of this table display summary statistics for observations in tests of whether there is a home bias in credit ratings. Panel A (Panel B) reports summary statistics for bond-month observations associated with home (outside) analysts. Each panel summarizes 443,349 bond-month-analyst observations. Panel C includes observations where analysts at both S&P and Moody's are home analysts, or both are outside analysts. Panel C summarizes 6,329,304 bond-month-analyst observations. An analyst is a home (outside) analyst if he/she received his/her social security number in the same state as the issuer (a different state than the issuer). *Rating level* is a numerical translation of S&P and Moody's 21-point alphanumeric scales. Ratings are increasing in credit quality, such that AAA or Aaa = 21, AA+ or Aa1 = 20, etc. *Moody's* is an indicator variable taking a value of one if the analyst works at Moody's and zero if the analyst works at S&P. *Female* is an indicator taking a value of one if the analyst's name is a traditionally female name and zero otherwise. *Advanced degree* is an indicator variable taking a value of one if the analyst has an advanced degree and zero if the analyst has a bachelor's degree or lower level of education. *Age* is the analyst's age in years, *Issuer tenure* is the number of years the analyst has provided ratings for the issuer. *Agency tenure* is the number of years the analyst has worked at his/her employing rating agency. We divide *Age*, *Issuer tenure*, and *Agency tenure* by ten in our regressions to ease interpretation of coefficients. *In-state rating* is an indicator variable taking a value of one if the analyst currently works in an office in the same state as the issuer whose bonds the analyst is rating and zero if the analyst works in a different state than the issuer. Panel D displays characteristics of 60,685 new municipal bond issues. *Offer yield* is the raw offer yield on the bond. *Spread to Treasury* is the difference between a bond's offer yield on the date of issue and the yield of the U.S. Treasury bond with the closest maturity on the same day. *After-tax spread to Treasury* is the difference between a bond's offer yield on the date of issue and the after-tax yield of the U.S. Treasury bond with the closest maturity on the same day. We assume a tax rate of 35%. If the bond is a Build America Bond, *After-tax spread to Treasury* is the difference between its after-tax offer yield (assuming a 35% marginal tax rate) and the after-tax yield of the U.S. Treasury bond with the closest maturity on the day of issuance. *S&P home analyst* is an indicator variable taking a value of one if the new issue is rated by a home analyst at S&P and zero if the new issue is rated by an S&P analyst born outside the issuer's state. *Moody's home analyst* is an indicator variable taking a value of one if the new issue is rated by a home analyst at Moody's and zero if the new issue is rated by a Moody's analyst born outside the issuer's state. *S&P rating level* (*Moody's rating level*) is a numerical translation of S&P's (Moody's) 21-point alphanumeric scale. Ratings are increasing in credit quality, such that AAA (Aaa) = 21, AA+ (Aa1) = 20, etc. *Par* is the bond's par value measured in millions of dollars. *Maturity* is the bond's maturity measured in years. *Coupon* is the bond's coupon expressed as a percentage. *Outstanding bonds* is the number of other bonds outstanding for the issuer at the time of issuance. *GO* is an indicator variable taking a value of one if the bond is a general obligation bond and zero if the bond is a revenue bond or other type. *BAB* is an indicator variable taking a value of one if the bond is a Build America Bond and zero if not. *Negotiated* is an indicator variable taking a value of one if the offering was negotiated and zero if it was competitive. *Callable* is an indicator taking a value of one if the bond is callable and zero if not.

