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To my son, Zhenyi. May I inspire you as you inspire me.

ABSTRACT

This thesis consists of two empirical essays that examine the determinants of municipal bond pricing. The first essay investigates the influence of political alignment on secondary market yields, while the second focuses on measuring ESG scores to uncover labeling gaps and assess their implications for primary market greenium. These studies contribute novel empirical evidence and datasets, employing diverse methodologies to analyze the roles of political favoritism and disclosure practices in shaping municipal bond pricing.

The first essay is "Taking Sides: Political Alignment and Municipal Bond Yield", joint with Weijia Zhao. In this research, we show that politically misaligned counties face higher yield spreads, while aligned ones benefit from lower spreads. The magnitude of the effect varies on bond characteristics: bonds with long maturity, backed by utility revenue, and issued by counties less reliant on state transfers are less sensitive to political alignment shock. In addition, yield spread variations correlate with changes in credit risk and intergovernmental transfers. Politically misaligned counties elevate bond issuance despite higher costs, offsetting reductions in intergovernmental transfers.

The second essay, "Shades and Traces of ESG in Public Finance: Evidence from 120,000 Municipal Official Disclosures," measures ESG scores in municipal bond primary market disclosures from 2012 to 2023 using large language models and Government Finance Officers Association (GFOA) guidelines, uncovering a persistent labeling gap between potential ESG alignment (from project content) and actual signaling (from explicit labels). This gap varies over time and across geography and is driven by political, economic, and social factors. Integrating these scores with Bloomberg data refines estimates of the municipal greenium, showing that substantive ESG disclosure practices influence primary market yields more than mere labels.

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CHAPTER 1

TAKING SIDES: POLITICAL ALIGNMENT AND MUNICIPAL BOND YIELD

1.1 Introduction

Understanding how politics shape the allocation of public resources has always been a central question in political economy research. Much work has focused on the effect of vertical political alignment or misalignment between upper-level government and lower-level government/geographical areas on government spending (Levitt and Snyder Jr [1995], Albouy [2013], Berry et al. [2010]). In a similar vein, recent research showed political and ideology alignment could facilitate international capital flow (Kempf et al. [2022]), account for partisan fertility gap (Dahl et al. [2022]) and explain loan spreads differentials (Dagostino et al. [2023]).

In this paper, we take a further step asking whether and how political alignment affects asset prices and the municipal bond market provides an ideal setting for our research. The municipal bond market is a market of great economic significance, with a market size of 4.1 trillion dollars in the US and the 400 billion annual issuance represents 25% of the 1.7 trillion local government spending. More importantly, the municipal bond is a type of financial instrument that naturally bridges politics and public finance. Elected officials are responsible for proposing, determining, and implementing a wide variety of economic and public finance policies, including directing inter-governmental transfer or public spending projects, designating tax-advantaged status, etc. Such decisions directly affect the fiscal condition and creditworthiness of municipal bond issuers. Previous research in distributive politics has shown the importance of partisanship in shaping such decisions. However, how investors price political alignment is ex-ante ambiguous but understudied. Direct and favorable inter-governmental transfers along or across partisan lines could strengthen municipal bond issuers' fiscal fundamentals and lead investors to perceive less credit risk. On the other

hand, this strengthening effect could be complicated by the possibility of moral hazard as local government may expand their balance sheet and spend less responsibly, leading to deteriorating creditworthiness. Motivated by the arguments above, we empirically investigate whether municipal bond investors recognize the variations of county financial strength and bailout probabilities induced by the political alignment status, and demand different yield spreads based on different political alignment statuses of the municipal bond issuers.

We analyze municipal bond yield spread between 2005-2020 by exploring U.S. gubernatorial elections in 49 states.¹ These elections provide an ideal setting to study the effect of political alignment for two reasons. First, state governors have significant power over virtually all major economic and public finance policies, such as state and (pass-through of) federal grants, and public spending projects, opening the possibility of affecting yields of municipal bonds issued by local governmental bodies. In particular, state governors play important roles in multiple stages of the development of state budget bills as well as intergovernmental transfer plans. Second, most of the U.S. states hold elections every four years, and the cycle is pre-determined,² exogenous to local economic conditions, and thus partially alleviates endogeneity concerns.³

1. We excluded the state of Alaska since partisanship measures could not be constructed on the county level. Alaska's gubernatorial voting records are reported on the electoral district level and each electoral district, in general, consists of multiple counties.

2. Over our sample period 2005-2020, there exist four off-cycle gubernatorial elections - 2010 UT, 2011 WV, 2012 WI and 2016 OR. None of these elections changed the governor's party affiliations.

3. By contrast, since U.S. federal elections in all states are held concurrently, the variations of political alignment between the federal government and lower-level government or geographical districts would be perfectly correlated. As a result, the effects of federal-local political alignment are hard to be distinguished from pure time variations. In addition, elections at the federal level, including both presidential and congressional ones, feature highly persistent partisanship, especially over the most recent 20 years when only a few swing states ever changed their votes. This leads to two challenges: first, persistent voting patterns may induce candidates' strategic reactions by paying systematically and disproportionately more attention to those swing states relative to their core voters; second, it is hard to tell how well we can generalize the results even if we find any, as most of the variations come from a handful (swing) states. In comparison, voters are more likely to break party ranks in gubernatorial elections (Sievert and McKee [2019]), giving us much more variations to explore. For example, California has been voting for Democratic presidential candidates since 1992, but two of its governors during the same period, Pete Wilson (1991-1999) and Arnold Schwarzenegger (2003-2011) are Republican. Similarly, Kentucky has been voting for the Republican Party in presidential elections since 2000, but three of its governors during the same period, Paul E Patton (1995-2003), Steve Beshear (2007-2015),

We begin our empirical analysis by collecting data from various sources outlined in Section 1.2. The main dataset used to perform the analysis is the secondary market trading records of municipal bonds from 2005 to 2020, coming from the Municipal Securities Rulemaking Board (MSRB). We complement this dataset with additional bond-level characteristics sourced from Mergent Municipal Bond Securities Database (MMBSD). County-level political alignment measures, as well as state-level governor election results, are constructed based on data from the CQ Voting & Elections Collection and Dave Leip’s Atlas. Finally, we rely on the Census of Governments as well as the Annual Survey of State and Local Government Finances to obtain the local government’s balance sheet information.

Data-wise, while both MSRB and MMBSD provide names of municipal bond issuers along with many other variables, they do not directly report the location of issuers that can be directly matched with county-level gubernatorial election records. We develop a multiple-step procedure to extract this information based on regular expression and further cross-validated our assignment algorithm. In particular, we aggregate municipal bond information at the county and state levels respectively and show that the total amount of municipal bonds outstanding and the total amount of debt outstanding (i.e. bond and other loans) are highly correlated both geographically and over time. The percentage of municipal bonds issued by state-level and county-level entities is also consistent with estimates offered by third-party market research agencies. By matching counties and municipal bonds, we are able to identify county-issued municipal bonds that allow us to study the impact of political (mis-)alignment on yield spreads of municipal bonds in the secondary market.

To study the effect of vertical political alignment, we define a county to be politically misaligned with the state governor if the county’s vote margin leans toward a party different from the incumbent governor’s political party. We first present panel evidence that agencies in politically misaligned counties face higher financing costs in the primary market, and

and Andy Beshear (2019-), are Democratic.

the larger the degree of political misalignment the county, the higher the yield spreads its municipal bonds traded are in the secondary market.

This panel evidence offers only first-pass evidence. To alleviate endogeneity concerns, we turn to a regression discontinuity design and further classify all county-month observations into four categories capturing all types of transitions into and out of political (mis)alignment: from aligned to aligned, from aligned to misaligned, from misaligned to aligned and from misaligned to misaligned. We then leverage (ex-post) close governor races to approximate the ideal experiment where the state governor’s party is randomly assigned to constituent counties. The results show that among all counties that start as politically aligned with the state governor, those that subsequently become politically misaligned after a close governor election experience higher yield spreads relative to those that remain aligned. On the other hand, among counties that start as politically misaligned, those that subsequently become politically aligned experience a decrease in the yield spreads of their municipal bonds traded in the secondary market. The magnitudes are largely symmetric starting from these two different status quo (i.e. starting from politically aligned or politically misaligned) and correspond to around 20 basis points, roughly one-sixth of the sample standard deviation.

Our point estimates are comparable to responses of municipal bond yields studied by other researchers using different events.⁴ Baber and Gore [2008] show that municipal bonds issued by states that mandated GAAP disclosure experience yields lower by 14-25 basis points on average. Similarly, exploiting an exogenous Moody’s rating recalibration, Adelino et al. [2017] found municipal bonds issued by upgraded local governments saw a reduction of 14 basis points in offering yields. Moreover, Painter [2020] found that long-term bonds exposed to more climate risk had 16-20 basis points higher yields. Our findings in the secondary markets show comparable yield responses from municipal bonds when the local government

4. One caveat is that most of the previous research focused on the primary market. We provide preliminary evidence on offering yield as well, but the magnitudes are much smaller relative to the ones we find in the secondary market.

becomes politically misaligned from the party of the governor following a close election.⁵

To establish the robustness of our main findings and rule out alternative explanations, we perform extensive checks, including using different bandwidths as well as cutoffs for close elections, different sample filtering standards, testing the existence of jumps in election results, etc. Our results are robust to alternative specifications and are not driven by common vulnerabilities of the regression discontinuity design.

Our analysis includes tens of thousands of municipal bonds, and their differences along multiple dimensions are naturally associated with heterogeneous treatment effects. Bonds with very long remaining maturity are less subject to the near-term political alignment shocks as any benefits/damages caused by political alignment status are likely to be reverted in the next election. Compared to general obligations bonds, which carry the full faith and credit of the issuing authority, the guarantee of repayment for revenue bonds comes only from the specific revenue-generating project. In particular, utility bonds are tied to essential and conservative services and are also less sensitive to political alignment changes. Lastly, counties vary in terms of their dependence on state transfer as the primary source of revenue and unsurprisingly, municipal bonds issued by those more fiscally independent counties are less vulnerable to political alignment changes.

In the last section of the paper, we investigate the potential mechanism of our results. As documented in earlier literature, most of the variations in municipal bond yield spread can be attributed to either credit risk or liquidity risk variations.⁶ To test liquidity risk as the primary mechanism, we check whether becoming politically aligned and misaligned changes the share of inter-dealer trade or the standard deviation of yield spread in the opposite directions, and it turns out not to be the case. We also restrict the sample to

5. Compared to other events, our estimated magnitudes are around twice as large as the yield responses from loss of public monitoring (Gao et al. [2020]) and 2.5 times larger than the corruption penalty estimated by Butler et al. [2009].

6. Another important factor is the tax factor. We exclude all taxable securities (for federal tax) from our main sample and adjusted the yields according to the tax rate of the highest income bracket for each state.

more liquid bonds and the regression coefficients remain the same. For the test on credit risk, we first replicate Ansolabehere and Snyder Jr [2006]’s exercise on political alignment and intergovernmental transfers in the close election setting. Our specification shows that changes in political alignment are associated with $\sim 5\%$ changes in state (to county) level intergovernmental transfer and state transfer alone, on the other hand, consists of over 30% of the local budget. When we add credit ratings or state transfers to the main regression, the coefficients of political alignment status become less or insignificant, suggesting that the effects on municipal bond yield spreads are mostly associated with changes in the credit risk of the municipal bonds and that changes in intergovernmental transfer following the shifts in political alignment status play a role explaining our results.

Local governments becoming politically misaligned with the state get less transfer from the state government and also face higher borrowing costs from the market, while those becoming politically aligned with the state enjoy both more transfer and lower borrowing costs. How do local governments adjust municipal bond issuing activities, a fully discretionary decision of the local government? By analyzing primary market issuance behaviors at the county level, we find that counties politically misaligned (aligned) with the state issue more (less) municipal bonds to counter-act the decreasing (increasing) state transfers despite facing higher (lower) borrowing costs. A back-of-envelope calculation with the estimated regression coefficients equates the annual cost of bond issuance to 0.8 billion dollars. Moreover, the change is mostly on extensive margin (i.e., changes in the number of issuance) rather than intensive margin (i.e., changes in the size of individual issuance).

The rest of the chapter proceeds as follows. Section 1.1.1 discusses related literature and highlights our contribution. Section 1.2 describes the data we used as well as our data curation and wrangling procedures, and presents basic statistics. Section 1.3 presents the baseline results of political alignment on municipal bond yield spread and addresses potential identification concerns by showing results following close elections. Section 1.4 checks the

robustness of our main results and offers discussions. Section 1.5 exploits credit risk and intergovernmental transfer as a potential mechanism for such effects. Section 1.6 concludes.

1.1.1 Literature

Our work contributes to the literature on the implication of political alignment on the asset (municipal bond) market. More specifically, it is related to three different literature.

First, our analysis is related to, and in large part, motivated by prior studies on partisanship and favoritism allocation of public resources. The theoretical foundation originates from testing the loyal voter models (Cox and McCubbins [1986], Kramer [1966]) and pivotal voter models (Lindbeck and Weibull [1987], Dixit and Londregan [1995, 1996]).⁷ One branch of the empirical work focuses on "presidential particularism" or "congressional particularism", where administrations are found to steer federal grants/stimulus/programs/projects to areas of the core state (Albouy [2013], Balla et al. [2002], Berry et al. [2010], Dynes and Huber [2015], Gimpel et al. [2012], Hoover and Pecorino [2005], Hudak [2014], Kriner and Reeves [2015], Larcinese et al. [2006], Levitt and Snyder Jr [1995]).⁸ Additional evidence outside the U.S. includes Arulampalam et al. [2009], Brollo and Nannicini [2012], Golden and Picci [2008], showing that municipalities/provincial governments politically aligned with the central government receive more transfers in Brazil, Italy and India. The study of

7. Also known as core voter model and swing voter model. "Both models envision two parties competing to win an election by promising to distribute targetable goods to various groups, should they be elected" (Cox [2009]). The core voter model claims that vote-maximizing parties will allocate distributive benefits primarily to their core voters as a reward for their strong support. The swing voter model argues that vote-maximizing parties will allocate distributive benefits to swing voters to attract more votes and increase chances of winning elections.

8. Loyal voter model might be a closer depiction of the reality of strategic behavior of politicians based on anecdotal evidence and empirical evidence also generally supports loyal voter model. Precisely testing the swing voter model is challenging, however, as the status of being a swing state or county is not affected by variations in the upper-level government (i.e. a swing state remains a swing state if a Republican president replaces a Democratic president, but a pro-Republican state becomes politically aligned with (loyal voter of) the president following such an event), causal inference techniques commonly seen in the literature such as difference-in-difference, regression discontinuity designs will not be effective in such settings. The only way to test the swing voter model is to rely purely on geographical variation, subject to substantial endogeneity concerns.

gubernatorial particularism is rather limited compared to the literature on the federal government, even though state governors in the U.S. system have discretion over important resources (Nicholson-Crotty [2015]). The earlier study by Ansolabehere and Snyder Jr [2006] finds that governing parties skew the distribution of funds in favor of areas with the strongest electoral support, while the recent study by Glick and Palmer [2022] does not find much evidence that governors systematically prioritized their partisan areas when allocating tax-advantaged status. Our paper provides new evidence using municipal bond yield spread, which captures both explicit benefits a county could receive from its politically aligned governor via grants/programs and implicit backups/guarantees not observable in earlier research. Moreover, our results show that the market access to funding is also positively/negatively impacted by political alignment/misalignment, apart from its effect on direct access to funding from the intergovernmental transfer, and this complementarity further amplifies the real cost partisan agenda.

Second, our work relates to research on the determinants of municipal bond yield spread or local government borrowing cost (beyond the risk-free rate). The three most important and fundamental factors are liquidity risk, credit risk and tax (Ang et al. [2014], Capeci [1991], Cestau et al. [2019], Slemrod and Greimel [1999], Wang et al. [2008]). Depending on the research setting and the decomposition method, previous researchers find that credit risk can account for between 20 percent (Ang et al. [2014]) to 80 percent (Schwert [2017]) of the overall variations in municipal yield spread. Most factors affecting yield spread can be attributed to one or more of these three fundamental factors, including underwriter spread (Sorensen [1980]), climate risks (Painter [2020]), political uncertainty (Gao et al. [2019b]), quality of disclosure and accounting principles (GAAP) (Baber and Gore [2008], Fairchild and Koch [1998], Wallace [1981]), state fiscal and, in particular, deficit policies (Poterba and Rueben [1999, 2001], Wagner [2004]), local distress-related laws and statutes (Gao et al. [2019a]) etc. Our contribution is that we study the importance of political alignment with

upper-level government officials, whose roles in the financial market, asset prices and local government borrowing cost, were largely ignored in the previous literature. We also show that the effect of political alignment can mostly be explained by changes in credit risk.

Finally, on a broader level, our paper is related to the large body of literature on the political economy of finance and, in particular, the study of asset market movements (Akey and Lewellen [2017], Belo et al. [2013], Brogaard and Detzel [2015], Chan and Marsh [2021], Kelly et al. [2016], Kim et al. [2012], Pástor and Veronesi [2020, 2013], Acemoglu et al. [2018]), and adds to the literature by analyzing the implication of partisanship on the 4 trillion dollar municipal bond market.

1.2 Data

1.2.1 Data Source

The empirical analysis in this paper employs the following three datasets.

Election records are contained in Congressional Quarterly (CQ) Press Voting & Elections Collection. CQ collects electoral votes for both presidential (1920-2020) and gubernatorial elections (1968-2020) from a number of authoritative press sources,⁹ with vote counts at the county level.¹⁰ We further complement CQ data with governor elections data from Dave Leip's Atlas for missing records and obvious data errors.¹¹ Most of the U.S. states hold gubernatorial elections every four years in even years in November, and altogether, we are able to collect 377 elections during the period 1991-2020. Section 1.8.1 provides additional institutional details.

9. Sources include America Votes biennial series, America at the Polls series, Politics in America biennial series, etc. See here for a description of data collection methodologies.

10. Except for the state of Alaska, for which we have to drop all the observations as the election results are reported on the electoral district level and each electoral district sits across multiple counties.

11. For example, votes for both Republican and Democratic candidates in Louisiana's gubernatorial election on 2015/10/24 were reported as 0 in CQ data.

Information on municipal bonds comes from several sources. Secondary market transaction records, including yield and transaction size, between 2005-2020 come from Municipal Securities Rulemaking Board (MSRB), which covers all historical transactions between all counter-party combinations such as dealer to customer, customer to dealer and inter-dealer. Following the literature, we collapse the data at the bond-month-counter party type level¹² by calculating the trade-size weighted average yield if there are multiple transactions in the same bond-month cell, where counter-party type can be any transactions or one of the counter-party combinations mentioned earlier.

Bond/issue-level characteristics of municipal bonds come from Mergent Municipal Bond Securities Database (MMBSD), including issue date, maturity date, size of issuance, coupon rate, credit rating, existence of embedded options, insurance status etc. We use this information to filter the sample and perform additional robustness checks.

Distribution of state- and county-level government revenue/expenditures comes from the Census of Governments, which is collected every five years since 1957¹³ complemented by the Annual Survey of State and Local Government Finances. This dataset is the only source of nationwide, comprehensive local government financial information and can be obtained from the Census Bureau. The Census/Survey includes usual balance sheet variables such as total debt outstanding and total revenue, including inter-governmental transfers among different levels of government.

1.2.2 Political Leanings

There are a variety of ways to measure party control of the state government as well as the political alignment between counties and states. For state control, we focus on the state governor as it is the single most important governmental agency in state-level public finance

12. We use CUSIP as the unique identifier of municipal bonds.

13. The government organization data and information are for October of the year preceding the Census (1956, 1961, etc.)

decisions. The state governor participates in shaping the final budget in at least four ways. First, the start of a new budget cycle is marked by the guidance provided by the state budget office, which is within the department of treasury and reports to the state governor. Second, upon receiving recommendations from the budget office, the state governor reviews and adjusts the proposal before passing it to the legislature. Third, state governors coordinate, participate in and influence the legislature debate committee hearings on the budget bill throughout the process. Fourth, the budget bill needs approval from the state governor after the legislature sends it back and the governor can veto the entire bill or particular items. Section 1.8.2 provides more detailed information on the budget process.