Panel A: Observations for Home Analysts in Home Bias Tests

	Mean	SD	10th pct	Median	90th pct
Rating level	19.55 (≈AA+/Aa1)	1.62	18 (=AA-/Aa3)	20 (=AA+/Aa1)	21 (=AAA/Aaa)
Moody's	0.45	0.50	0	0	1
Female	0.57	0.50	0	1	1
Advanced degree	0.93	0.26	1	1	1
Age	39.8	8.16	30	38	53
Issuer tenure	3.24	2.74	0.33	2.42	7.50
Agency tenure	6.57	3.67	2.00	6.25	11.83
In-state rating	0.55	0.50	0	1	1

Panel B: Observations for Outside Analysts in Home Bias Tests

	Mean	SD	10th pct	Median	90th pct
Rating level	19.52 (≈AA+/Aa1)	1.68	18 (=AA-/Aa3)	20 (=AA+/Aa1)	21 (=AAA/Aaa)
Moody's	0.55	0.50	0	1	1
Female	0.58	0.49	0	1	1
Advanced degree	0.94	0.24	1	1	1
Age	38.63	9.45	30	36	50
Issuer tenure	2.44	2.43	0.25	1.58	5.83
Agency tenure	6.09	3.39	1.92	5.75	10.75
In-state rating	0.54	0.50	0	1	1

Panel C: Observations for Tests with Analyst FE or Analyst Characteristics

	Mean	SD	10th pct	Median	90th pct
Rating level	19.51 (≈AA+/Aa1)	1.55	18 (=AA-/Aa3)	20 (=AA+/Aa1)	21 (=AAA/Aaa)
Moody's	0.50	0.50	0	0	1
Female	0.50	0.50	0	0	1
Advanced degree	0.92	0.27	1	1	1
Age	40.29	9.94	30	38	53
Issuer tenure	2.80	2.52	0.33	2.00	6.42
Agency tenure	6.68	3.47	2.25	6.50	11.58
In-state rating	0.16	0.37	0	0	1

Panel D: Observations in Tests with Spreads as Dependent Variables

	Mean	SD	10^{th} pct	Median	90^{th} pct
Offer yield	3.6425	1.1167	2.0500	3.7900	4.9000
Spread to Treasury	-0.6498	0.9016	-1.6000	-0.7700	0.4900
After-tax spread to Treasury	0.7911	0.8626	-0.2320	0.7320	1.8270
Home analyst at either rater	0.17	0.38	0	0	1
S&P home analyst	0.11	0.31	0	0	1
Moody’s home analyst	0.10	0.30	0	0	0
S&P rating level	19.49	1.59	18	20	21
	(≈AA)		(=AA-)	(=AA+)	(=AAA)
Moody’s rating level	19.07	1.68	17	19	21
	(≈Aa2)		(=A1)	(=Aa2)	(=Aaa)
Par	1.2	1.0	0.2	1.0	2.7
Maturity	9.4	6.2	2	9	18
Coupon	4.20	0.97	3.00	4.25	5.10
Outstanding bonds	5.8	1.1	4.4	5.7	7.2
GO	0.72	0.45	0	1	1
BAB	0.04	0.20	0	0	0
Negotiated	0.50	0.50	0	1	1
Callable	0.86	0.35	0	1	1

Table 2
Home Bias Regressions
This table displays results from OLS regressions with *Rating level* as the dependent variable. *Rating level* is a numerical translation of S&P and Moody's 21-point alphanumeric scales. Ratings are increasing in credit quality, such that AAA or Aaa = 21, AA+ or Aa1 = 20, etc. *Home analyst* is an indicator variable taking a value of one if the bond was issued by a municipality in the analyst's home state. Panel A defines an analyst's home by where he/she received his/her social security number. Panel B defines an analyst's home by where he/she earned his/her first college degree. *Moody's* is an indicator variable taking a value of one if the analyst works at Moody's and zero if the analyst works at S&P. *Post recalibration* is an indicator variable taking a value of one if the bond-month observation occurs after April 2010, the month that Moody's recalibrated its municipal bond rating scale. Standard errors clustered by bond are in parentheses below coefficient estimates. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Panel A: Home Is the State Where an Analyst Received His/Her SSN