For county political leanings, we use the average voting margin in each gubernatorial election between 2000 and 2020, which means that our county-level political leaning measure is time-invariant. As alternative measure we could have directly used county voting records (i.e. time-varying without taking average over time) or include elections prior to 2000 in the average. Our measure is better than both these alternative measures for three reasons.

First, counties are much smaller geographical units compared to states and most counties have small population sizes. As a result, the voting pattern of a particular county, especially one with a small population size, may be fickle. As we want our county political leaning measure to be highly visible to both the elected governors and the investors trading municipal bonds, we will ignore swing counties defined as those whose partisan voting margin is lower than a certain threshold. Fickleness in one particular governor race may result in an otherwise strongly partisan county being dropped from the analysis if one uses time-varying measures.¹⁴

Second, the time-varying county political leaning may suffer from potential endogeneity concerns. For example, gubernatorial election candidates may make promises on the local economy or public finances that help them win an election and at the same time, affect bond

14. However, as the voting behaviors of different groups (across the state, rural v.s. urban, race, social-economic status etc.) have been rather stable since 2000, the correlation between this "smoothed" measure and raw votes is over 0.8. Whether we use one over the other measure does not make a big difference in our empirical analysis.

yield spread. In addition, abnormally high municipal bond yield spread may be correlated with measures that reflect county residents' sentiments that their county has been adversely targeted by state government (but in reality, not necessarily so). However, such sentiments could be strong predictors for future election voting patterns. On the other hand, bond yield is also likely to be auto-correlated. As a result, researchers will find the impact of political alignment on yield spread even if there is no casual relationship.

Third, as our current measure is subject to look ahead bias,¹⁵ one might consider taking the average for elections before 2000. However, the look-ahead bias should be quite small as the correlation of voting margin on the county level is very high over time. Using dated election records will also unnecessarily expose us to more complexities in counties or county-equivalent entities involving reshaping, addition, and deletion. Moreover, political scientists have long recognized a geographical shift and realignment of partisan lines in the U.S. between the 1980s and 1990s (Miller and Schofield [2003]). We replicate similar findings using gubernatorial election votes. As one can see from the correlation plot in Fig. 1.1, the correlations of gubernatorial voting patterns since 1992 can be roughly split into two blocks: 1992-1999 and 2000-2019, as evidenced by the strong within-block correlations and low across-block correlations.

As mentioned above, the political leaning of a county is given by the relative difference of votes going to the Republican and Democratic Parties, shown in the following equation. The political leaning variable lies between -1 and +1, where a larger positive number indicates more pro-Republican.

$$PL = \frac{\text{Rep Vote} - \text{Dem Vote}}{\text{Rep Vote} + \text{Dem Vote}}$$

In Fig. 1.2, we plotted both the histogram and geographical map of county-level average political leaning measures since 2000. As one can see in the graph, most counties are

15. For example, when the governor was making decisions in 2006 whether to shift resources to or away from a county, (s)he may have a slightly different view on which county is loyal, swing, or opponent from the view indicated by our measure as it also incorporates information in later years.

pro-Republican and located in rural areas in the U.S.¹⁶

The (time-varying) state-county political alignment measure is defined as the following:

$$PA_{cs,t} = \mathbb{1}_{PL_{cs} * PL_{s,t} > 0}$$

where PL_{cs} is the (time-invariant) political leaning of a county c in state s , and $PL_{s,t}$ is the party affiliation of the state governor at time t . As PL_{cs} is a continuous variable, we can naturally define $PA_{cs,t}$ in a continuous way to reflect the degree/strength of political alignment/misalignment.

1.2.3 Political Alignment

Simple Political Alignment Measure

We construct the political alignment measure on the basis of county political leaning. In its simplest format, the political alignment status for a county at a specific time can be determined by comparing the political leaning of this county and the party affiliation of the incumbent state governor. Fig. 1.3 illustrates the classification of political alignment status.

Focusing on a hypothetical Democratic-leaning county D, suppose that the state holds gubernatorial elections every four years and a Democratic candidate won the election in 1998/2002/2014/2018, then this county is labeled as politically aligned with the state governor in those four-year periods immediately following the elections.¹⁷ On the contrary, this county D is labeled as politically misaligned with the state governor in 2007-2010, 2011-2014 as the Republican candidate won the 2006 and 2010 gubernatorial elections.

16. The map aligns well with its counterpart constructed using presidential voting records. This result is in line with the evidence of a decline in "split" states in recent years (Jacobson [2013]). "Split" states vote for different party candidates in different Federal elections (e.g. Republican senator with Democratic presidential candidate).

17. Even though the newly elected governors do not take office until the following January, investors immediately observe the election outcome in November and the effects of political alignment may take place given any changes.

Political Alignment Measure by Status Quo

A major concern with directly comparing outcomes for politically aligned counties and politically misaligned counties is that these counties may differ in characteristics besides political alignment status and these additional dimensions can be corrected with the outcome variable as well. We take several steps to address the potential endogeneity problems.

First, as different counties/states start from different political misalignment statuses before an election, we split our sample (bond-month) into two sub-samples according to different status quo. This split could generate meaningful comparisons as different status quo could have different impacts on yield spreads. For illustration, we use the same hypothetical Democratic-leaning county D and the same election results every four years starting from 1998 as Section 1.2.3 in Fig. 1.4. For 2002 and 2006 elections, county D is politically aligned with the state governor before the elections as the winners in 1998 and 2002 elections are both Democratic candidates. After the election, however, the political alignment status diverges as the winner is still from the Democratic party in 2002 but from Republican party in 2006. The observations in 2002/11-2006/10 and 2006/11-2010/10 are grouped together as they share the same status quo (politically aligned with the governor before an election). Within the group, the events are labeled as "Stay Aligned" and "Become Misaligned" to reflect different post-election political alignment statuses. Similarly, observations in 2010/11-2014/10 and 2014/11-2018/10 are grouped together as they share the same status quo as politically misaligned with the governor before the election. Within their group, they are labeled as "Stay Misaligned" and "Become Aligned" accordingly.

Splitting and grouping, however, cannot solve all problems. For example, when we compare the two groups in the first sub-sample (status quo: politically aligned), one natural concern is whether these county-month observations are really comparable, conditional on the status quo and other co-variates. The majority rule feature of gubernatorial elections naturally fits into a (sharp) regression discontinuity design, where the election outcome can be expressed

as an indicator function denoting whether the running variable (vote margin) is above or below a certain cutoff.¹⁸ Papers in both economics and political science literature have been exploiting the quasi-natural experiment made possible by close elections to study a wide range of questions, including the analysis of incumbent advantage in congressional elections (Lee [2008]), the economic impact of being represented by a politician in the ruling party (Asher and Novosad [2017]), and impact on the allocation of state expenditures by governor party affiliation (Beland and Oloomi [2017]) etc. By focusing only on marginal elections, we can ensure that the current political alignment statuses of counties are approximately randomly assigned and thus ideally uncorrelated with other unobserved covariates.

The last concern is whether the election result is truly exogenous in our setting since we are looking at outcome variables at the county level and the state election result itself is a function of all constituent counties' aggregated votes. Specifically, the number of counties in each state ranges from 3 to 254 (with a mean 62.78 and median 64), and in many cases, one or two counties in a state account for a substantial fraction of the state population.¹⁹

18. Our main specification uses ex-post voting margin to measure the closeness/surprise of an election and we focus on these elections exclusively to make sure our treated groups and control groups only differ in the election results but not any other characteristics. Indeed, Beland and Oloomi [2017] shows pre-election income, population, state house majority, and governor gender do not differ across (ex-post) close gubernatorial elections. However, it is up to debate whether ex-post close elections are good natural experiments to approximate the random assignment of state governor's party affiliation. For example, it is possible that one election is predicted to be a landslide ex-ante but turns out ex-post to be very close. If investors' expectations are anchored by ex-ante prediction and the ex-post election result align with the ex-ante prediction, then classifying such events as close elections may be problematic since the underlying trend could be quite different from "true" close elections. On the other hand, there could be other elections that are predicted to be very close ex-ante but turn out to be one-sided. In principle, we wish to include such events if investors trade on their ex ante predictions even after election results are known. In general, using ex-ante close elections should be preferable to ex-post close elections as investors trade in response to the resolution of uncertainty after elections happen and the yield spread responses are what we wish to capture. However, in reality, there are two major obstacles to gubernatorial election polls. First is data availability. Unlike presidential elections, there are very few sources publishing gubernatorial election polls even during recent time periods, not to mention a single source that covers our entire sample period and maintains consistent polling methodologies over time. Second and perhaps more important is the segregation of the pool market and the financial market. Participants in these markets are not necessarily the same and predictions made by polls might be a very biased measure of actual predictions used by municipal bond traders.

19. Eg: According to the 2019 official estimate, Cook county (IL) has a population of 5.15 million, compared with State of Illinois' population 12.67 million. Clark County (NV) has a population of 2.3 million, compared with the State of Nevada's population of 3.1 million.

Considering that the most populous counties also tend to issue more municipal bonds, creates additional endogeneity problems: changes of votes in the populous counties in a state between two elections is an important determinant of the governor election results, and these changes in votes and variations in municipal bond yield spreads may have common origins such as economic growth, risk appetites, etc. (Pástor and Veronesi [2020]). However, this is worrisome as we measure counties' political leaning by taking the average of all vote margins since 2000. Due to its time-invariant property, this measure is unlikely to be correlated with time-series changes of the associated state's gubernatorial election results.

1.2.4 Bond Geocoding and Sample Selection

To examine its effects on bond yield spreads, we need to match bond data to the same geographical level. One difficulty with MSRB and MMBSB data is that county information is not readily available. To overcome this difficulty, we develop a geocoding algorithm based on regular expression and rely on a comprehensive list of U.S. counties/cities/townships (with over 100,000 geographical records) and associated crosswalks from SimpleMaps developed by Pareto Software LLC. The detailed string matching procedure and associated data validation steps can be found in Section 1.8.5.²⁰

After obtaining geo-coded bond-level data, we follow the literature and further apply several filters to obtain the final sample for empirical analysis. We first exclude all state bonds as they are issued by the state government or its affiliated agencies and thus not subject to the political alignment channel we examine here. We then remove all irregular debt instruments including (bond anticipation, construction loan, collateralized, etc) notes, certificates (of obligation, participation), commercial paper, derivatives etc, and only keep securities of the most common bond type. Next, we remove bonds with variable interest rates and only kept bonds with either fixed or zero coupon rate, as such information is necessary for calculating

²⁰ In the next version, we further incorporate GIS information sourced from Atlas Muni. The pros and cons of different matching methods are discussed in the Section 1.8.5.

yield spreads. Taxable and AMT bonds are further removed to keep the contract of securities in our analysis sample comparable and avoid measurement errors in bond yield. Green bonds, tribal bonds, university and college bonds²¹ are also removed for similar consideration since certain holders may enjoy incremental tax advantages. In addition, we exclude all trades that took place before bond issuance or after bond maturity as these observations are likely results of data entry errors. Table 1.1 presents the number of unique bonds/CUSIPs and bond-month trading records after each filter. The full (collapsed) MSRB sample includes 2.8 million bonds with over 22 million bond-month records, and the main sample used in our empirical analysis (after applying all filters except those with asterisk items) includes 1.8 million bonds with around 13 million bond-month observations. On average, each municipal bond is associated with roughly 7.2 months of tradings.

In robustness analysis, we apply several additional filters previously adopted in the literature. Firstly, it is known that newly issued municipal bonds exhibit high price dispersion since a major chunk of trades occurs during this period. Most investors subsequently hold the securities to maturity. High price dispersion could lead to yield spread movement independent of political alignment status. Similarly, small price deviation could lead to large changes in yields when bonds are close to maturity. To avoid such confounding effects, we remove trades three months after issuance and three months before maturity. We further remove all non-straight bonds including bonds with tranche structure, sinking fund provision, bond insurance, and embedded option since they can obviously affect the risk profile of bonds and thus their yield spreads. However, one should be cautious about certain filters as these characteristics are endogenously determined and some (insurance, embedded options) have major impacts on sample size.

21. All categories except tribal bonds, university and college bonds are directly flagged in MMBSD. We identify tribal, university and college bonds by searching for specific strings (eg: "COLLEGE", "UNIVERSITY", "TRIBE") within the issuer name. This process may cause incidental exclusion of certain bonds such as all bonds issued by agencies in College Station city, Brazos county, Texas.

1.2.5 Summary Statistics

In this section, we report the summary statistics for our main empirical sample (i.e. applying the first six filters) of both time-varying and time-invariant county-level and bond-level variables.

Table 1.2 reports summary statistics for county-level variables. Time-invariant characteristics include population and GDP in 2010, as well as average political leaning since 2000. The main sample includes 2843 unique counties. Consistent with the graphical evidence shown in Fig. 1.2, the average and median county are pro-Republican. Time-varying characteristics are presented in the table as well. Municipal bonds issuers in an average county-month have 94 unique bonds outstanding. The degree of heterogeneity is noticeable as the standard deviation is more than 3 times of the sample average. This is largely driven by populous and large counties such as Los Angeles (CA), Kings (NY), Queens (NY), New York (NY) etc that issue more municipal bonds than the average county. Similar observations can be made for the dollar amount of bonds outstanding for an average county-month. Certain balance sheet variables are also presented. The average county runs a balanced budget and receives the majority of total transfers from the state government. Regarding political alignment measures, one could first observe the similarity of distributions of our preferred "smoothed" version of county political leaning and the political leaning measure from last election. Variables "Stay Aligned" and "Become Misaligned" include observations that are politically aligned *before* the nearest upcoming gubernatorial election. Among all these observations, 73% stay aligned *after* the most recent gubernatorial election while 27% become misaligned. On the other hand, considering politically misaligned counties *before* the nearest upcoming gubernatorial election (i.e. variables "Become Aligned" and "Stay Misaligned"), 59% of the counties remain misaligned and 41% become aligned *after* the most recent gubernatorial election. In any year, on average, $\frac{14287*0.73+9770*0.41}{14287+9770} * 100 = 60\%$ of the counties are politically aligned with the state governor. The ratio is larger than 50% which is as expected as the party affiliation

of state governor itself is determined by the majority rule.

Table 1.3 reports the information for bond-level variables. Panel (a) includes time-invariant characteristics. The average offering yield is 3.06% and the average offering amount is 1.93 million. The average maturity at issuance is 10 ($10=123/12$) years and duration is 7.96 years as most of the bonds are not zero-coupon bonds. Puttable bonds are fairly unusual, representing fewer than 1% of the sample while callable bonds comprises roughly 48% of the sample. The average yield on bond-month level in the secondary market is 2.71%, smaller than the average offering yield mainly because trading is more concentrated during recent time periods when risk free rate is low. Average tax adjusted spread for all transactions is 1.79% and the average tax adjusted spread for purchases of municipal bonds from a customer by a dealer is higher than the average tax adjusted spread for other types of transactions, reflecting a premium earned (higher yield is associated with lower price) by dealers for mediating the market. The average par value traded is large and it is mostly driven by some very large outliers.

1.3 Political Misalignment and Yield Spread

1.3.1 Panel Evidence

We start off by looking at whether political alignment between a county and the then governor helps explain the variations in municipal bond yield spread. Recall that we define political alignment by comparing the counties' time-invariant political leaning measure and the party affiliation of the incumbent governor, as illustrated in Section 1.2.3.

Table 1.4 reports regression results using primary market information. The left hand side variable is the municipal bond offering yield and the right hand side variable is an indicator variable whether the issuer of the municipal bond is in a county that is currently politically misaligned with the state governor. As we can see, the coefficient is positive and significant

across all specifications, suggesting that it is more costly for agencies in counties that are politically misaligned with the state governors to raise funding in the municipal bond market.

Results from primary market is only suggestive as neither of the two most important factor, liquidity and credit risk, can be easily measured or captured in the regression. Differences in offering yield may just be a result of different seniority, different sources of fund, or even different skills of underwriters. To address such concerns effectively, we will focus on the secondary market in the remaining part of the paper. The extra time dimension within each single municipal bond allows us to parse out much of the heterogeneity across municipal bonds and instead to only focus on the yield spread changes over time.

As political leaning is continuously defined, we unify measures of political alignment and misalignment together using the variable political misalignment. It takes positive values when misaligned and negative ones otherwise, and its magnitudes represent the degree of misalignment/alignment. We run the following regression for different cut(off) values to understand the relationship between municipal yield spread and degree of misalignment.

$$YS_{icst} = \beta_0 + \beta_1 \mathbb{1}_{Misalign_{cst} > cut} + \gamma_i + \eta_{st} + \epsilon_{isct}$$

where YS_{icst} is the yield spread for municipal bond i issued by county c in state s at time t , $\mathbb{1}_{Misalign_{cst} > cut}$ equals 1 for counties whose degree of misalignment at time t is greater than cut and 0 for counties with negative degree of misalignment,²² γ_i and η_{st} stand for bond fixed effects and state-month-year fixed effects respectively, and standard errors are clustered at the county level since we expect municipal bonds issued by agencies in the same county co-move strongly with respect to changes in the county's political alignment.

22. Observations with degree of misalignment between $[0, cut]$ are dropped so that the comparison group stays the same across regressions. We also tried two alternative specifications. One dropped all observations with degree of misalignment between $[-cut, cut]$ so that we ignore all swing counties, and the other directly added a group of dummy variables corresponding to different misalignment level. Results are almost exactly the same, except that coefficients in the last specification are not precisely estimated. In addition, the specification labeling all observations with degree of misalignment smaller than cut as 0 is problematic as the comparison group will become increasingly political misaligned with the state governor as cut increases.

The literature has documented dozens of factors that can explain municipal bond yield spread (Ang et al. [2014], Baber and Gore [2008], Capeci [1991], Cestau et al. [2019], Fairchild and Koch [1998], Gao et al. [2019b,a], Poterba and Rueben [1999, 2001], Schwert [2017], Slemrod and Greimel [1999], Wagner [2004], Wallace [1981], Wang et al. [2008]) and here we take an easier approach exploiting the panel structure of our dataset, rather than constructing those measures one by one. Since most of the measures are constant or close to constant along one or more particular dimensions, bond fixed effects and state-month-year fixed effects are able to absorb bond-level time-invariant characteristics and state-specific (non-linear) time-trend.

Fig. 1.5 plots the coefficients along with the 95% confidence interval obtained from the regressions against corresponding cut(off). As one can see, all coefficients are significant and positive, suggesting that misalignment between county's political leanings and state governor's party is indeed associated with higher municipal bond yield spread. Perhaps more interesting and reassuring is the almost monotonic relationship between coefficient/significance and cutoff: as counties become more firmly supportive of the opposition party, governors could be less concerned about the potential loss of votes when designing public finance policies, investors may price in such misalignment effects, and the yield spread of municipal bonds issued by agencies in those counties indeed experienced larger yield spread increases.²³

One obvious caveat of the panel evidence is that it is subject to endogeneity concerns and thus can only be interpreted as correlation instead of causation. For example, Republican party is relatively stronger at the state level election in general, meaning that Democratic counties are more likely to be politically misaligned with the state governor than Republican counties. At the same time, Democratic counties are relatively looser in budget management and more likely to run a deficit, leading to higher municipal bond yield spread. In addition, any time-varying bond-level characteristics may be omitted variables in our specification.

23. The monotonicity no longer holds as we push to the "boundary" as the number of counties that could be classified as having an "extreme" level of political misalignment drops significantly.

Many municipal bonds had exotic embedded call options, and issuers may choose to exercise any amounts. Even though we have tried to directly adjust the yield spread, such adjustment may still be inadequate to fully capture investors' reactions in the secondary market. If these factors are also correlated with election results, then our results will suffer from potential biases.

1.3.2 Evidence From Close Elections

To alleviate the endogeneity concern discussed in the previous section, we group observations based on the political alignment status prior to the most recent gubernatorial election, and focus exclusively on close elections. As illustrated in Section 1.2.3, this guarantees that the within group characteristics are similar and the current political alignment status of these observations is approximately random.

With these two features, our empirical design can be viewed as a combination of Diff-in-Diff and RDD.²⁴ Specifically, we run the following regressions:

$$YS_{icst} = \beta_0 + \beta_1 v_{st} + \beta_2 v_{st} D_{cst} + \beta_3 D_{cst} + \beta_4 x_{st} + \eta_t + \gamma_i$$

where the left hand side variable is the yield spread of a municipal bond i issued by county c in state s at time t . The alignment indicator D_{cst} is an indicator variable that varies at the county level and equals 1 when there is a change in the status quo.²⁵ The running variable v_{st} is the vote margin on the state level and the interaction between the running variable and alignment indicator allows slopes to differ on either side of the cutoff, x_{st} includes other potential control variables, and η_t and γ_i are time fixed effects and bond fixed effects,

24. Compared with Diff-in-Diff, we restrict our attention to close elections to analyze the effect following a surprising election outcome. Compared with the RDD, we do not stop at the jump of state-level election outcome as vote margin changes, but further interact this jump with pre-determined county-level political leaning measures to study the effect of changes in political alignment status.

25. For example, when the status quo is politically aligned, this indicator takes value 1 when counties become politically misaligned after an election and 0 if the status quo remained intact.

respectively.

To further mitigate data snooping concerns, we choose a prefixed bandwidth of 0.05 for gubernatorial elections (i.e., the winning party wins less than 52.5% of the total votes), remove swing counties with average political leaning between -0.2 and +0.2, and fix these values in all of the analysis hereafter.²⁶

Table 1.5 reports our main regression results with two-way clustered standard errors on both county and month level. We only reported estimates of β_2 as it is our main variable of interest. Odd numbered columns have politically aligned as the status quo with the "shock" being "Become Misaligned." Even numbered columns, on the other hand, have politically misaligned as the status quo with the "shock" being "Become Aligned." Columns (1) and (2) are the baseline regression results. As we can see, starting from being politically aligned, the county receiving the alignment shock following a close gubernatorial election subsequently saw its associated municipal bond yield spreads rising by 20 basis points on average compared to its counterpart whose status quo remained intact. On the other hand, counties that started out as being politically misaligned but subsequently became aligned following a close gubernatorial election saw their associated municipal bond spreads drop by 29 basis points on average, relative to their counterparts whose status quo remained intact. In columns (3)-(4), we instead interact the "shock" with the degree of average political leaning of the counties, and the results remain statistically significant. The coefficient estimates showed that one additional degree of misalignment leads to 0.6 basis points higher yield spread for municipal bonds associated with counties that became politically misaligned following a close gubernatorial election, relative to their counterparts that stayed politically aligned. On the other hand, one additional degree of alignment reduces yield spread by 1 basis point

26. The results are highly robust to the choice of bandwidth and cutoff of swing counties. Less than 10% of the regressions had β_2 with statistical significance less than 5% when we ran regressions on a grid of bandwidth and swing counties cutoff values. In addition, the results are also highly robust to the use of alternative measures of misalignment. In fact, the measure constructed by votes in the 2000 election cycle gives slightly larger and more significant regression using the cutoffs reported in Table 1.5.

for municipal bonds issued by entities residing in counties that became politically aligned following a close governor election, relative to their counterparts that stayed politically misaligned.

In Fig. 1.6, we present the bin scatter plot of (residualized) municipal bond yield spreads against winning margin of the challenger party. Panel (a) includes the sub-sample where the status quo of the county before the nearest upcoming gubernatorial election is being politically aligned with the state governor,²⁷ while Panel (b) includes the sub-sample where the status quo of the county before the nearest upcoming gubernatorial election is being politically misaligned with the state governor. To isolate differences in bond characteristics, we residualize yield spreads using the bond and time fixed effects. We then gridify the running variable "winning margin" in $[-5\%, 5\%]$ into small intervals of length 0.5% and compute the par-weighted average yield spread residuals in each interval. Consistent with the regression results, Fig. 1.6 shows a positive jump to the right of winning margin 0 in Panel (a), and a negative jump to the right of winning margin 0 in Panel (b).

One merit of the secondary market data lies around its panel structure (i.e. county/vote margin dimension and time dimension). In the analysis above, Table 1.5 pool both dimensions together while Fig. 1.6 pools the time dimension together and analyzes the effect of vote margin on yield spread. Alternatively, we adopt the spirit of difference-in-difference/event study analysis and look at the dynamics in yield spread around the election. As usual, we separate the cases where the status quo is politically aligned/misaligned before the most recent election. In Fig. 1.7, we plot the regression coefficients against the months after the election. As we can see, there is generally no pre-trend before the election, and the yield spread exhibits an immediate jump two months after the election, followed by a prolonged slow strengthening (further increase or decrease) period. Considering that most of the elections take place in November and the newly elected governor only swear in January of the next year, the event

²⁷. Thus a positive vote margin to the challenger party (i.e. a candidate from the challenger party wins the election) means the political alignment status will switch to misaligned after the election.

study results suggest that municipal bond market reacts based on expectations rather than the realization of any benefit or harm those politically aligned/misaligned counties receive. The other interesting fact from Fig. 1.7 is that in both of the cases, the yield spread for counties experiencing a change in political alignment status seems to be higher than the counties maintaining the status quo, which may be related to the higher degree of political uncertainties in these cases.

1.4 Additional Specifications and Discussions

1.4.1 *Economic Significance*

The size of the regression coefficients presented in Table 1.5 indicates that being politically aligned with the state governor is associated with roughly 20 basis points reduction in municipal bond yield spread, all else equal. For in-sample comparison, the standard deviations of yield spread in primary market (offering yield) and secondary market (trading yield) are 1.43 and 1.53, respectively. Therefore the effect of political alignment can explain up to 1/6 of the sample standard deviation. As an alternative measure, the average yield spread difference between AAA-rated and BBB-rated bonds is ~ 90 basis points, thus the effect of our political measure represents about a quarter of the BBB-AAA spread.

In a very closely related paper, Gao et al. [2019b] shows that gubernatorial election uncertainty itself is associated with a 7.2 basis point increase in municipal bond yield spread. The effect when restricting to close elections is larger, however, equals around 13 basis points. The effect of political alignment is roughly 1.5x of the effect of political uncertainty.²⁸

28. However, there are two important differences in the definition of close election in Gao et al. [2019b] and our analysis. First, they rely on polls, which are ex-ante expectations in its virtue but subject to the several shortcomings we discussed in Section 1.3.2. Second, Gao et al. [2019b] apply a much looser criteria defining "close elections" using the sample median 12% difference (i.e. 56% v.s. 44%). Under similar criteria, states traditionally viewed as deep blue such as Illinois, Connecticut, or states traditionally viewed as deep red such as Texas, South Dakota will be classified as swing states. It is thus unclear whether many elections, even in their close elections sub-sample, really introduce enough political uncertainty ex-ante. In the robustness checks presented in Table 1.7, we also try the sample median as an alternative definition of close elections

Comparing with other estimates of municipal bond yields studied by other researchers using different events in the literature, one could notice that they are largely comparable.²⁹ Baber and Gore [2008] showed that municipal bonds issued by states that mandated GAAP disclosure saw yields lowered by 14-25 basis points on average. Similarly, exploiting an exogenous Moody’s rating recalibration, Adelino et al. [2017] found municipal bonds issued by upgraded local governments saw a reduction of 14 basis points in offering yields. Moreover, Painter [2020] found that long-term bonds exposed to more climate risk had 16-20 basis points higher yields. Our findings in the secondary markets show comparable yield responses from municipal bonds issued by local government affiliates that changed political alignment status following a close governor election. Compared to other events, our estimated magnitudes are around twice as large as the yield responses from loss of public monitoring (Gao et al. [2020]) and 2.5 times larger than the corruption penalty estimated by Butler et al. [2009].

1.4.2 *Balance Test*

Regression discontinuity design requires that any unobservables should be similar on average across states where incumbents barely win the elections and the ones where incumbents barely lose the elections. Grimmer et al. [2011], however, finds structurally advantaged candidates are more likely to win close elections.³⁰ Eggers et al. [2015] show that Grimmer et al. [2011]’s results are exceptions by systematically analyzing a much larger sample. Nevertheless, we perform checks to ensure that our results are not driven by effects claimed by Grimmer et al. [2011].

Following Grimmer et al. [2011]’s definition of structurally advantaged candidates, we test whether running as a candidate in incumbent governor party is associated with a higher

and the coefficients shrink to ~ 0.15 . In general, the effect of political alignment on municipal bond yield spread is roughly comparable to (or slightly larger than) the effect of political uncertainty.

29. As mentioned in the introduction, one caveat is that most of these estimates are in the primary market.

30. They claim that the party of the Governor or election administrator or the party that dominates the state legislature might reflect advantages for a candidate for federal office in that state.

probability of winning a close election.³¹³² Fig. 1.8 plots the histogram of vote margin by the candidate from incumbent party for all races since 2005 (Panel (a)) and as one can see, there exists no abnormal excess density to the right of the treatment threshold zero. Panel (b) shows the fit of a McCrary test of continuity around zero and it does not reject the null hypothesis that there are no jumps for the running variable around the zero cutoff, indicating that the candidates aligned with the ruling party do not have the ability to selectively push themselves across the winning margin.³³

Using a similar exercise, Fig. 1.9 presents the binscatter plot of winning margin against the fraction of winning candidates that were aligned with the incumbent state governor. In particular, we test for jumps at threshold zero and five (percent) and find no evidence supporting either one, i.e. the probability that candidates aligned with the incumbent state governor win a very close election is NOT significantly higher than (1) the probability that candidates from the challenging party win a very close election (2) the probability that candidates aligned with the incumbent state governor win a landslide election.

1.4.3 Falsification Checks

In Table 1.6, we present results from two falsification checks to make sure that our results are not driven by randomness. The first check is to test whether we can find similar significant results for variables that should not be affected by political alignment changes. As we control for bond fixed effects in our main specification, time varying variables are needed. As most of the time-varying bond-level variables such as duration, convexity, are deterministic functions

31. This is different from the incumbent advantage documented in the literature as it does not restrict to same-candidate retention but only requires the candidate is affiliated with the same party as the current governor.

32. We also performed similar tests looking at whether the candidate aligned with the state legislation is associated with a higher probability of winning a close election and results are very similar. The test regarding alignment with election administrator is not performed currently due to data limitation.

33. Results using all races since 1990 show essentially the same results.

of time, finding insignificant regression coefficients are more of mechanical results.³⁴ Instead, we choose to search for (pre-determined) time-varying covariates on county-level to make falsification checks more meaningful. In particular, we use the (log) dollar amount and (log) number of municipal bonds matured in each month as the left hand side variables. The main argument is that the number or amount of municipal bonds matured in each month are predetermined at issuance by time to maturity, and given that the maturity of an average municipal bonds spans across several governor terms, changes of political alignment status following a recent close election should not affect objects determined by events in the past. Indeed, this is confirmed by results shown in columns (1)-(4).

As a second check, we also constructed fake election results where election winners are classified as "Republican" if the absolute value of vote margin is greater than 20% and as "Democratic" if the absolute value of vote margin is smaller than 20%. We constructed the political alignment measure accordingly. This fake "political alignment" measure should not convey any information about alignment and we indeed found statistically insignificant results. Moreover, we did not find opposite-sign results in columns (5)-(6). As a more general extension, we also experimented with random number generator to assign political alignment status, ran regressions using simulated alignment status, and noticed that our baseline results are at the tail of such distributions.

1.4.4 *Robustness*

In this subsection, we present additional robustness checks in addition to the baseline results as well as results controlling for degree of political uncertainty presented in Table 1.5.

One recent study by Gao et al. [2019b] documented that political uncertainty leads to higher municipal bond yield spread. *Ceteris paribus*, closer elections are associated with greater political uncertainty. However, in principle, political uncertainty alone could not

34. Empirically, they are indeed not statistically significant.

entirely explain away our baseline results.³⁵ Still, a simple but effective exercise to address this concern is to directly add in the regression the absolute value of voting margin, the most commonly used measure of political uncertainty in the literature (Boutchkova et al. [2012], Çolak et al. [2017], Gao et al. [2019b], Julio and Yook [2012]). As presented in columns (1)-(2) of Table 1.7, the regression coefficients have the same sign as before and they remain statistically significant.

Additionally in Table 1.7, we also performed a series of common robustness checks widely used in the regression discontinuity literature. Columns (3)-(4) use quadratic fitting for the underlying running variable.³⁶ Columns (5)-(6) use the sample median as the criteria for close elections. It is widely known that RDD results are sensitive to bandwidth choice and the sample median (corresponding to 56.5% v.s. 43.5%) seems a relatively loose definition of close elections. Our baseline results hold nevertheless despite reduced statistical and economic significance. Lastly, columns (7)-(8) use the sample median average voting margin at the county level as the criteria for partisan v.s. swing counties. As we can see, the results are robust across all alternative specifications.³⁷

We apply several filters when constructing the main empirical sample and many of those filters have significant impacts on sample size, as show in Table 1.1. Although most of the filters are directly borrowed from Schwert [2017], we keep the asterisked ones in Table 1.1

35. By fixing the 0.05 bandwidth for gubernatorial elections, only sufficiently close elections are included in our analysis and we do not expect the degree of political uncertainties caused by these selected elections to be too different. More importantly, by splitting the sample according to different status quo before the nearest upcoming election, our hypothesis makes stronger predictions. The regression coefficients of "Become Misaligned" and "Become Aligned" both need to be significant and of the opposite sign. Even if a certain fraction of the effects is driven by political uncertainty, it is difficult to come up with a reason why such effects have opposite directions depending on different political alignment status quo.

36. In the next draft we are currently working on, we also include results using higher degrees polynomials as well as nonparametric methods such as local linear regressions.

37. Additionally, we also tried using different political leaning measures as well as excluding county-election records where the sum of vote share to Democratic and Republican candidates is smaller than 60% (i.e. third party candidates won a significant shares of votes in the election from that county). The baseline results still stand.

off in the baseline results.³⁸ In Table 1.8, we vary the number filters applied and provide evidence that the results are not driven by specific choice regarding sample filters. Columns (1) and (2) use the full sample before applying any filters (except for state bonds, which are naturally excluded as they do not have the vertical political alignment measure). Columns (3) and (4) remove all trades three months after issuance in addition to the filters used in main analysis. Columns (5) and (6) remove all trades three months before maturity in addition to the filters used in columns (3) and (4). Columns (7) and (8) additionally remove all bonds with special risk mitigation strategies including tranche structure, sinking fund provision and bond insurance. Columns (9) and (10) additionally remove all bonds with embedded options, either put or call. As we can see, results remain very similar to the baseline in each of the alternative sample selection procedure, though the coefficients in the last two alternatives become somewhat large due to significantly reduced sample size as the majority of municipal bonds are insured and have embedded options.

1.4.5 *Heterogeneity*

The merged MSRB-Mergent dataset consists of over 1.8 million unique municipal bonds and the number is still over 120,000 in the regression analysis after all sample restrictions. Bond fixed effects included in the regression ensure that previous results are not just capturing compositional shifts in traded bonds. It is, however, possible that heterogeneity in bond/-county characteristics leads to heterogeneous treatment effect even for the same shock in political alignment.

Most of the municipal bonds have relative low coupon rate with bond principal as the single largest repayment burden. Given that our sample only consist of close elections by regression discontinuity design, investors may speculate less about bonds matured in far

38. With all the filters applied, the final sample analyzed in Schwert [2017] only consists of 1.08% and 1.70% of the original raw dataset in terms of number of bonds and number of trades respectively. Also note that the RDD used in empirical analysis in our paper imposes another layer of filters implicitly.

future since the all the benefits/damages caused by political alignment status in the near term can be reverted if a candidate from the other party win the next election. In columns (1)-(2) of Table 1.9, we interact the changes in political alignment with an indicator for long term to maturity bonds, where a bond is defined as long term to maturity if it's maturity date is at least 10 years (roughly the sample median) after the tenure of the newly elected state government. As we can see, the interaction terms have the opposite sign compared to the main regression, regardless of the status quo (though the coefficient is not statistically significant when the status quo is misaligned), suggesting that longer maturity are less affected by changes in political alignment status.

One other prominent characteristics of municipal is revenue bonds versus general obligations. The guarantee of repayment for revenue bonds comes solely from revenues generated by a specific revenue-generating entity associated with the purpose of the bond while general obligation bonds, on the other hand, carry the full faith and credit of the issuing government unit and are secured by the issuing authority's pledge to use all legally available resources including tax credits and other revenues. Revenue bonds are generated perceived as being more risky (Kidwell and Koch [1982], Swensen [1974]) and on average are issued with higher yield spread, compared to otherwise the same general obligation bonds. In our setting, however, as revenue bonds normally do not enjoy the benefit of issuers' other resources/revenues, their yield spreads should also be less sensitive to changes in such resources/revenues, which are further caused by changes in political alignment status. One concern is that there are still a lot of heterogeneity even within revenue bonds depending on the type of pledged revenues. Certain revenues bonds including education, hospital can be heavily affected by the overall financial strength of the issuing authority while risk profile of other bonds are more driven by idiosyncratic factors. We focus on utility bonds (including water, gas and other utilities) as these bonds are tied to "essential and conservative services" and columns (3)-(4) in Table 1.9 reports results adding the interaction between utility bonds with changes

in political alignment status. As we can see, the coefficients are large and significant, with the opposite sign of the main regressors, confirming our conjecture.

Third, at the county level, different counties depend on state transfer³⁹ or other benefits to varying degrees for operations or debt repayment. We use the fraction received state transfer as a fraction of total expenditure for each county as a measure of state transfer dependence and test whether being less dependent on state transfer is associated with less vulnerability to shocks in political alignment status. This is confirmed in columns (5)-(6) of Table 1.9.

Finally, the risk of default on coupon or principal payments mostly concentrate on high yield bonds, defined as bonds below Baa in Moody's rating or BBB in S&P's or Fitch ratings. Due to its equity component, high yield bonds are more sensitive to idiosyncratic risk and thus changes in political alignment status with the state government may have a larger impact on high yield bonds. In Columns (7)-(8), we interact the changes in political alignment with an indicator for high yield bond⁴⁰ and confirm this hypothesis.

Table 1.10 reports additional heterogeneity analysis based on other characteristics. In columns (1)-(2), we calculate the realized changes in inter-governmental transfers for each county post election (residualized by time trend) and define a county as low reduction/increase if the changes is less than 5%. This grouping of counties do not see significant changes in inter-governmental transfer and we expect the municipal bond yield spread is also less sensitive. In columns (3)-(4) and (5)-(6), we analyze two provisions facilitating municipal bond repayment: bond insurance and sinking fund. When bond issuers are in financial distress, bond investors may seek repayment from the insurance protection provider or sinking fund and thus reduce the credit risk. Indeed, we see a smaller sensitivity to changes in political alignment for insured bonds and sink-fund protected bonds. Lastly, Republican

39. See Section 1.5 for more discussion.

40. Classified with the credit rating 6 months before the election.

party is known to have more conservative/stricter budget policy and the degree of budget discretion/flexibility might be lower when the state is under Republican control. Columns (7)-(8) shows, however, there are no significant differences in bond yield changes under Republican control versus Democratic control.