			Full sample split by ratings from outside analysts			
	Full sample	Exclude AAA/Aaa benchmarks	Speculative grade	BBB/Baa	A/A	AA/Aa
	(1)	(2)	(3)	(4)	(5)	(6)
Home analyst	-0.01	0.12	1.34	0.63	0.20	0.07
	(0.01)	(0.01)***	(0.10)***	(0.09)***	(0.03)***	(0.01)***
Moody's	-0.36	-0.38	0.08	0.01	-0.20	-0.44
	(0.01)***	(0.01)***	(0.10)	(0.14)	(0.04)***	(0.01)***
Moody's × Post recalibration	0.34	0.45	-0.32	-0.30	0.33	0.51
	(0.01)***	(0.01)***	(0.07)***	(0.14)**	(0.05)***	(0.01)***
Constant	19.67	18.77	10.79	12.99	16.26	19.30
	(0.01)***	(0.01)***	(0.02)***	(0.09)***	(0.02)***	(0.01)***
Bond-month FE?	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.93	0.91	0.78	0.70	0.68	0.74
N	886,698	548,948	1,602	12,084	63,620	471,642

Panel B: Home Is the State Where an Analyst Received His/Her First College Degree

	Full sample	Exclude AAA/Aaa benchmarks	Full sample split by ratings from outside analysts			
			Speculative grade	BBB/Baa	A/A	AA/Aa
	(1)	(2)	(3)	(4)	(5)	(6)
Home analyst	0.01	0.14	1.31	0.55	0.29	0.11
	(0.01)	(0.01)***	(0.13)***	(0.07)***	(0.04)***	(0.01)***
Moody's	-0.36	-0.40	0.11	-0.11	-0.16	-0.44
	(0.01)***	(0.01)***	(0.13)	(0.08)	(0.04)***	(0.01)***
Moody's × Post recalibration	0.45	0.63	-0.34	-0.21	0.68	0.66
	(0.01)***	(0.01)***	(0.10)***	(0.12)*	(0.06)***	(0.01)***
Constant	19.59	18.73	10.79	12.87	16.11	19.20
	(0.01)***	(0.01)***	(0.03)***	(0.04)***	(0.03)***	(0.01)***
Bond-month FE?	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.90	0.87	0.67	0.70	0.60	0.62
N	1,021,174	651,728	1,596	13,402	66,768	569,962

Table 3
Home Bias Regressions Using Only Initial Ratings or Rating Changes
This table displays results from OLS regressions with *Rating level* as the dependent variable. *Rating level* is a numerical translation of S&P and Moody's 21-point alphanumeric scales. Ratings are increasing in credit quality, such that AAA or Aaa = 21, AA+ or Aa1 = 20, etc. *Home analyst* is an indicator variable taking a value of one if the bond was issued by a municipality in the analyst's home state. We define an analyst's home by where he/she received his/her social security number. We exclude observations with AAA or Aaa ratings from outside analysts. *Moody's* is an indicator variable taking a value of one if the analyst works at Moody's and zero if the analyst works at S&P. *Post recalibration* is an indicator variable taking a value of one if the bond-month observation occurs after April 2010, the month that Moody's recalibrated its municipal bond rating scale. The regressions in Panel A use bond-month-analyst observations from the first month that a bond has ratings from both a home and outside analyst. The regressions in Panel B include bond-month-analyst observations where the home analyst or outside analyst (or both) changed his/her rating for the bond in the month. We cluster standard errors at the issuer level in Panel A and the bond level in Panel B. Standard errors are in parentheses below coefficient estimates. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Panel A: Initial Ratings

		Sample split by initial ratings from outside analysts		
		BBB/Baa	A/A	AA/Aa
	(1)	(2)	(3)	(4)
Home analyst	0.13	0.57	0.14	0.13
	(0.07)**	(0.18)***	(0.16)	(0.07)*
Moody's	-0.47	-0.47	-0.14	-0.53
	(0.09)***	(0.35)	(0.19)	(0.09)***
Moody's × Post recalibration	0.64	0.51	0.72	0.65
	(0.13)***	(0.39)	(0.41)*	(0.12)***
Constant	18.66	13.06	16.14	19.20
	(0.04)***	(0.16)***	(0.08)***	(0.05)***
Bond FE?	Yes	Yes	Yes	Yes
Adjusted R^2	0.87	0.78	0.58	0.62
N	29,666	552	4,186	24,928

Panel B: Rating Changes

		Sample split by ratings from outside analysts			
		Speculative grade	BBB/Baa	A/A	AA/Aa
	(1)	(3)	(4)	(5)	(6)
Home analyst	0.34	2.21	1.12	0.24	0.24
	(0.03)***	(0.18)***	(0.16)***	(0.07)***	(0.02)***
Moody's	-0.09	-0.88	1.87	0.17	-0.29
	(0.03)***	(0.18)***	(0.29)***	(0.07)**	(0.03)***
Moody's × Post recalibration	-0.07		-2.36	-0.89	0.46
	(0.06)		(0.35)***	(0.07)***	(0.06)***
Constant	18.43	11.07	13.42	16.80	19.26
	(0.03)***	(0.01)***	(0.08)***	(0.07)***	(0.02)***
Bond FE?	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.86	0.76	0.44	0.69	0.53
N	16,420	174	459	3,455	12,332

Table 4
Directional Updating

This table displays results from tests of whether rating changes by home and outside analysts exhibit equal likelihoods of being upgrades or downgrades. We start with the sample of 443,349 bond-months with ratings from home analysts and outside analysts summarized in Panels A and B of Table 1. We drop observations that occur in 2010 and later years, as well as bond-months where the outside analyst awards AAA or Aaa. We compute the probability that home and outside analysts issue upgrades or downgrades in the bond-months, and test for differences between the two groups. Standard errors appear in parentheses below differences. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

	N bond-months	% of bond-months that contain upgrades	% of bond-months that contain downgrades
Home analyst	161,583	1.32	1.38
Outside analyst	161,583	1.03	2.02
Difference		0.30	-0.64
		(0.0260)***	(0.0145)***

Table 5
Home Bias Regressions with Analyst Fixed Effects or Analyst Controls
This table displays results from OLS regressions with *Rating level* as the dependent variable. *Rating level* is a numerical translation of S&P and Moody's 21-point alphanumeric scales. Ratings are increasing in credit quality, such that AAA or Aaa = 21, AA+ or Aa1 = 20, etc. *Home analyst* is an indicator variable taking a value of one if the bond was issued by a municipality in the analyst's home state. We define an analyst's home by where he/she received his/her social security number. *Moody's* is an indicator variable taking a value of one if the analyst works at Moody's and zero if the analyst works at S&P. *Post recalibration* is an indicator variable taking a value of one if the bond-month observation occurs after April 2010, the month that Moody's recalibrated its municipal bond rating scale. We define the analyst control variables in the legend of Table 1. We cluster standard errors at the bond level. Standard errors are in parentheses below coefficient estimates. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)
Home analyst	0.11	0.13	0.11
	(0.01)***	(0.01)***	(0.01)***
In-state rating		0.06	0.05
		(0.01)***	(0.02)***
Home analyst × In-state rating			0.03
			(0.02)
Female		0.02	0.02
		(0.00)***	(0.00)***
Advanced degree		-0.08	-0.08
		(0.01)***	(0.01)***
Age		-0.01	-0.01
		(0.00)***	(0.00)***
Issuer tenure		-0.06	-0.07
		(0.01)***	(0.01)***
Agency tenure		0.15	0.15
		(0.01)***	(0.01)***
Moody's	-0.19	-0.26	-0.25
	(0.01)***	(0.00)***	(0.00)***
Moody's × Post recalibration	0.44	0.38	0.38
	(0.00)***	(0.00)***	(0.00)***
Constant	19.39	19.59	19.59
	(0.04)***	(0.01)***	(0.01)***
Analyst FE?	Yes	No	No
Bond-month FE?	Yes	Yes	Yes
Adjusted R^2	0.93	0.91	0.91
N	6,329,304	6,329,304	6,329,304