1.5 Mechanism

Liquidity risk and credit risk are known as the two most important determinants of yield spread in municipal bond market, after adjusting for its tax-exempt status. The two combined can explain more than 95% of the variations in the municipal bond yield spread (Ang et al. [2014], Schwert [2017]). Pretty much all other factors uncovered in the literature can be partly or fully attributed to either liquidity risk or credit risk, or both, such as political uncertainty, underwriter spread, climate risk, etc.

In this section, we analyze the potential mechanism underlying our political alignment factor. Decomposing yield spread into liquidity risk and credit risk is a challenging task as these two factors are highly correlated in practice: bonds issued by large, high quality issuers have lower credit risk and they also tend to be more actively traded compared to bonds issued by small, low quality issuers. Instead, we will follow a heuristic approach and provide some suggestive evidence. A precise analysis requires CDS data or changes in pre-funding status (Schwert [2017], Jiang et al. [2020]) and reduces our sample size by over 99.5 percent, raising concerns on its generalizability.⁴¹

Finally, it is worth noting that our baseline results are bi-directional - the effects of becoming politically aligned and of becoming politically misaligned have opposite signs. Therefore, any candidate mechanism also needs to follow the same "symmetric" structure to be valid.

41. Another major limitation is that we cannot directly test the effects of political alignment on default probabilities as the actual default episodes of municipal bonds are rare both in our dataset and in the broad economy. From MMBS data, defaulted bonds only consist of around 0.1% of all observations.

1.5.1 *Municipal Bond Liquidity*

Municipal bond trading is done over-the-counter with a high fraction of retail clientele. It has been documented in the literature that the secondary market is featured with low liquidity and high transaction costs, due to high dealer market power and search frictions (Green et al. [2007a,b], Li and Schürhoff [2019], Schultz [2012]). Liquidity risk premium, thus, plays an important role in municipal bond yield spread variations. The following Fig. 1.10 plots the distribution of one municipal bond liquidity proxy using the number of months in which there are any trading records for a given municipal bond. Panel (a) plots the distribution at the bond level and Panel (b) plots the distribution at the sample observation level. As we can see, the distribution is highly positively skewed and the majority of bonds are only traded in the issuance month.

In Table 1.11, we test the municipal bond liquidity as a possible mechanism for changes in yield spread following changes in political alignment status. We first test whether there are any systematic changes in liquidity for bonds whose issuer counties just become politically aligned or politically misaligned. As we can see, the total par value traded in the market increases in either case, consistent with the price discovery hypothesis in Chae [2005]. The author found that trading volume decreases inversely to information asymmetry prior to scheduled announcements (election results in our setting) and increases after the scheduled announcement. In columns (3)-(4), we replicate exactly the same exercise, but only include inter-dealer trades from the sample. The magnitudes of regression coefficients decreases by about half but remain positive and statistically significant. In columns (5)-(6), we include all trading records but use within-month yield spread standard deviations for each bond as the left hand side variable. Similarly, the two coefficients are both positive and significant. A possible explanation for this result is consistent with the price discovery process: market participants have more disagreement following changes in the status quo, leading to more within-bond trading price variations (Fama et al. [1969]). The fact that both trading volume

and within-bond price deviations rise regardless of how the status quo changes and at the same time municipal bond yield spreads react differently suggests liquidity issue is unlikely to be the reason for such change. As a final test, we replicate our baseline specification in columns (7)-(8) but only include the more liquid bonds (thus less subject to illiquidity concerns) in the regression. Both coefficients remain quantitatively similar as before, indicating liquidity reason may not be the main mechanism driving our empirical findings.

1.5.2 Intergovernmental Transfer

A major share of both revenue and expenditure for local governments involves intergovernmental transactions. Governors can heavily influence local government fiscal conditions with their roles in state-wide economic and public finance policies, in particular the development of budget bills and allocation of intergovernmental transfer. Section 1.8.2 and Section 1.8.3 provide more information on institutional background of appropriations legislation and magnitudes of intergovernmental transfers respectively.

Correctly linking the budget with corresponding decision date is critical to disentangling the relationship between partisan control of the state government and state-local transfers. It is complicated by institutional details, special treatments as well as actual adjustments (compared to the proposed numbers in the budget bill) spread over the fiscal year. Being aware of the difficulties in perfectly addressing all the concerns, we follow a multi-step strategy to get our best measure. Starting from the (actual) inter-governmental transfers obtained from the Annual Survey of State and Local Government Finances (ASSLGF), we

- Set the base decision year to be

$$\text{fiscal year} + \left\{ \begin{array}{l} -2 \quad \text{Annual Budget} \\ -2 \quad \text{Odd Budget \& Odd Fiscal Year} \\ \quad \quad \text{Even Budget \& Even Fiscal Year} \\ -3 \quad \text{Odd Budget \& Even Fiscal Year} \\ \quad \quad \text{Even Budget \& Odd Fiscal Year} \end{array} \right.$$

- Define Decision year=Base decision year+1 for selected states

Under ASSLGF’s convention, fiscal year X starts from a month in year X-1 and ends in the same month in year X. Since the budget is drafted and reviewed by the budget office/state governor before the start of a new calendar year and the inauguration of newly elected state governors takes place in January, we need to subtract another year to link the budget and its actual decision year. For states with biennial budgets starting from odd years, the odd fiscal years are similar to the annual budget. Even fiscal years, on the other hand, are the second year in a budget cycle and we need to subtract one more year to get the corresponding decision year. The cases are exactly the opposite for states with biennial budgets starting from even years.

A few states including MI, AL start their fiscal years later than the widely used July 1st and the drafting/reviewing process by budget office/state governors is pushed back accordingly. In addition, several states establish special extension policies following election years to accommodate newly elected governors. We add one year back for these states to reflect such adjustments.⁴²

42. The results are, however, robust to the adjustment. The main reasons are two-fold:

- Election years only represent roughly 1/4 of the total number of observations and the adjustment for extension is yet a subset of these observations.
- Governors still have the chance to negotiate the budget items with the state legislature in later stages.

A simple but instructive analysis on the relationship between partisanship and inter-governmental transfer is to directly compare the transfer to aligned counties and misaligned counties. To rule out confounding factors such as the Democratic party's strength in populous municipalities, we normalize total transfer by population. In Table 1.12, we present statistics separately for Democratic-leaning and Republican-leaning counties, for both state transfer and local transfer.⁴³ As we can see, for state transfer, when the state government is under Democratic control (column (1)), Democratic counties get more transfer (\$2,110 per person) than Republican counties (\$1,760 per person). On the other hand, Republican counties are offered more state transfers (\$1,890 per person) than Democratic counties (\$1,720 per person) under Republican governors. Local transfers, as we expected, are on average much smaller in size and do not show such a "reversion" pattern.

Regression results are presented in Table 1.13. We take natural logarithm of the transfer variable to reduce skewness. The effect of the population is absorbed by county fixed effects so that regression coefficients can be interpreted in a per capita manner. Standard errors are two-way clustered at county and time level. The coefficients of both Become Aligned and Become Misaligned have the expected sign, although the coefficients of Become Misaligned are only significant at the 10% level. In terms of economics magnitude, from politically aligned to politically misaligned, the drop of state level government transfer is $1 - \frac{e^{0.663-0.0409}}{e^{0.663}} = 4.5\%$. On the other hand, from politically misaligned to politically aligned, the increase of state level government transfer is $\frac{e^{0.531+0.0435}}{e^{0.531}} - 1 = 6.5\%$. This evidence supports the hypothesis that state transfers are affected by political misalignment/alignment.

To test whether credit risk is a potential mechanism for changes in municipal bond yield spread following changes in political alignment status, In columns (1)-(2) of Table 1.14, we

43. From cities or other counties, local transfer includes transfers as payment for performing specific public functions, providing general financial support, serving as agents for other local governments in financial matters, or purchasing/selling commodities, property, services from other local governments. Here local transfer is more preferred to federal transfer as a benchmark for comparison due to the "pass-through" mechanism as the state government plays a role in determining the allocation of federal funding to local government.

first replicate the baseline regression results for comparison. In columns (3)-(4), we include the credit rating of municipal bonds in the regression⁴⁴. We pool all ratings together and take the average in presence of multiple ratings from different credit rating agencies. We translate the credit ratings in a way that a smaller rating number is associated with a better credit rating.⁴⁵ Notice that credit rating agencies are revising their ratings over time by continuously incorporating the municipal bond's current status and future outlook, thus the credit rating variable is time-varying and survives the inclusion of bond fixed effects. The credit rating variable has the expected sign (higher value means lower rating and is associated with higher yield spread) and is highly statistically significant. Moreover, the inclusion of credit rating reduces both the size and significance of the political alignment variable. Such mediation test results suggest that a sizable fraction of political alignment's effect on municipal bond yield spread takes place via changes in credit risk. In columns (5)-(6), we directly include the amount of state transfer to a county in the next fiscal year⁴⁶ and we see quite similar results as in columns (3)-(4): the state transfer variable has the expected negative sign as more transfer is associated with better fiscal fundamentals and thus lower yield spread. Similarly, the sign and significance of political alignment measure shrink after the inclusion of state transfer, suggesting that changes in state transfer are important reasons why political alignment matters for municipal bond yield spread⁴⁷. In columns

44. We include the credit ratings one year ahead to account for the lag between expected and realized changes in local government fundamentals induced by intergovernmental transfers, as well as the decision lag of credit rating agencies.

45. e.g. "AAA/Aaa" encoded as 1, "AA+/Aa1" encoded as 2, etc.

46. We acknowledge that this analysis is imperfect due to frequency mismatch: the bond trading data are collapsed at the monthly frequency while the intergovernmental transfer is reported at the yearly frequency. Matching them together requires duplicating transfer data by up to 12 times (not always equal to 12 as many bonds do not have trading records for every single month). Further collapsing trading records to yearly frequency yield similar results, although it becomes harder to compare with our baseline results.

47. While change in state transfer leads to change in credit risk following the change in political alignment status, there might be other indirect channels for credit risk changes as well, such as changes in investors' perceived state bailout/intervention probabilities. While it is difficult to distinguish calculate this probability due to lack of CDS data, we do provide some preliminary evidence with simple regressions in Section 1.8.4.

(7)-(8), we directly test if political alignment can be used to forecast future credit ratings. The answer is yes and moreover, we find a pattern similar to the yield spread regression: including future realized intergovernmental transfer will reduce the size and significance of the political alignment variables.

In columns (3)-(6) of Table 1.14, the coefficients of political alignment measures are NOT exactly 0 even after including credit rating or intergovernmental transfer. Several possible reasons may lead to this unexplained residual effect. First, there might be measurement error in yield spread since the market is not liquid enough and a small number of trading records dominate the calculation in many bond-month observations. Second, market participants are fast to incorporate new information such as political alignment (as suggested in Fig. 1.7), and thus the trading yield spread in the market could already reflect expected changes in fiscal fundamentals soon after the release of election results. On the contrary, actual changes in intergovernmental transfer will not materialize until months after the inauguration of the new governor when (s)he finally participates in the formulation or revision of the budget bill. Similarly, credit risk agencies do not revise their ratings on a real-time basis and it takes time for them to collect, validate and incorporate new data. In this sense, our political alignment measure could be viewed as a leading factor of the municipal bond yield spread.

1.5.3 Local Government Reaction

As shown in Section 1.5.2, shocks in political alignment status lead to changes in intergovernmental transfer: local governments becoming politically misaligned with the state governor receive more transfer while those becoming politically aligned with the state governor receive less. Given the substitution relationship between intergovernmental transfer and proceeds from municipal bond issuance in funding local projects, a natural follow-up question is whether and how do local governments adjust their municipal bond issuance activities accordingly?

We answer this question in Table 1.15 by testing the effect of political alignment status

on changes in primary market issuance by collapsing the Mergent dataset at the county level. To account for the lag between the issuance decision date and the dated date, we take a 12-month lag for all the left-hand side variables. In columns (1)-(2), we use the log of total issuance amount as the left-hand side variable. As we can see, starting from politically aligned, if a county becomes politically misaligned with the state government, then the county increases the total new issuance by $\sim 4\%$, compensating for the decreases in intergovernmental transfers, even though the cost of municipal bond issuance increases. Conversely, starting from politically misaligned, if a county becomes politically aligned with the state government, the county decreases the total new issuance by $\sim 3\%$, offsetting the increases in intergovernmental transfers, even though the cost of municipal bond issuance decreases. This "incorrectly timing the market behavior" (i.e., issue more when the cost is high and issue fewer when the cost is low) represents the economic cost of political favoritism: a back-of-envelope analysis assuming 20 basis point leads to a total annual cost of $500 * 4 \text{ Billion} * 0.60 * 0.35 * 1.04 * 0.002 = 0.8 \text{ Billion}$ dollars for local municipal bond issuance alone.⁴⁸ Section 1.4.5 shows that the yield spread of bonds with certain characteristics are less sensitive to changes in political alignment status, among which utility bond versus general obligation is one of the most robust one. Columns (3)-(4) test if local government strategically re-balance the issuance composition and the results is no. To decompose the changes in municipal bond issuance amount, we regress the total number of issuances (columns (5)-(6)) and the average size of the new issuance (columns (7)-(8)) on political alignment status. The results show that the change is mainly on the extensive margin (i.e., changes in the number of issuance).

48. The annual issuance of municipal bonds is 500 billion dollars in 2021, with 60% issued by sub-state local governments. 35% of the municipal bonds are issued by counties that are politically misaligned with the state government, and they, on average, issue 4% more compared to the hypothetical case when they are politically aligned with the state government. Lastly, the extra yield those counties bear is 20 basis points.

1.6 Conclusion

What consequences do election outcomes have for the local economies? In this paper, we examine a particular aspect of this question, namely the effect of political economy on the yield spread of municipal bonds issued by counties. Relying on the quasi-experiment driven by close elections, our empirical analysis shows that the yield spread of municipal bonds issued by counties that become politically aligned with the state governor decreases following the most recent gubernatorial election, while it increases for counties that become politically misaligned with the state governor following the most recent gubernatorial election. Being aligned versus misaligned with the state governor is associated with ~ 20 bps difference in yield spread, all else equal. State governors appear to shape policy in such a way to favor counties where they enjoy stronger electoral support.

Additional results address the standard concerns in regression discontinuity designs and establish the robustness of our baseline findings. Following the municipal bond literature, we explore the potential mechanism of our results, and find that a big portion of the changes in municipal bond yield spread can be attributed to changes in credit risk rather than changes in the liquidity premium. As intergovernmental transfers from the state government consist of a substantial fraction of the local budget, an a priori explanation for (part of the) changes in credit risk is changes in transfer. Our results confirm this. Counties politically misaligned with the state experience lower amount of intergovernmental transfer, and they partially undo the change by issuing more (fewer) municipal bonds even though facing higher (lower) borrowing costs.

Both economics and political science literature have documented that partisanship affects the allocation of government funding, at the federal and state level. The results presented in this paper show that the market access to funding is also negatively impacted, in addition to the direct access to funding from the intergovernmental transfer. As this aspect is silent in existing literature but can be economically important for local government operations,

economists and policymakers trying to quantify the cost of partisanship should take the indirect cost into account.

1.7 Figures and Tables from Chapter 1

1.7.1 Figures

Figure 1.1: U.S. Counties Gubernatorial Voting Correlation

Note: This graph plots the correlations of election cycle-based political leanings on the county level since 1992. Political leaning is defined as $PL = \frac{\text{Rep Vote} - \text{Dem Vote}}{\text{Rep Vote} + \text{Dem Vote}}$. For states (NH, VT) with a two-year gubernatorial election cycle (i.e. two elections in each four-year cycle), the average PL is used. Off-cycle elections that did not change the governor's party affiliation and the governor race won by independent candidates are excluded (exception off-cycle election - 2003 CA; 2010 RI race was won by an independent candidate).

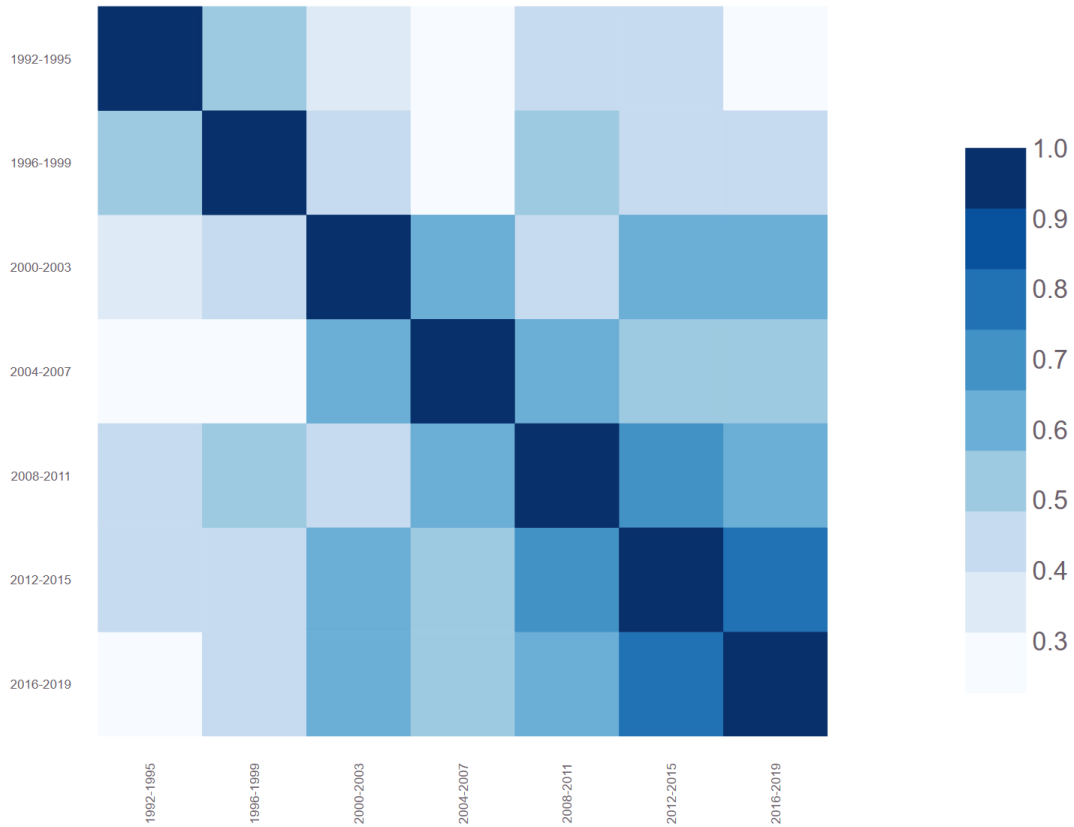
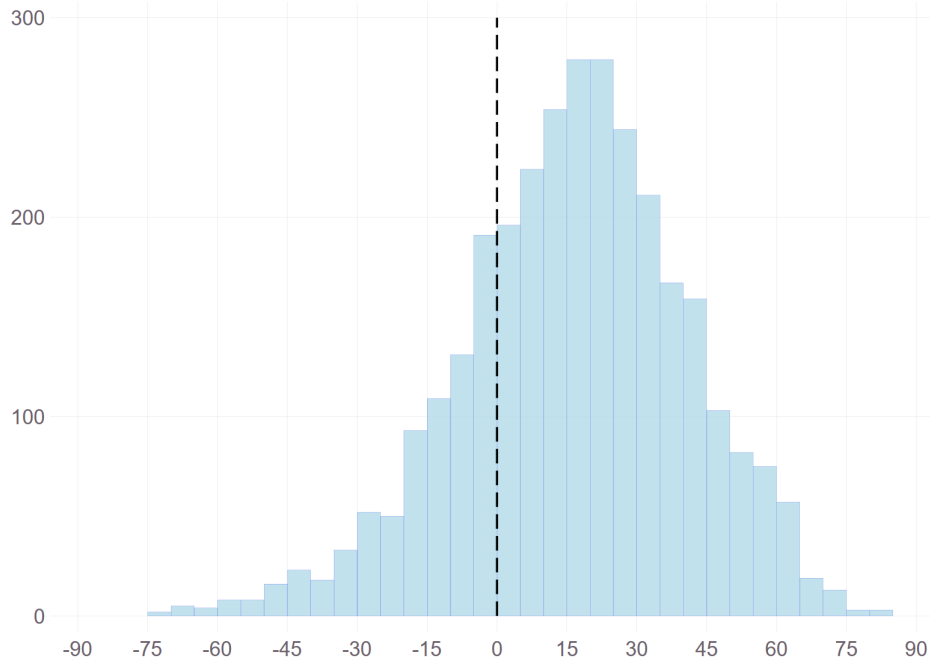
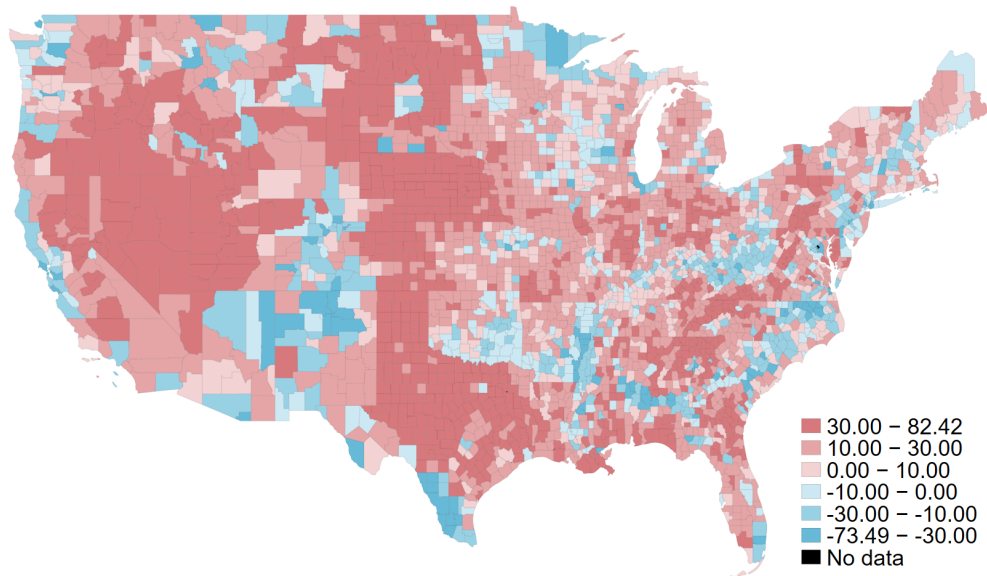


Figure 1.2: County Political Leaning

Note: This graph plots the distribution of average political leanings on the county level since 2000. Political leaning is defined as $PL = \frac{\text{Rep Vote} - \text{Dem Vote}}{\text{Rep Vote} + \text{Dem Vote}}$ for each gubernatorial election. Off-cycle elections that did not change the governor's party affiliation and governor races won by independent candidates are excluded.