Table 6
The Influence of Home Analysts' Early Life Experiences

This table displays results from OLS regressions with *Rating level* as the dependent variable. *Rating level* is a numerical translation of S&P and Moody's 21-point alphanumeric scales. Ratings are increasing in credit quality, such that AAA or Aaa = 21, AA+ or Aa1 = 20, etc. *Home analyst* is an indicator variable taking a value of one if the bond was issued by a municipality in the analyst's home state. We define an analyst's home by where he/she received his/her social security number. *High per capita income* (*High per capita GDP*) is an indicator variable taking a value of one if a home analyst grew up in a state with per capita income (per capita GDP) above the sample median. For each home analyst, we measure in 2012 dollars the average annual per capita income (per capita GDP) from the year of their birth to twenty years later. *High tightness* is an indicator variable taking a value of one if a home analyst grew up in a state with an above-median tightness score according to the tightness-looseness rankings in Harrington and Gelfand (2014). *High collectivism* is an indicator variable taking a value of one if a home analyst grew up in a state with above-median collectivism according to the collectivism index in Vandello and Cohen (1999). Columns (5) and (6) split the sample by whether a home analyst grew up in a red state or a blue state. *Red state* is an indicator variable taking a value of one (zero) if a home analyst grew up in a state where the majority of the population voted for a Republican (Democratic) candidate in at least half of the presidential elections from the year of their birth to twenty years later. We exclude the election if the largest percentage of the state's population voted for an independent candidate. We collect state-level vote outcomes on presidential elections from http://www.270towin.com/states/. *Moody's* is an indicator variable taking a value of one if the analyst works at Moody's and zero if the analyst works at S&P. *Post recalibration* is an indicator variable taking a value of one if the bond-month observation occurs after April 2010, the month that Moody's recalibrated its municipal bond rating scale. We cluster standard errors at the bond level. Standard errors are in parentheses below coefficient estimates. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

					Home analyst grew up in red state	Home analyst grew up in blue state	Pooled
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Home analyst × High collectivism	0.19 (0.02)***						
Home analyst × High tightness		0.00 (0.02)					
Home analyst × High per capita income			-0.19 (0.02)***				
Home analyst × High per capita GDP				-0.05 (0.02)***			
Home analyst × Red state							-0.01 (0.02)
Home analyst	-0.01 (0.01)	0.12 (0.01)***	0.20 (0.01)***	0.13 (0.01)***	0.12 (0.01)***	0.14 (0.02)***	0.14 (0.02)***
Moody's	-0.43 (0.01)***	-0.43 (0.01)***	-0.38 (0.01)***	-0.38 (0.01)***	-0.36 (0.02)***	-0.35 (0.02)***	-0.36 (0.01)***
Moody's × Post recalibration	0.59 (0.01)***	0.58 (0.01)***	0.47 (0.01)***	0.45 (0.02)***	0.39 (0.02)***	0.49 (0.02)***	0.44 (0.02)***
Constant	18.82 (0.01)***	18.82 (0.01)***	18.74 (0.01)***	18.94 (0.01)***	18.92 (0.01)***	18.66 (0.01)***	18.72 (0.02)***
Bond-month FE?	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.92	0.91	0.91	0.91	0.92	0.89	0.90
N	548,948	548,948	548,948	438,222	249,856	208,442	458,298

Table 7
The Influence of Secondary Analysts

This table displays results from OLS regressions with *Rating level* as the dependent variable. *Rating level* is a numerical translation of S&P and Moody's 21-point alphanumeric scales. Ratings are increasing in credit quality, such that AAA or Aaa = 21, AA+ or Aa1 = 20, etc. *Home analyst* is an indicator variable taking a value of one if the bond was issued by a municipality in the lead analyst's home state. We define an analyst's home by where he/she received his/her social security number. *Home analyst's secondary analyst is home* is an indicator variable taking a value of one if the bond was issued by a municipality in the home state of the secondary analyst working under the home analyst. This variable takes a value of zero if the secondary analyst working under the home analyst grew up in an outside state. *Outside analyst's secondary analyst is home* is an indicator variable taking a value of one if the bond was issued by a municipality in the home state of the secondary analyst working under the outside analyst. This variable takes a value of zero if the secondary analyst working under the outside analyst grew up in an outside state. *Moody's* is an indicator variable taking a value of one if the analyst works at Moody's and zero if the analyst works at S&P. *Post recalibration* is an indicator variable taking a value of one if the bond-month observation occurs after April 2010, the month that Moody's recalibrated its municipal bond rating scale. We cluster standard errors at the bond level. Standard errors are in parentheses below coefficient estimates. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)
Home analyst × Home analyst's secondary analyst is home	0.22	
	(0.02)***	
Home analyst × Outside analyst's secondary analyst is home		-0.08
		(0.03)***
Home analyst	0.04	0.13
	(0.01)***	(0.01)***
Moody's	-0.34	-0.39
	(0.01)***	(0.01)***
Moody's × Post recalibration	0.42	0.45
	(0.01)***	(0.01)***
Constant	18.80	18.78
	(0.01)***	(0.01)***
Bond-month FE?	Yes	Yes
Adjusted R^2	0.91	0.91
N	548,948	548,948

Table 8
Home Analysts and New Bond Issues
This table displays results from OLS regressions with measures of new issuance activity as dependent variables. Panel A reports results for all new bond issues. Panel B reports results for new general obligation issues, only. Columns (1) through (3) use the average number of new issues per month and columns (4) through (6) use the average par value of new issues per month. For each instance a home analyst begins rating an issuer's bonds, we compute the monthly average of new bond issues in the six-month period before the home analyst's arrival and, separately, the monthly average of new bond issues in the six-month period after the home analyst's arrival. Therefore, the arrival of a home analyst is associated with two observations per issuer. We exclude new issues that occur during the month the home analyst begins rating the issuer's bonds. *Home analyst at either rater* is an indicator variable taking a value of one in the six-month period after a home analyst at S&P or Moody's begins rating the issuer's bonds, and zero in the six-month period before. *Home analyst at S&P* (*Moody's*) is an indicator variable taking a value of one in the six month period after a home analyst at S&P (Moody's) begins rating the issuer's bonds, and zero in the six month period before. Standard errors are in parentheses below coefficient estimates. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Panel A: All Bond Issues

	(1)	(2)	(3)	(4)	(5)	(6)
Home analyst at either rater	0.75			37.4		
	(0.30)**			(104.4)		
Home analyst at S&P		0.84			-24.2	
		(0.33)**			(107.8)	
Home analyst at Moody's			0.98			84.1
			(0.47)**			(162.5)
Constant	1.58	1.28	2.11	321.9	231.8	514.1
	(0.21)***	(0.23)***	(0.33)***	(73.8)***	(76.2)***	(114.9)***
Issuer-year FE?	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.37	0.23	0.52	0.48	0.07	0.66
N	382	262	182	382	262	182

Panel B: General Obligation Bond Issues

	(1)	(2)	(3)	(4)	(5)	(6)
Home analyst at either rater	0.52			62.7		
	(0.21)**			(36.2)*		
Home analyst at S&P		0.35			8.0	
		(0.28)			(37.8)	
Home analyst at Moody's			1.15			126.8
			(0.28)***			(63.4)**
Constant	0.85	0.90	0.80	112.6	72.5	168.1
	(0.15)***	(0.28)***	(0.19)***	(25.6)***	(26.7)***	(44.9)***
Issuer-year FE?	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.48	0.01	0.72	0.88	0.00	0.91
N	382	262	182	382	262	182