(a) Histogram of Average County Political Leaning



(b) Map of Average County Political Leaning

Figure 1.3: Political Alignment Groups for Panel Regression

Note: This graph shows an example of political alignment group classification used in panel regressions. Our sample starts from 2005 and ends at 2020. County D is classified as a pro-democratic county by averaging its gubernatorial votes across 2000-2020. County D will be classified as politically aligned with the state governor if a Democratic candidate won the most recent gubernatorial election and as politically misaligned with the state governor if a Republican candidate won the most recent gubernatorial election.

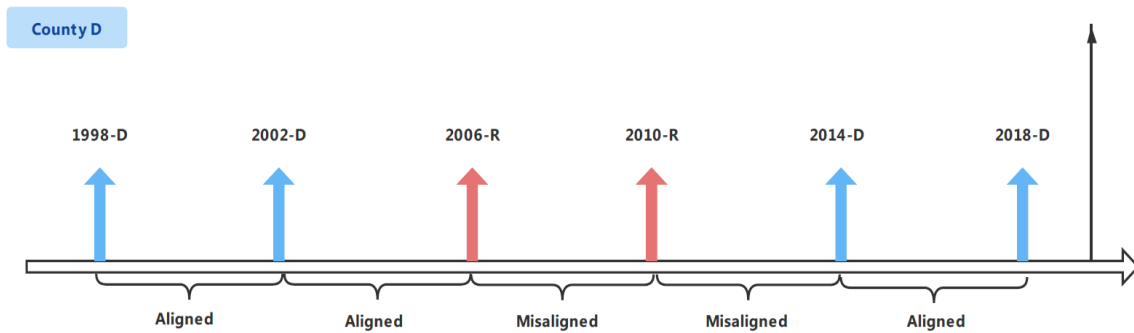


Figure 1.4: Political Alignment Groups for RD Regressions

Note: This graph shows an example of political alignment group classifications used in close election regression. Our sample starts from 2005 and ends in 2020. County D is classified as a pro-democratic county by averaging its gubernatorial votes across 2005-2020. County D will be classified as politically aligned with the state governor if a Democratic candidate won the most recent gubernatorial election and classified as politically misaligned with the state governor if a Republican candidate won the most recent gubernatorial election. At any point in time, the status quo is defined as the political alignment status before the nearest upcoming election (e.g.: in 2007, the status quo refers to political alignment status before the 2006 election). Labels for political alignment groups are shown at the bottom, reflecting various post-election alignment changes.

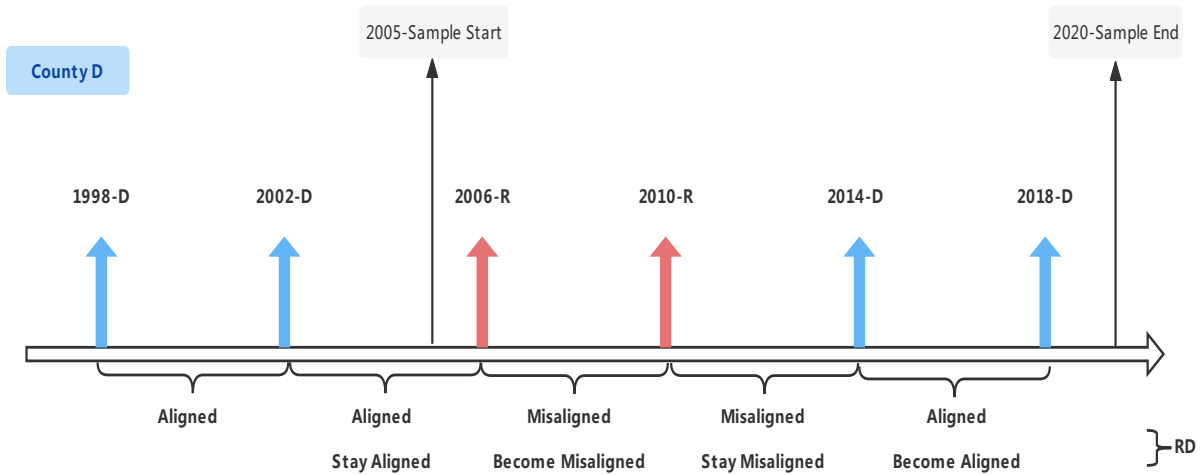


Figure 1.5: Degree of Misalignment v.s. Yield Spread

Note: This figure plots the regression coefficients (β_1) obtained from a series of panel regressions. For each cutoff value, we run the panel regression in the form of $YS_{icst} = \beta_0 + \beta_1 \mathbb{1}_{Misalign_{cst} > cut} + \gamma_i + \eta_{st} + \epsilon_{icst}$ after dropping all the observations with $Misalign_{cst} \in (0, cutoff)$, i.e. we hold the control group (counties with average political leanings the same as the current state governors' party affiliation) the same across regressions and increase the degree of political misalignment of the "treatment" group.

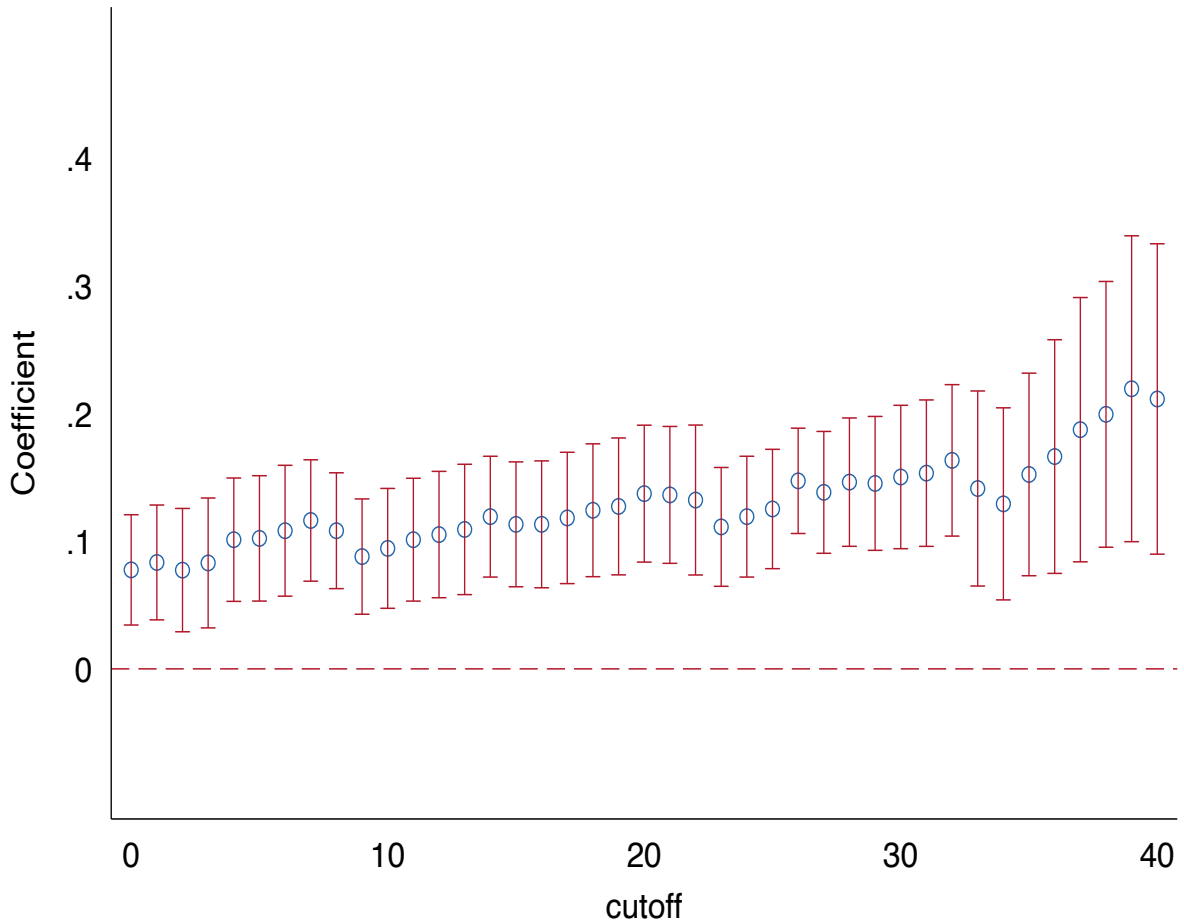
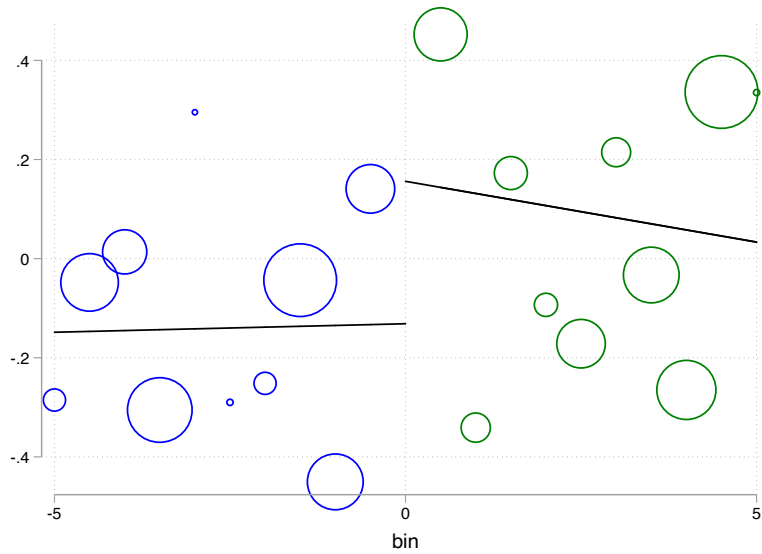
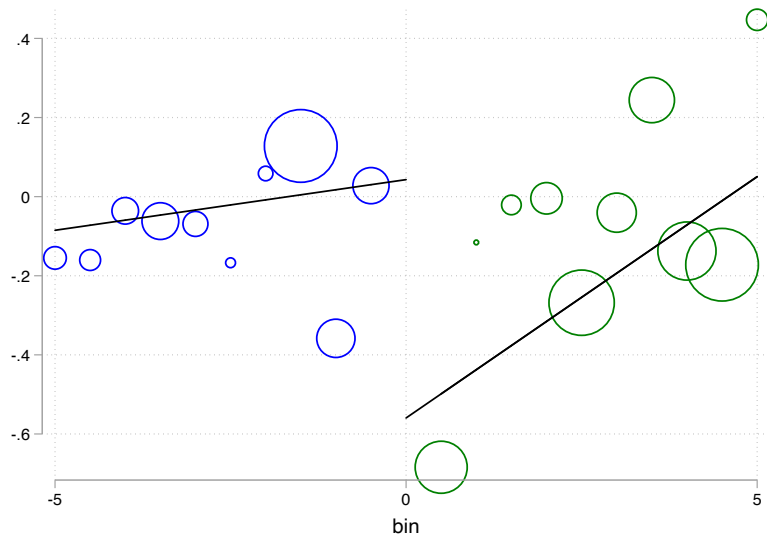


Figure 1.6: Yield Spread versus Winning Margin of Challenger

Note: This graph shows the binscatter plot of (residualized) municipal bond yield spread against winning margin of the challenger party. Panel (a) include the sub-sample where the status quo of the county before the nearest upcoming gubernatorial election is being politically aligned with the state governor, while Panel (b) include the sub-sample where the status quo of the county before the nearest upcoming gubernatorial election is being politically misaligned with the state governor. Circles are weighted by the size of par value traded and fitting lines are plotted.



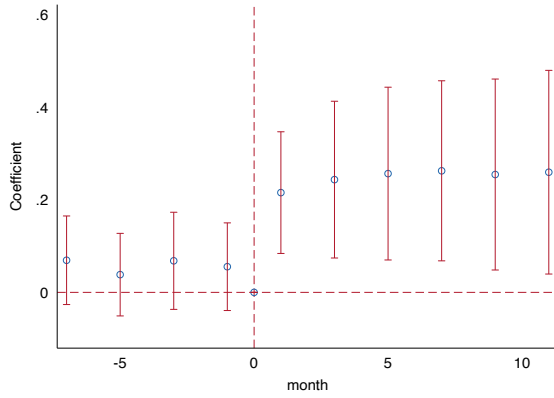
(a) Status Quo=Aligned



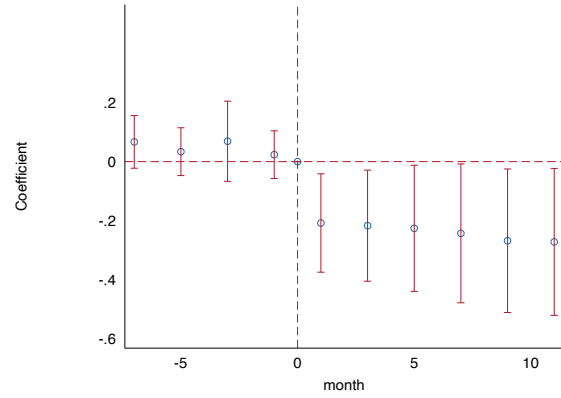
(b) Status Quo=Misaligned

Figure 1.7: Yield Spread versus Months after the Election

Note: This graph shows the regression coefficients in the event study analysis $YS_{icst} = \beta_0 + \sum_{i=-8}^{12} \mathbb{1}_{\text{Alignment Change}} * \mathbb{1}_{i_{th} \text{ Month after Election}} + \gamma_i + \eta_{st} + \epsilon_{i,scst}$. Panel (a) include the sub-sample where the status quo of the county before the nearest upcoming gubernatorial election is being politically aligned with the state governor, while Panel (b) include the sub-sample where the status quo of the county before the nearest upcoming gubernatorial election is being politically misaligned with the state governor. We group every two months together for more precise estimation but the results are quantitatively similar when include individual months in the regression, except that the standard errors are very large for a certain months with very few number of observations.



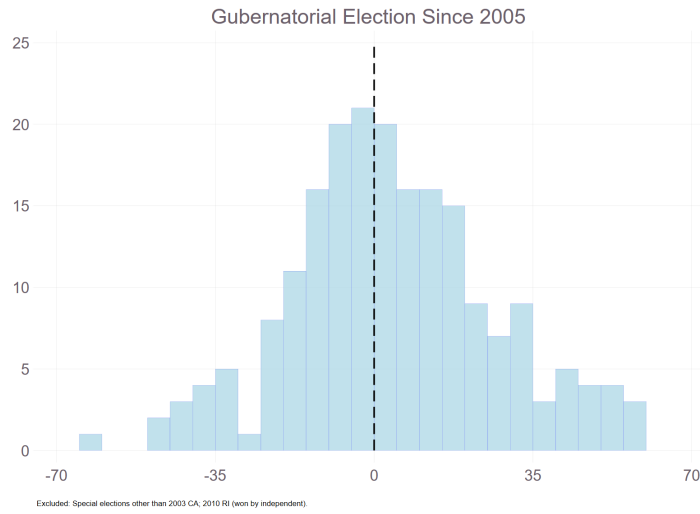
(a) Status Quo=Aligned



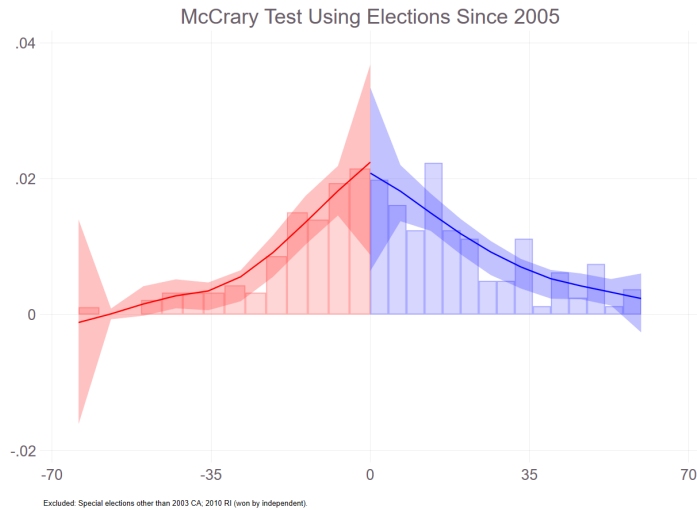
(b) Status Quo=Misaligned

Figure 1.8: Distribution of Running Variable (Vote Margin)

Note: This figure shows the distribution of the winning margin of the incumbent party candidate for U.S. gubernatorial elections between 2005-2020, the sample used in the main specification. Panel A is a histogram of this margin. Panel B plots a nonparametric regression to each half of the distribution following McCrary [2008], testing for a discontinuity at zero.



(a) Histogram of Winning Margin of Incumbent Party Candidate



(b) McCrary Test

Figure 1.9: Distribution of Running Variable (Vote Margin)

Note: This figure shows the binscatter plot of winning margin against the fraction of winning candidates that were aligned with the incumbent state governor, using all gubernatorial election results since 1990. Each bin represents 0.5% of the winning margin.