Table 9
Home Analysts and Yields and Spreads on New Bond Issues

This table displays results from OLS regressions with offer yields and spreads on new issues as dependent variables. The dependent variable in column (1) is *Offer yield*, the bond's raw offer yield. The dependent variable in column (2) is *Spread to Treasury*, the difference between a bond's offer yield on the date of issue and the yield of the U.S. Treasury bond with the closest maturity on the same day. The dependent variable in column (3) is *After-tax spread to Treasury*, the difference between a bond's offer yield on the date of issue and the after-tax yield of the U.S. Treasury bond with the closest maturity on the same day. We assume a tax rate of 35%. If the bond is a Build America Bond, *After-tax spread to Treasury* is the difference between its after-tax offer yield (assuming a 35% marginal tax rate) and the after-tax yield of the U.S. Treasury bond with the closest maturity on the day of issuance. The independent variables in Panel A include indicator variables for S&P's ratings assigned to new issues. The independent variables in Panel B include indicator variables for Moody's ratings assigned to new issues. Panels A.2 and B.2 display results from F-tests of whether the sums of regression coefficients in Panels A and B, respectively, are significantly different from zero. F-test statistics appear below summed values in parentheses. *S&P home analyst* is an indicator variable taking a value of one if the new issue is rated by a home analyst at S&P and zero if the new issue is rated by an S&P analyst born outside the issuer's state. *Moody's home analyst* is an indicator variable taking a value of one if the new issue is rated by a home analyst at Moody's and zero if the new issue is rated by a Moody's analyst born outside the issuer's state. We define the bond control variables in the legend of Table 1. We cluster standard errors at the issuer level. Standard errors are in parentheses below coefficient estimates. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Panel A: S&P Home Analysts and Offer Yields and Spreads

	(1)	(2)	(3)
AAA	-0.7510	-0.9226	-0.8649
	(0.1219)***	(0.1741)***	(0.1554)***
AA+	-0.7070	-0.9012	-0.8448
	(0.1211)***	(0.1742)***	(0.1553)***
AA	-0.6073	-0.7534	-0.7126
	(0.1205)***	(0.1729)***	(0.1543)***
AA-	-0.4843	-0.6184	-0.5850
	(0.1212)***	(0.1746)***	(0.1551)***
A+	-0.4887	-0.6075	-0.5861
	(0.1321)***	(0.1819)***	(0.1626)***
A	-0.3488	-0.4866	-0.4552
	(0.1309)***	(0.1854)***	(0.1663)***
A-	-0.0935	-0.2999	-0.2288
	(0.1311)	(0.1979)	(0.1733)
S&P home analyst	-0.2066	-0.4529	-0.3701
	(0.1566)	(0.1905)**	(0.1747)**
Moody’s home analyst	-0.0339	-0.0312	-0.0286
	(0.0387)	(0.0453)	(0.0410)
AAA × S&P home analyst	0.1800	0.4090	0.3326
	(0.1709)	(0.2036)**	(0.1862)*
AA+ × S&P home analyst	0.1863	0.4224	0.3546
	(0.1644)	(0.1996)**	(0.1807)*
AA × S&P home analyst	0.2417	0.5108	0.4194
	(0.1653)	(0.2003)**	(0.1831)**
AA- × S&P home analyst	0.1577	0.3130	0.2740
	(0.1926)	(0.2136)	(0.1991)
A+ × S&P home analyst	0.6886	0.8293	0.7718
	(0.2275)***	(0.2755)***	(0.2639)***
A × S&P home analyst	0.3568	0.4817	0.4507
	(0.1792)**	(0.2096)**	(0.1949)**
A- × S&P home analyst	0.3995	0.5228	0.4834
	(0.1925)**	(0.3005)*	(0.2556)*
Constant	2.1185	-0.8447	0.2684
	(0.1736)***	(0.1986)***	(0.1837)
Bond controls?	Yes	Yes	Yes
State FE?	Yes	Yes	Yes
Year FE?	Yes	Yes	Yes
Adjusted R^2	0.70	0.49	0.59
N	60,685	60,685	60,685

Panel A.2: F-tests of Summed Regression Coefficients

	(1)	(2)	(3)
AAA × S&P home analyst + S&P home analyst	-0.0266	-0.0439	-0.0375
	(0.14)	(0.28)	(0.26)
AA+ × S&P home analyst + S&P home analyst	-0.0203	-0.0305	-0.0155
	(0.12)	(0.17)	(0.07)
AA × S&P home analyst + S&P home analyst	0.0351	0.0579	0.0493
	(0.35)	(0.62)	(0.59)
AA- × S&P home analyst + S&P home analyst	-0.0489	-0.1399	-0.0961
	(0.18)	(1.80)	(0.90)
A+ × S&P home analyst + S&P home analyst	0.4820	0.3764	0.4017
	(8.77)***	(3.41)*	(4.01)**
A × S&P home analyst + S&P home analyst	0.1502	0.0288	0.0806
	(2.86)*	(0.08)	(0.71)
A- × S&P home analyst + S&P home analyst	0.1929	0.0699	0.1133
	(2.34)	(0.08)	(0.33)