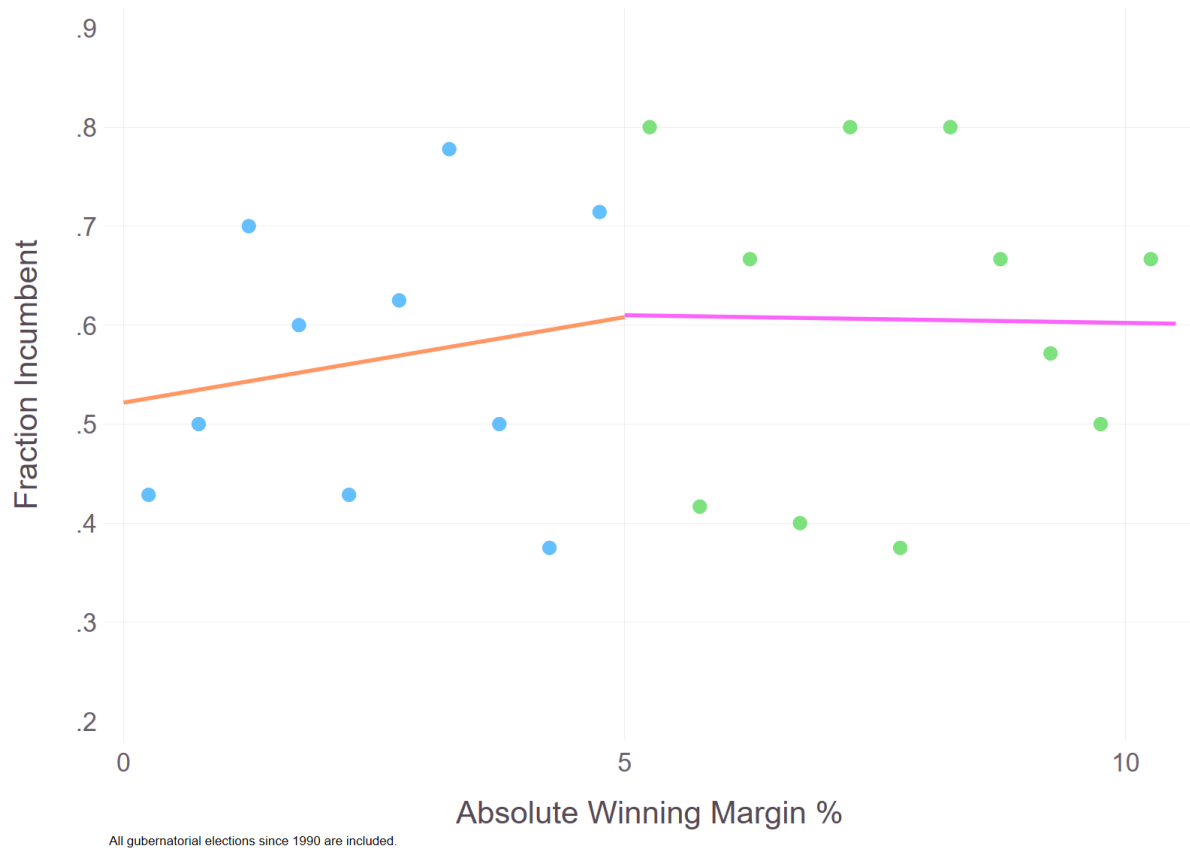
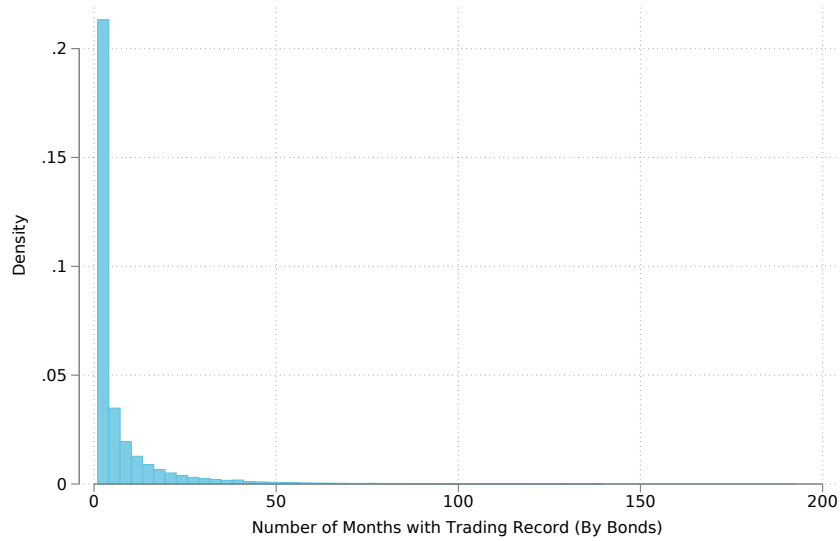
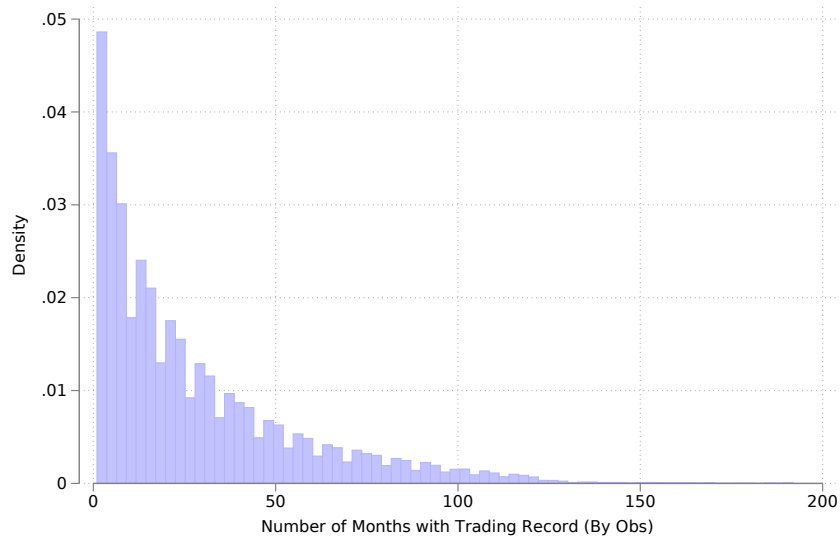


Figure 1.10: Municipal Bond Liquidity

Note: The following graph plots the liquidity of municipal bonds. The X-axis is the number of months and Y-axis is the relative frequency. Panel (a) plots the distribution of the number of months with trading records at the bond level while Panel (b) plots the distribution of the number of months with trading records at the sample observation level (i.e. multiple counts for one bond traded in multiple months).



(a) Liquidity by Bonds



(b) Liquidity by Observations

Figure 1.11: State Budget Cycle

Note: The following graph plots the budget cycle for a representative state with annual budgeting.

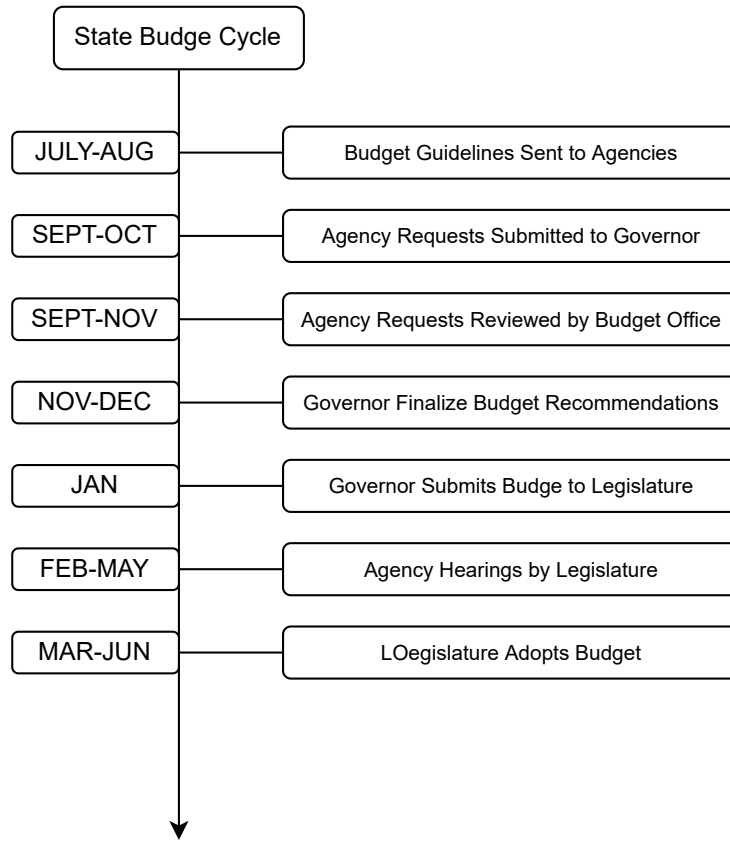


Figure 1.12: Intergovernmental Transfer

Note: This graph plots the (average) state transfer, federal transfer and local transfer as a fraction of total revenue across counties, 2005-2017.

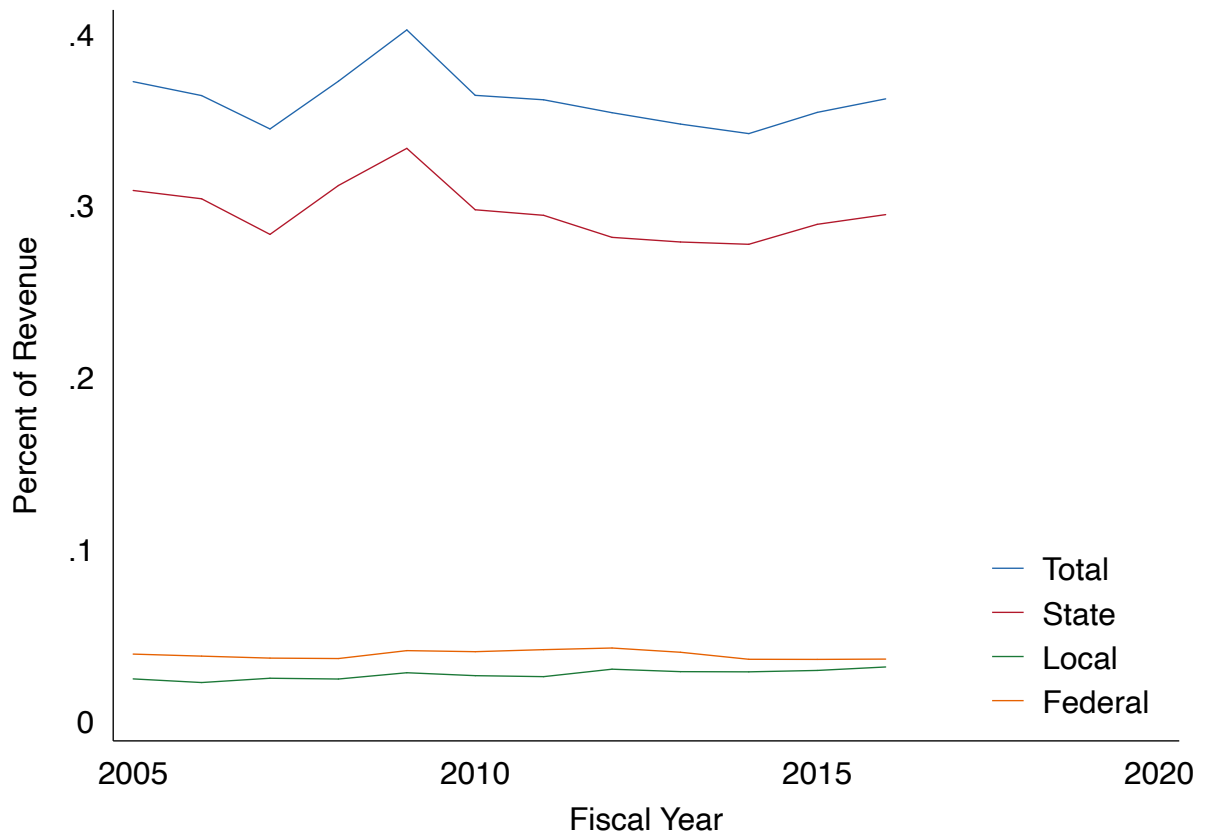
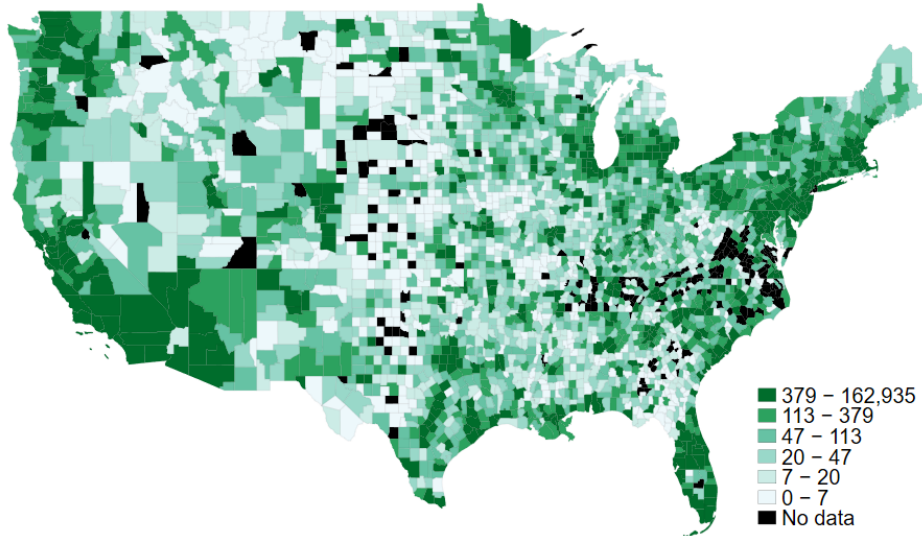
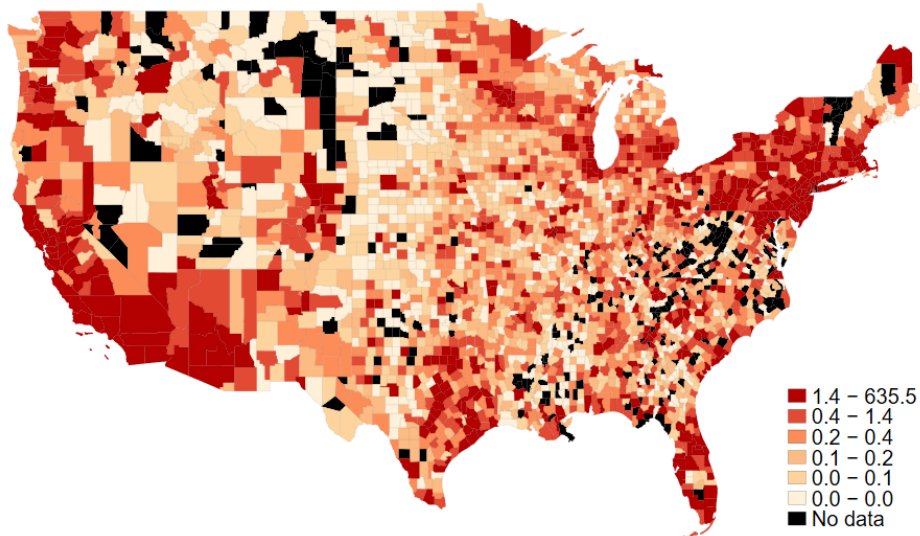


Figure 1.13: Total Debt v.s. Matched Bond Value

Note: This graph contrasts the total amount of debt outstanding (Panel (a)) and the total value of municipal bonds outstanding (Panel (b)) at the county level, as of 2016. Debt value is obtained directly from the Annual Survey of State and Local Government Finances. Municipal bond value is calculated by summing the face value of all outstanding (i.e. already issued but haven't matured or retired) municipal bonds for each county.



(a) Total Debt



(b) Bond value matched

1.7.2 Tables

Table 1.1: Total Debt

Note: This table describes the steps involved in cleaning the MSRB data. Transaction records are first collapsed and reshaped into security-month units. Column *Bonds* reflects the number of unique bonds remaining after each cleaning step, while column *Bond-Month* reflects the number of bond-month records (as the unit of observations) in the sample. Asterisk items are only adopted in robustness check section but not in the main analysis. See Section 1.8.5 for a detailed description of the geocoding algorithm needed to perform certain cleaning steps.

Cleaning Step	Bonds	Bond-Month
Full MSRB sample	2800430	22294603
Remove state bond	2217314	15386166
Remove certificates, notes and other irregular debt instruments	1995686	14101057
Remove floating bond, bond with missing coupon	1978840	13690935
Remove taxable and AMT bond	1868138	13032106
Remove green bond, tribal bond, university and college bond	1838206	12746776
Remove trades before issuance, after maturity	1837107	12741320
*Remove trades three months after issuance	1271376	11534300
*Remove trades three months before maturity	1163769	10633438
*Remove bonds with tranche structure	1159230	10567607
*Remove bonds with sinking fund provision	1046705	8726451
*Remove insured bonds	600343	5019096
*Remove bonds with embedded option	321051	2462576

Table 1.2: County Summary Statistics

Note: This table reports summary statistics for the counties included in the main sample. It includes both time-invariant characteristics and time-varying ones. *Pop (2010)* and *GDP (2010)* are the population (in thousand) and GDP (in million USD) of the county in year 2010. *Vote (average)* is the average political leaning defined in Section 1.2.2 for all gubernatorial elections since 2000. *Num bonds*, *Value bonds* are the number of bonds and value of bonds outstanding for a county in a given year. *Total Debt*, *Total Rev*, *Total Exp*, *Transfer (Federal)*, *Transfer (Local)*, *Transfer (State)* are the total debt outstanding (bonds included), total revenue, total expenditure, federal transfer (inflow), local transfer (gross inflow), state transfer (inflow) respectively. *Vote (Last Election)* is the county level political leaning in the most recent election. Both *Stay Aligned* and *Become Misaligned* start from the status quo of being politically aligned with the governor before the most recent election, while both *Become Aligned* and *Stay Misaligned* start from the status of being politically misaligned with the governor before the most recent election.

	Mean	Std	Min	P25	Median	P75	Max	N
Pop (2010)	104.62	324.06	.29	12.65	28.45	74.75	9818.6	2843
GDP (2010)	5.29	21.63	.01	.4	.97	2.74	574.26	2802
Vote (average)	.15	.23	-.7	.01	.17	.31	.82	2831
Num bonds	93.09	317.63	1	8	24.5	73	14062	24106
Value Bonds	240.03	2949.07	0	3.11	16.66	81	175283.36	24106
Total Debt	438.15	2984.33	0	16.9	51.56	181.55	162934.59	13562
Total Rev	453.3	2809.53	0	37.5	91.71	253.89	134443.94	7564
Total Exp	449.35	2810.45	.01	36.66	89.84	250.23	129637.26	7563
Transfer (Federal)	14.94	111.72	0	.23	1.31	5.91	6331.29	12812
Transfer (Local)	14.03	67.31	0	.46	1.89	6.87	2454.83	13250
Transfer (State)	132.61	568.86	0	15.14	36.44	94.35	29034.11	13691
Vote (Last Election)	.16	.3	-.89	-.04	.17	.37	.98	24057
Stay Aligned	.73	.44	0	0	1	1	1	14287
Become Aligned	.41	.49	0	0	0	1	1	9770
Become Misaligned	.27	.44	0	0	0	1	1	14287
Stay Misaligned	.59	.49	0	0	1	1	1	9770

Table 1.3: Bond Summary Statistics

Note: This table reports summary statistics for the bond sample used in the analysis. Panel (a) presents the primary market (bond level) characteristics and Panel (b) presents the secondary market (bond-month level) characteristics. In Panel (a), *Amount* is the size of issuance in million USD; *Duration (year)*, *Mod-duration (year)*, *Convexity* and *Maturity* are bond duration, modified duration, convexity and the number of months toward maturity, all measured at issuance; *Funded* takes value 1 if there exists companion sinking fund, including invested/mandatory/optional/anticipated fund type; *General Obligation* bonds (backed by the general revenue of the issuing municipality) are in contrast with revenue bonds (supported by project-specific revenue source). In Panel (b), *Weighted Yield* is the yield of municipal bond weighted by *Par* (in thousand USD) value in the transaction, prior to tax adjustment; *Spread* is the yield spread of bond, adjusted for tax treatment; *Spread_D*, *Spread_P*, *Spread_S* are yield spreads only for inter-dealer trade (D), purchase from a customer by a dealer (P) or sale to a customer by a dealer (S); *Std Yield* is the standard deviation of yield in each transaction if there are multiple transactions for a given security in a specific month; *Age* and *Maturity* are the number of months between this trading month to bonds' issuing month and to maturity; *Since Last Election* and *To Next Election* are the number of months since the last election and to the next election respectively.

(a) Primary Market (Bond) Characteristics

	Mean	Std	Min	P25	Median	P75	Max	N
Coupon	3.7	1.28	0	3	4	4.75	16	1837107
Offer Price	102.7	10.6	.73	99.96	101.21	105.64	496.01	1801685
Offer Yield	3.06	1.43	0	1.95	3.11	4.08	100	1801478
Amount	1.93	14.12	0	.22	.5	1.34	8815	1821096
Duration	7.96	4.20	0.5	4.69	7.86	10.89	55	1837107
Mod-duration	7.82	4.09	0.11	4.65	7.74	10.68	52.95	1837107
Convexity	95.26	94.6	0.02	24.75	69.77	140.09	2829.14	1837107
Maturity	123.41	78.13	0	62	112	172	1255	1837107
Putable	0	.03	0	0	0	0	1	1837107
Callable	.48	.5	0	0	0	1	1	1837107
Funded	.09	.29	0	0	0	0	1	1837107
Insured	.36	.48	0	0	0	1	1	1837107
General Obligation	.4	.49	0	0	0	1	1	1837107

(b) Secondary Market (Bond-Month) Characteristics

Variable	Mean	Std	Min	P25	Median	P75	Max	N
Weighted Yield	2.71	1.39	.27	1.56	2.6	3.75	6.61	12638282
Spread	1.79	1.53	-1.92	.82	1.54	2.46	7.47	12559127
Spread (Inter Dealer)	1.49	1.34	-1.71	.63	1.25	2.19	6.47	4610097
Spread (Dealer Buy)	2.19	1.74	-1.51	1.03	1.87	2.97	8.6	9245699
Spread (Dealer Sell)	1.47	1.48	-2.57	.6	1.28	2.17	6.71	11236630
Par	901.78	6943.45	0	50	135	430	8763955	12741320
Std Yield	.32	1.16	0	.06	.14	.29	86.36	10599393
Age	52.86	49.13	-2	14	44	81	1021	12741320
Maturity	110.58	82.03	0	45	93	160	761	12741320
Since Last Election	25.29	13.91	2	13	25	37	50	12741320
To Next Election	22.84	13.88	1	11	21	35	49	10808103

Table 1.4: Primary Market Evidence

Note: This table reports the effect of political alignment on municipal bond offering yield. *Misaligned County* takes value of 1 if the issuer of the municipal bond is in a county that is currently politically misaligned with the state governor and takes value of 0 otherwise. Column (1) performs the uni-variate analysis with *Misaligned County* as the only RHS regressor. Columns (2)-(4) adds *Log(Issuance Amount)*, *Convexity*, *Modified Duration*, *Coupon* as additional control variables. Columns (3)-(5) adds time fixed effect, issuer fixed effect and both respectively. Standard errors are two way clustered at the issuer and time level.

	(1)	(2)	(3)	(4)	(5)
	Offering Yield	Offering Yield	Offering Yield	Offering Yield	Offering Yield
Misaligned County	0.3163*** (0.0569)	0.2023*** (0.0320)	0.0214** (0.0094)	0.1508*** (0.0294)	0.0219*** (0.0083)
Log(Issuance Amount)		-0.1551*** (0.0110)	-0.0694*** (0.0042)	-0.2221*** (0.0079)	-0.0483*** (0.0028)
Convexity		-0.0017*** (0.0002)	-0.0030*** (0.0001)	-0.0020*** (0.0002)	-0.0035*** (0.0001)
Modified Duration		0.2164*** (0.0040)	0.2333*** (0.0026)	0.2306*** (0.0037)	0.2452*** (0.0023)
Coupon		0.4479*** (0.0090)	0.1904*** (0.0044)	0.3864*** (0.0084)	0.1589*** (0.0040)
Observations	420858	417092	417091	416570	416570
R^2	0.011	0.514	0.858	0.660	0.909
Adjusted R^2	0.011	0.514	0.858	0.652	0.907
Time FE	N	N	Y	N	Y
Issuer FE	N	N	N	Y	Y

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 1.5: RD Regression Results

Note: This table analyze the impact of becoming politically (mis)-aligned with state governors on yield spreads of municipal bonds issued by these counties. The specification of the regressions resembles a RDD with bandwidth 0.05 (i.e. $\frac{(\text{votes by winning party}-\text{votes by losing party})}{(\text{votes by winning party}+\text{votes by losing party})} < 0.05$). Swing counties where absolute value of political leaning smaller than 0.2 are not included in the regressions. Columns (1)-(2) report the baseline results, and columns (3)-(4) interact the discontinuity variable "Become (Mis)Aligned" with the degree of political leaning. Odd columns use the subsample where the status quo was politically aligned (with the state governor) before the most recent gubernatorial election while even columns use the subsample where the status quo was politically misaligned (with the state governor). Time fixed effects and bond fixed effects are included in the regressions and standard errors are two way clustered at the time and county level.

LHS Var	Yield Spread			
	Aligned	Misaligned	Aligned	Misaligned
Become Misaligned	0.197*** (0.0745)			
Become Aligned		-0.288** (0.132)		
Become Misaligned (Cont)			0.00635*** (0.00183)	
Become Aligned (Cont)				-0.0114*** (0.00317)
Observations	646,159	323,443	646,159	323,443
R-squared	0.711	0.709	0.712	0.709
Num Counties	522	289	522	289

Standard errors are two-way clustered on security and time.

*** p<0.01, ** p<0.05, * p<0.1

Table 1.6: Falsification Checks

Note: This table present results from three falsification checks. Odd columns use the subsample where the status quo was politically aligned before the nearest upcoming election, while even columns use the subsample where the status quo was politically misaligned before the nearest upcoming election. For column (1)-(2) and (3)-(4), observations are on county-time level. The left hand side variables are the (log) dollar amount (*Maturing Amount*) and (log) number of municipal bonds (*Maturing Number*) matured in each month respectively. Columns (5)-(6) have observations on bond-time level with yield spread as left hand side variable but political alignment defined using fabricated election results. Election winners are classified as “Republican” if the absolute value of vote margin is greater than 20%, and as “Democratic” if the absolute value of vote margin is smaller than 20%. County and time fixed effects are included in columns (1)-(4), and bond and time fixed effects are included columns (5)-(6). Standard errors are two way clustered on the county and time level.

LHS Var/Check	Maturing Amount		Maturing Number		Fake Alignment	
	Aligned	Misaligned	Aligned	Misaligned	Aligned	Misaligned
Become Misaligned	0.0954 (0.150)		0.0713 (0.0905)		0.158 (0.151)	
Become Aligned		0.0400 (0.292)		-0.318 (0.194)		0.237 (0.467)
R-squared	0.539	0.559	0.473	0.513	0.728	0.771
Num Counties	522	289	522	289	515	665

Standard errors are two-way clustered on security and time.

*** p<0.01, ** p<0.05, * p<0.1

Table 1.7: Robustness: Alternative Specification and Bandwidth

Note: This table presents the regression results under several alternative specifications as robustness check. Odd columns use the subsample where the status quo was politically aligned before the nearest upcoming election, while even columns use the subsample where the status quo was politically misaligned before the nearest upcoming election. Columns (1)-(2) additionally control for the absolute voting margin to deal with political uncertainty. Columns (3)-(4) use quadratic polynomial to fit running variables on either side of the cutoff. Columns (5)-(6) use the same median (13) state-level vote margins as the bandwidth to define close gubernatorial elections. Columns (7)-(8) define partisan vs swing counties using the sample median (15) absolute value of “average political leaning”. All columns share the same specifications as the one used for main analysis with the same set of control variables (not reported due to space constraint) and fixed effects. Standard errors are two way clustered on the county and time level.

LHS Var	Yield Spread								
	Status Quo	Aligned	Misaligned	Aligned	Misaligned	Aligned	Misaligned	Aligned	Misaligned
Become Misaligned	0.295*** (0.0887)	0.306*** (0.0461)	0.153** (0.0742)	0.192*** (0.0733)	-0.383*** (0.132)	-0.107* (0.0566)	-0.358*** (0.116)		
Become Aligned		-0.330** (0.134)							
R-squared	0.711	0.709	0.709	0.712	0.709	0.686	0.692	0.707	0.712
Num Counties	522	289	289	522	289	675	518	627	375
Bandwidth	5	5	5	5	5	13	13	5	5
Cutoff	20	20	20	20	20	20	20	15	15
Polynomial	Abs	Abs	Quad	Quad	Quad	Linear	Linear	Linear	Linear

Standard errors are two-way clustered on security and time.

*** p<0.01, ** p<0.05, * p<0.1

Table 1.8: Robustness: Sample Construction

Note: This table presents the regression results with different filters in the sample construction process. Columns (1), (3), (5), (7), (9) use the subsample where the status quo was politically aligned before the most recent election while columns (2), (4), (6), (8), (10) use the subsample where the status quo was politically misaligned before the most recent election. Columns (1) and (2) use the full sample before applying any filters (except for state bonds, which are naturally excluded as they do not have the vertical political alignment measure); columns (3) and (4) remove all trades three months after issuance maturity in addition to the filters used in main analysis; columns (5) and (6) remove all trades three months before maturity in addition to the filters in columns (3) and (4); columns (7) and (8) remove all bonds with special risk mitigation strategies including tranche structure, sinking fund provision and bond insurance; columns (9) and (10) remove all bonds with embedded options, either put option or call options. Details on these filters and their impact on the sample can be found in Table 1.1. All columns share the same specifications as the main analysis with the same set of control variables (not reported due to space constraint) and fixed effects. Standard errors are two way clustered at the county time level

Sample	Full Sample		Issuance		Mature		Insured		Option	
	Aligned	Misaligned	Aligned	Misaligned	Aligned	Misaligned	Aligned	Misaligned	Aligned	Misaligned
Status Quo										
Become Misaligned	0.272*** (0.0454)		0.265*** (0.0510)		0.251*** (0.0524)		0.270*** (0.0675)		0.347*** (0.0734)	
Become Aligned		-0.291*** (0.0917)		-0.420*** (0.0966)		-0.438*** (0.103)		-0.819*** (0.102)		-0.696*** (0.0560)
Observations	613,655	303,108	465,119	224,364	459,840	221,662	201,392	112,930	103,065	58,767
R-squared	0.762	0.753	0.732	0.728	0.741	0.738	0.790	0.767	0.793	0.768

Standard errors are two-way clustered on security and time.

*** p<0.01, ** p<0.05, * p<0.1

Table 1.9: Heterogeneity

Note: This table reports the interaction effects between changes in political alignment and bond/county characteristics. In columns (1)-(2), changes in political alignment (Become (Mis)aligned) are interacted with Long term to Maturity indicator, where a bond is defined as long term to maturity if it's maturity date is at least 10 years (\sim sample median) after the tenure of the newly elected state governor. In columns (3)-(4), changes in political alignment are interacted with utility revenue bonds (water, gas and other utilities). In columns (5)-(6), changes in political alignment are interacted with whether a county's dependence on state transfer (measured by received state transfer as a fraction of total expenditure for each county) is below sample median. In columns (7)-(8), changes in political alignment are interacted with the whether a municipal bond has a credit rating of A or above. Odd columns use the subsample where the status quo is politically aligned (with the state governor) before the nearest upcoming gubernatorial element while even columns use the subsample where the status quo is politically misaligned (with the state governor). Time fixed effects and bond fixed effects are included in the regressions and standard errors are two way clustered at time and county level.

VARIABLES	Time to Maturity		Utility Bond		Transfer Dependence		Rating	
	Aligned	Misaligned	Aligned	Misaligned	Aligned	Misaligned	Aligned	Misaligned
Become Misaligned	0.270*** (0.0762)		0.248*** (0.0858)		0.362*** (0.0989)	*	0.174** (0.0551)	
Become Aligned		-0.322*** (0.0910)		-0.405** (0.178)		-0.333*** (0.0866)		-0.188* (0.131)
Become Misaligned*Long T2M	-0.116* (0.0601)							
Become Aligned*Long T2M		0.0607 (0.131)						
Become Misaligned*Utility			-0.138*** (0.0357)					
Become Aligned*Utility				0.377*** (0.0959)				
Become Misaligned*Transfer%					-0.130* (0.0681)			
Become Aligned*Transfer%						0.0389* (0.0218)		
Become Misaligned*High Rating							-0.133* (0.0697)	
Become Aligned*High Rating								0.0956 (0.0938)
Observations	630,669	320,111	445,519	236,138	630,669	320,111	401,827	200,037
R-squared	0.734	0.871	0.782	0.842	0.734	0.871	0.699	0.882

Standard errors are two-way clustered on county and time.

*** p<0.01, ** p<0.05, * p<0.1

Table 1.10: Heterogeneity

Note: This table reports the interaction effects between changes in political alignment and bond/county characteristics. In columns (1)-(2), changes in political alignment (Become (Mis)aligned) are interacted with Low Reduction indicator, where a county is defined as low reduction if the ex-post change in intergovernmental transfer is smaller than 5% (time FE adjusted). In columns (3)-(4), changes in political alignment are interacted with utility insured bonds. In columns (5)-(6), changes in political alignment are interacted with an indicator that the municipal bond has a sinking fund. In columns (7)-(8), changes in political alignment are interacted with the whether the state is under Republican control. Time fixed effects and bond fixed effects are included in the regressions and standard errors are two way clustered at time and county level.

Heterogeneity Status Quo	Reduction in Transfer		Insured Bond		Sink Fund		Republican	
	Aligned	Misaligned	Aligned	Misaligned	Aligned	Misaligned	Aligned	Misaligned
Become Misaligned	0.266*** (0.0577)		0.252*** (0.0652)		0.292*** (0.0889)		0.204*** (0.0703)	
Become Aligned		-0.317*** (0.0917)		-0.355** (0.156)		-0.341*** (0.0921)		-0.278** (0.125)
Become Misaligned*LowRdc	-0.158*** (0.0571)							
Become Aligned*LowRdc		0.121* (0.061)						
Become Misaligned*Insured			-0.0641* (0.0322)					
Become Aligned*Insured				0.0711 (0.0689)				
Become Misaligned*SinkFund					-0.117** (0.0501)			
Become Aligned*SinkFund						0.144* (0.0813)		
Become Misaligned*Republican							-0.0443 (0.0751)	
Become Aligned*Republican								0.0419 (0.0857)
Observations	630,669	320,111	445,519	236,138	630,669	320,111	630,669	320,111
R-squared	0.734	0.871	0.782	0.842	0.734	0.871	0.734	0.871

Standard errors are two-way clustered on county and time.

*** p<0.01, ** p<0.05, * p<0.1

Table 1.11: Mechanism: Municipal Bond Liquidity

Note: This table tests liquidity as a potential mechanism for changes in municipal bond yield spread following changes in political alignment status. The status quo before the nearest upcoming gubernatorial election for a county is being politically aligned with the state governor in odd columns and misaligned in even columns. Columns (1)-(2) use the total par value (in million US dollars) traded in each month as the left hand side variable. Columns (3)-(4) replicate the specification in columns (1)-(2) but only include inter-dealer transactions in the regression. Columns (5)-(6) include all the trading records and use within-month yield spread standard deviations for each bond as the left hand side variable. Columns (7)-(8) replicate the baseline results reported in Table 1.5 but only include liquid bonds in the sample, where the criteria of liquid bonds is to have 10 or more trading months in the full sample. Bond fixed effects and time fixed effects are included in the regressions. Standard errors are two-way clustered at the county and time level.

Specification	All		Inter-Dealer		Yield Std. Dev.		Liquid Bond	
	Aligned	Misaligned	Aligned	Misaligned	Aligned	Misaligned	Aligned	Misaligned
Becoming Misaligned	0.860*** (0.253)		0.415*** (0.155)		0.061** (0.031)		0.165*** (0.069)	
Becoming Aligned		0.186* (0.103)		0.083** (0.041)		0.151** (0.063)		-0.317** (0.147)
Observations	908,637	1,357,042	530,777	797,542	653,300	985,754	498,857	248,231
R-squared	0.541	0.440	0.411	0.325	0.447	0.469	0.708	0.710

Standard errors are two-way clustered on security and time.

*** p<0.01, ** p<0.05, * p<0.1

Table 1.12: State vs Local Transfer

Note: This table reports per capita state and local intergovernmental transfer (in thousand US dollars) at the county level. Columns (1)-(2) report the state transfer and columns (3)-(4) report the local transfer. (1) and (3) indicate Democratic control of the state government (i.e. governor in the office is affiliated with the Democratic party) while columns (2) and (4) indicate Republican control of the state government. Rows (1)-(3) are mean, standard deviation and number of observations for Democratic-leaning counties and rows (4)-(6) are for Republican-leaning counties.

		State Transfer		Local Transfer	
		Democratic Control	Republican Control	Democratic Control	Republican Control
Democratic County	Mean	2.11	1.72	0.178	0.119
	Std	1.13	1.38	0.511	0.218
	Obs	6390	3195	6391	3161
Republican County	Mean	1.76	1.89	0.131	0.117
	Std	1.44	0.93	0.455	0.292
	Obs	2094	9062	2094	9063

Table 1.13: RD Evidence - Transfer

Note: This table presents the relationship between political alignment status and the size of the intergovernmental transfer. Columns (1)-(2) are for local transfer and columns (3) and (4) are for state transfer. The status quo for a county before the nearest upcoming gubernatorial election is being politically aligned with the state governor in odd-numbered columns and politically misaligned in even-numbered ones. The observation unit is county*time with county fixed effect and time fixed effects included in the regression. Standard errors are two-way clustered at the county and time level.

LHS Var	Local Transfer		State Transfer	
	Aligned	Misaligned	Aligned	Misaligned
Become Misaligned	0.00553 (0.0110)		-0.0391* (0.0208)	
Become Aligned		0.00797 (0.00994)		0.0548** (0.0255)
Observations	4,015	2,923	5,119	2,090
R-squared	0.701	0.706	0.734	0.821

Standard errors are two-way clustered on security and time.

*** p<0.01, ** p<0.05, * p<0.1

Table 1.14: Mechanism: Credit Risk

Note: This table tests credit risk as a potential mechanism for changes in municipal bond yield spread following changes in political alignment status. The status quo before the nearest upcoming gubernatorial election for a county is being politically aligned with the state governor in odd columns and misaligned with the state governor in even columns. Columns (1)-(2) replicate the baseline regression reported in Table 1.5. Columns (3)-(4) include the then credit rating of municipal bonds in the regression, with "AAA/Aaa" encoded as 1, "AA+/Aa1" encoded as 2, and so on. Columns (5)-(6) include the intergovernmental transfer from the state government in the regression. Columns (7)-(8) adopt the same regression specification but use one year forward looking credit rating as the dependent variable. Bond fixed effects and time fixed effects are included in the regressions. Standard errors are two-way clustered at the county and time level.