Panel B: Moody's Home Analysts and Offer Yields and Spreads

	(1)	(2)	(3)
Aaa	-0.7591	-0.8602	-0.8230
	(0.1057)***	(0.1589)***	(0.1398)***
Aa1	-0.7357	-0.8406	-0.8056
	(0.1057)***	(0.1594)***	(0.1401)***
Aa2	-0.6911	-0.7628	-0.7441
	(0.1051)***	(0.1583)***	(0.1394)***
Aa3	-0.6031	-0.6852	-0.6656
	(0.1029)***	(0.1567)***	(0.1375)***
A1	-0.3937	-0.4616	-0.4451
	(0.1118)***	(0.1591)***	(0.1413)***
A2	-0.4545	-0.5492	-0.5318
	(0.1195)***	(0.1734)***	(0.1539)***
A3	-0.2886	-0.2603	-0.2626
	(0.1637)*	(0.1901)	(0.1748)
Moody's home analyst	0.0292	0.0576	0.0570
	(0.1856)	(0.2871)	(0.2488)
S&P home analyst	-0.0022	-0.0319	-0.0178
	(0.0384)	(0.0469)	(0.0404)
Aaa × Moody's home analyst	-0.0455	-0.0245	-0.0416
	(0.2058)	(0.3011)	(0.2642)
Aa1 × Moody's home analyst	0.0434	0.0557	0.0346
	(0.1942)	(0.2929)	(0.2547)
Aa2 × Moody's home analyst	-0.0887	-0.1783	-0.1427
	(0.1996)	(0.2983)	(0.2598)
Aa3 × Moody's home analyst	-0.0928	-0.0999	-0.1026
	(0.1918)	(0.2935)	(0.2543)
A1 × Moody's home analyst	-0.0718	-0.1136	-0.1011
	(0.2064)	(0.3023)	(0.2636)
A2 × Moody's home analyst	0.1259	0.0406	0.0702
	(0.2189)	(0.3067)	(0.2707)
A3 × Moody's home analyst	-0.2789	-0.3937	-0.3783
	(0.2599)	(0.3314)	(0.2972)
Constant	2.1865	-0.8710	0.2717
	(0.1594)***	(0.1804)***	(0.1653)
Bond controls?	Yes	Yes	Yes
State FE?	Yes	Yes	Yes
Year FE?	Yes	Yes	Yes
Adjusted R^2	0.70	0.49	0.59
N	60,685	60,685	60,685

Panel B.2: F-tests of Summed Regression Coefficients

	(1)	(2)	(3)
Aaa × Moody's home analyst + Moody's home analyst	-0.0163	0.0331	0.0154
	(0.04)	(0.14)	(0.03)
Aa1 × Moody's home analyst + Moody's home analyst	0.0726	0.1133	0.0916
	(1.64)	(3.07)*	(2.51)
Aa2 × Moody's home analyst + Moody's home analyst	-0.0595	-0.1207	-0.0857
	(0.55)	(1.57)	(0.99)
Aa3 × Moody's home analyst + Moody's home analyst	-0.0636	-0.0423	-0.0456
	(1.07)	(0.34)	(0.49)
A1 × Moody's home analyst + Moody's home analyst	-0.0426	-0.056	-0.0441
	(0.23)	(0.29)	(0.23)
A2 × Moody's home analyst + Moody's home analyst	0.1551	0.0982	0.1272
	(1.80)	(0.78)	(1.41)
A3 × Moody's home analyst + Moody's home analyst	-0.2497	-0.3361	-0.3213
	(1.97)	(4.01)**	(3.89)**