LHS Var	YS		YS		YS		Rating	
	Aligned	Misaligned	Aligned	Misaligned	Aligned	Misaligned	Aligned	Misaligned
Become Misaligned	0.197*** (0.0745)		0.121* (0.0639)		0.144* (0.0788)		0.553 (0.296)	
Become Aligned		-0.288** (0.132)		-0.134 (0.141)		-0.279 (0.190)		-0.692* (0.351)
Rating			0.166*** (0.00672)	0.0999*** (0.0203)				
State Transfer					-0.0327 (0.0234)	-0.117* (0.0626)	-0.457** (0.214)	-0.525* (0.269)
Observations	646,159	323,443	411,706	204,501	468,388	216,541	333,192	184,317
R-squared	0.711	0.709	0.663	0.663	0.712	0.712	0.757	0.755

Standard errors are two-way clustered on security and time.

*** p<0.01, ** p<0.05, * p<0.1

Table 1.15: Mechanism: Local Government Reaction

Note: This table presents the relationship between political alignment status and the county primary market issuance activities. Columns (1)-(2) are for (log) total issuance, columns (3)-(4) are for the fraction of utility bonds compared to all, columns (5)-(6) are for number of issuance and columns (7)-(8) are for average issue size. We take twelve months lag for all measures. The status quo for a county before the nearest upcoming gubernatorial election is being politically aligned with the state governor in odd-numbered columns and politically misaligned in even-numbered ones. The observation unit is county*time with county fixed effect and time fixed effects included in the regression. Standard errors are two-way clustered at the county and time level.

Specification VARIABLES	Log Total Amount		Utility%		#Issuance		Log Ave Size	
	Aligned	Misaligned	Aligned	Misaligned	Aligned	Misaligned	Aligned	Misaligned
Becoming Misaligned	0.0416** (0.0188)		-0.000 (0.0103)		1.729 (0.979)		0.0032 (0.0495)	
Becoming Aligned		-0.0322* (0.0166)		-0.001 (0.0152)		-1.427* (0.734)		0.0011 (0.0372)
Observations	7,212	6,995	7,212	6,995	7,216	7,000	7,212	6,995
R-squared	0.542	0.483	0.509	0.457	0.426	0.368	0.528	0.438

Robust standard errors in parentheses

Table 1.16: Election Cycle

Note: This table summarizes the gubernatorial election cycles. The first column lists the cycle length and frequency and the second column displays the states that adhere to the corresponding U.S. gubernatorial election cycles listed in the first column. Off-cycle special/recall elections are not included.

Election Cycle	State (special month)
Two-year cycle starting from 1990	NH, VT
Four-year cycle starting from 1991	KY, LA (10/11), MS
Four-year cycle starting from 1992	DE, IN, MO, MT, NC, ND, UT, WA, WV
Four-year cycle starting from 1993	NJ, VA
Two-year cycle from 1990 to 1994,	RI
Four-year cycle starting from 1994	
Four-year cycle starting from 1990	Others

Table 1.17: Summary Statistics by State

Jurisdiction	Cycle	Ext	Dev	VETO	Line Item					Entire Bill	RSA	Override
					FEPA	LAA	LFFA	PCL	RSA			
AK	A		G	✓	✓	✓	✓	✓	✓	R	3/4	
AL	A	✓	G	✓	✓			✓	✓	S	1/2	
AR	A	✓	J	✓	✓			✓	✓		1/2	
AZ	A		J	✓	✓		✓	✓	✓		2/3	
CA	A		J	✓	✓	✓	✓	✓	✓	R	2/3	
CO	A		J	✓	✓	✓	✓	✓	✓		2/3	
CT	E	✓	G	✓	✓			✓	✓		2/3	
DE	A		G	✓	✓			✓	✓		3/5	
FL	A	✓	G	✓			✓	✓	✓		2/3	
GA	A		G	✓	✓	✓	✓	✓	✓		2/3	
HI	E		G	✓				✓	✓		2/3	
IA	A		G	✓	✓	✓	✓	✓	✓		2/3	
ID	A		G	✓				✓	✓		2/3	
IL	A		G	✓	✓			✓	✓	R	3/5	
IN	E	✓	G					✓	✓		1/2	
KS	A	✓	G	✓			✓	✓	✓		2/3	

KY	O	✓	G	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	1/2	
LA	A	✓	G	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	2/3	
MA	A	✓	G	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	R	2/3
MD	A	✓	G																	1/2	
ME	E	✓	G	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	R	1/2
MI	A	✓	G	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓		2/3
MN	E	✓	G	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓		2/3
MO	A		G	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	R	2/3
MS	A	✓	J	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓		2/3
MT	E	✓	G	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓		2/3
NC	E		G																	R	3/5
ND	E		J	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓		2/3
NE	E	✓	G	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	R	3/5
NH	E		G																		2/3
NJ	A	✓	G	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	R	2/3
NM	A		J	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓		2/3
NV	E		G																		2/3
NY	A	✓	G	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓		2/3
OH	E	✓	G	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓		3/5

OK	A	✓	G	✓	✓	✓	✓	✓	✓	✓	✓	2/3
OR	E	✓	G	✓								2/3
PA	A	✓	G	✓	✓							2/3
RI	A	✓	G									3/5
SC	A		G	✓	✓	✓	✓	✓	✓	✓	✓	2/3
SD	A	✓	G	✓								2/3
TN	A	✓	G	✓	✓						R	2/3
TX	E		J	✓	✓				✓			2/3
UT	A		J	✓								2/3
VI	O		G	✓	✓	✓	✓	✓	✓	✓	R	2/3
VT	A	✓	J									2/3
WA	E		G	✓	✓	✓	✓	✓	✓	✓		2/3
WI	E		G	✓	✓	✓	✓	✓	✓	✓	R, S	2/3
WV	A	✓	G	✓	✓	✓	✓	✓	✓	✓	R	1/2
WY	O		J	✓	✓	✓	✓	✓	✓	✓		2/3

^a Column Cycle reports the budget cycle of each state where "A" stands for annual budget, "E" stands for biennial budget starting from even years and "O" stands for biennial budget starting from odd years. Column Ext reports whether the state has special accommodations for newly elected governors including extended budget deadlines. Column "Dev" reports whether the governor's budget is introduced as bill(s) in legislature (G) or the budget proposal is developed by a joint legislative body (J).

^b Line item veto is a provision that allows a governor to reject particular items of the legislative budget on a line-by-line basis. FEPA/LAA/LF-FA/PCL stands for the veto rights on funding for an entire program or agency, on language accompanying appropriation itself, on language in footnote or following appropriation explaining how budget to be spent, on proviso or contingency language on expenditure of appropriation respectively.

^c Column "RSA" stands for reduce (R) amounts or substitute (S) amounts for legislature to consider. Column "Override" stands for legislative votes required to override governor's veto

Table 1.18: Default Episodes

Note: This table reports the statistics on municipal bond default episodes. Panel (a) contrast the number of county*month units, the number of bond*month units and the number of default episodes by political alignment status. Panel (b) reports the regression results of political misalignment on the probability of default and probability of reinstatement.

	Aligned	Misaligned	Ratio
#County*Month	9 445	2 609	2.61
#Bond*Month	51 664	20 463	2.52
#Default	1 249	784	1.59

(a) Panel A: Counts by Alignment

	(1) Default	(2) Reinstated
Misaligned	0.010*** (0.000)	-0.242* (0.127)
R^2	0.01	0.166

(b) Panel B: Default-Probability Regressions

Table 1.19: Check State Matching

Note: This table shows the accuracy of state assignment algorithm based on regular expression. Each observation is a unique bond CUSIP. We take the state information from MMBSB as the target and focus on matching 49 states excluding AK as well as the state NA (not applicable) from MMBSB. *Correctly Matched* includes cases where the algorithm assigns the same state as given by MMBSB and cases where the algorithm does not assign any states and MMBSB assigns the state NA. *Missing* means the algorithm does not assign any states but the state information given by MMBSB is not NA. *Mismatched* means the algorithm assigns different states from those given by MMBSB.

	Freq	Percent	Cum
Correctly Matched	2,677,961	96.64	96.64
Missing	66,439	2.40	99.04
Mismatched	26,677	0.96	100.00

Table 1.20: Sample Construction Statistics

Note: This table presents the statistics on our sample construction process with Mergent Municipal Bond Securities Database (MMBSD) full sample. Column *Bonds(No)* is the number of unique bonds (identified by CUSIP) in the raw MMBSD sample in each state; column *Match(No)* is the number of unique bonds that are matched with a county by our program; column *Match(No%)* is the percent of unique bonds that are matched with a county; column *Flag (No)* is the number of unique bonds that are flagged for manual check and column *Flag (No%)* is the percent of unique bonds that are flagged for manual check

State	Bonds(No)	Match(No)	Match(No%)	Match(Val%)	Flag(No)	Flag(No%)
AK	7216	2830	.39	.4	10	0
AL	42227	37570	.89	.7	1272	.03
AR	43040	35726	.83	.66	2460	.06
AZ	33614	26667	.79	.65	282	.01
CA	274759	217325	.79	.54	16083	.06
CO	42331	28118	.66	.49	845	.02
CT	43786	31289	.71	.35	842	.02
DC	4326	342	.08	.08	0	0
DE	3993	1468	.37	.16	43	.01
FL	71422	51932	.73	.63	3067	.04
GA	32813	27125	.83	.65	1695	.05
HI	6485	3671	.57	.36	105	.02
IA	58994	50256	.85	.52	648	.01
ID	8228	5082	.62	.27	409	.05
IL	110386	94230	.85	.56	10708	.1
IN	75504	63414	.84	.57	6730	.09
KS	52588	47770	.91	.75	4883	.09
KY	49123	40802	.83	.6	2561	.05
LA	25687	21096	.82	.49	643	.03

MA	75465	54858	.73	.27	1219	.02
MD	28678	18244	.64	.49	461	.02
ME	13849	6834	.49	.17	98	.01
MI	90709	74428	.82	.53	6295	.07
MN	108690	98543	.91	.65	9119	.08
MO	62675	52027	.83	.57	3848	.06
MS	21246	17145	.81	.38	1711	.08
MT	10178	7121	.7	.43	53	.01
NC	34662	26834	.77	.51	1926	.06
ND	14916	11979	.8	.62	213	.01
NE	66867	61170	.91	.55	4374	.07
NH	9981	5023	.5	.24	16	0
NJ	100843	85523	.85	.41	5035	.05
NM	16677	11540	.69	.38	377	.02
NV	13378	9636	.72	.81	28	0
NY	201517	155352	.77	.5	12836	.06
OH	92605	75270	.81	.63	7689	.08
OK	28765	21433	.75	.52	477	.02
OR	32047	20447	.64	.5	1153	.04
PA	135846	117720	.87	.65	35058	.26
PR	5029	128	.03	0	10	0
RI	11686	6263	.54	.37	18	0
SC	26707	20604	.77	.56	1641	.06
SD	10665	7376	.69	.3	306	.03
TN	37012	32566	.88	.75	1684	.05
TX	347411	305233	.88	.65	36473	.1

UT	18303	14341	.78	.55	90	0
VA	40799	25173	.62	.53	1595	.04
VT	4994	1080	.22	.17	11	0
WA	55698	43482	.78	.59	7283	.13
WI	55698	42489	.76	.55	1182	.02
WV	6313	3828	.61	.45	457	.07
WY	2409	2156	.89	.97	41	.02
All	2809786	2261858	.8	.54	195656	.07

1.8 Appendix from Chapter 1

1.8.1 *Gubernatorial Election Cycle*

In Table 1.16 summarizes the gubernatorial election cycles for different states. Almost all states hold elections in early November except for Louisiana, for which the election was held in later October in 1999, 2007, and 2011.

1.8.2 *Appropriations Legislation*

The frequency the budget for each state is released as well as the exact timeline for the budget cycle vary across states (Kioko and Marlowe [2016]). States have the choice of using either annual or biennial budgets, though the overall trend over the past 70 years has been to switch to annual budgeting.⁴⁹ All states began fiscal year on July 1 with only four exceptions: NY (April 1), Texas (Sept 1), AL (Oct 1), MI (Oct 1).

Fig. 1.11 shows a typical budget cycle for an annual budget. A new budget cycle begins when the state budget office⁵⁰ provides guidance to agencies within state government to submit budget requests. The budget office makes recommendations to the governor on the overall budget proposals after reviewing, consolidating, and analyzing those funding requests, while the governor reviews and makes additional direction/adjustment on the recommendations before presenting to the legislature, serving as a starting point for legislative deliberations. Legislature reviews the budget proposal in committee hearings in Winter/Spring, makes additional direction/adjustment and resolve differences between two chambers. The budget

49. Forty-four states enacted biennial budgets in 1940 but only 16 states as of 2020. In addition, the difference between annual v.s. biennial budgeting is sometimes vague as a number of states effectively use a combination of annual and biennial budgeting in practice. For IA/MI, while classified as annual budgets, the governor will still release detailed spending recommendations for two fiscal years (though subject to additional revisions). In many of the states with biennial budget, they still have a detailed and thorough supplemental budget process for the second year of the biennial budget, effectively making the budget cycle annual.

50. The state budget office can be within the governor's office or report directly to the governor's office or be within the Department of Treasury/Department of Finance/Department of Administrative Services etc and report indirectly to the governor's office.

is then passed by legislature and sent to the governor. Governors may have the choice of approving or vetoing,⁵¹ the entire bill or particular items, as described in Table 1.17.

1.8.3 Intergovernmental Transfer

At the start of the sample in 2005, the transfers accounted for 38% of all local government revenues, ranging from a low of 19.2% in Hawaii to a high of 70.2% in Vermont percentage wise or a low of \$400 million in Hawaii to a high of \$91.5 billion in California in absolute value.

Fig. 1.12 depicts the federal, state and local transfers to all local governments in the U.S. since fiscal year 2005. The scale of the figure is the magnitude of these transfers as a proportion of all local government revenues and, thus, reflects their relative importance as a source of financing for localities. Although intergovernmental transfers increased a lot in the last century, its relative importance has been relatively flat in the recently years. With rare exceptions, transfers from federal government to localities are modest and the exercise of federal regulatory powers over localities is mediated through state governments in most cases.

1.8.4 Default Episodes

Municipal bond market is notable for infrequent defaults and extraordinary stability. The average 5 year municipal bond default rate is less than 0.1% compared to $\sim 7\%$ for corporate bond. Table 1.18 report the statistics on municipal bond default episodes. In Panel (a), we contrast the number of observations at different levels by political alignment status. As we can see from the table, ratio of the number of observations for aligned versus misaligned is 2.61 at county*month level or 2.52 at the bond*month level, but this ratio is only 1.59 for the number of default episodes, reflecting the disproportional number of defaults in counties

51. This again varies across states: in most of the states a bill will become law unless it is vetoed by the governor within a specified number of days while in a smaller number of states, bill fails unless they are formally signed by the governor within a specified number of days

politically misaligned with the state governor. In Panel (b), we run a simple regression to formally confirm that political misalignment is associated with higher probability of default and lower probability of reinstatement following the default.

1.8.5 Data Matching

As the census and gubernatorial election information are reported at the county level⁵², we need to extract the county information from MSRB/Mergent database. One major difficulty is to match the municipal bonds with county partisanship as neither MSRB nor MMBSB directly reports the county/city government with which a particular municipal bond is associated. To do so, we perform both string matching and geocoding exercises outlined below.

String Matching

In MSRB database, researchers have access to security description data. The first method only uses such information to assign counties to each municipal bond traded on the secondary market from 2005 to 2020.

Step one assigns state information to each security. The 2005-2020 MSRB database contains secondary market transactions for $\sim 2.8M$ unique bonds. Researchers that have access to MMBSB could merge the two databases together and directly obtain issuing state information from MMBSB for $\sim 99\%$ of all unique bonds in MSRB. We show in Table 1.19 that our algorithm based on regular expression obtains an accuracy rate of over 96% for the sample of municipal bonds with states information provided by MMBSB.⁵³ For the remaining

52. The exception is Alaska, which reports on house district level.

53. MMBSB have 57 unique states. This includes the 50 US states plus DC, PR, GU, VI, AS, MP and NA (not applicable). For our purposes, we only focus on 49 of the US states excluding AK since partisanship could not be measured on county levels in those other states. To check our algorithm's accuracy, we compare with the 49 states and NA from MMBSB and count the not-assigned cases from our algorithm as being matched with NA.

1% of unique bonds where state information from MMBSD is missing, we use the state assignment algorithm to impute and are able to assign state to 94% of the remaining sample.

Step two assigns county information to each security using state information obtained from step one. Since municipal bonds can be issued by different affiliates of levels of local government such as state, county, and city (town), we obtain a list of all U.S. cities/counties from Simple Maps provided by Pareto Software LLC.⁵⁴ Within each state,⁵⁵ we use regular expression to match all the exact appearance of city/county names in security description given by MSRB. The matching process is done in the following steps:

1. [Preprocessing] We remove a list of special characters such as “, ”, “-” and compress successive spaces to improve the matching accuracy.⁵⁶
2. [Direct County Match] We match bond description/issuer with county name+“ COUNTY” keyword.
3. [Start of String Match] We match at the start of the bond description/issuer first with the city list and then using the county list.
4. [Full String Match] We match the full string of bond description/issuer first with the city list and then using the county list.
5. [Same Name Match] We skip a small subset of counties with the same name as their states in step 3-4 and we match them in this step.

54. We use the Professional version of the dataset for completeness. The database was built from the ground up using authoritative sources such as the U.S. Geological Survey, the U.S. Census, American Community Survey, etc., and covers 108,000 cities and towns from 3,243 counties in 50 states, DC and U.S. overseas territories.

55. State-by-state assignment is necessary since county names are not unique across state borders in the US. For example, 12 counties in the US share the same name Adams in CO, ID, IL, IN, IA, MS, NE, ND, OH, PA, WA, WI. Within a state, no counties share the same name. There exists a small number of counties involving independent cities that share similar names (e.g. Baltimore City (FIPS 24510) and Baltimore (FIPS 24005) County in MD).

56. For example, PRINCE GEORGE’S v.s. PRINCE GEORGES

For each step described above, we preserve the results obtained in previous steps and only modify the county if it is not matched yet in case of a conflict. A record is flagged whenever such a conflict exists.⁵⁷ Such a design reflects the degree of confidence we have in each step: the match in step 1 is almost decisive and the accuracy is over 99.9% when we manually check a random sample. The match in step 2 is based on the observation that many of the security descriptions follow a pattern of Agency+(State)+Project+Series (eg: "**ADAIR MEM HOSP IOWA HOSP PROJ SER A**") and majority of public agencies start their name with location. This step also has over 98% accuracy in the manual checking step. Step 3 is to find the expand step 2 to other positions of the string beyond its start, it can capture cases such as "**CENTRAL LYON IOWA CMNTY SCH REF**" but the caveat is false positivity as some of the cities/counties take very general names (eg: city "**HEALTH**" in county "**MADISON**" can be spuriously matched with "**ARKANSAS DEV FIN AUTH HEALTH CARE REV**"). Even so, this step still generates around 90% accuracy in manual check. Lastly, there are seven counties with the same name as the state they locate in: "**ARKANSAS**", "**HAWAII**", "**IDAHO**", "**IOWA**", "**NEW YORK**", "**OKLAHOMA**", "**UTAH**" and we can spurious assign state bonds to those counties (eg: "**ARKANSAS DEV FIN AUTH ST AGY FACS REV REF & CONSTR JUSTICE BLDG PROJ**"). We put the matching for such counties in the end of the line and records are matched with these counties only if they are not matched with anything else in previous steps. All such records are flagged for manual checking.

The steps above leave us 10% of the records to be checked manually. For counties with the same as states, we check state bonds by looking for a list of key words such as "**DEV FIN AUTH**", "**ST WASTE DISP**" etc. For records that are matched with multiple counties,

57. We only consider it to be a conflict when the associated county of two matches are different. For example, in state of Iowa, the record "**BURLINGTON IOWA TAXABLE CORP PURP SER B**" can possibly be matched twice, the first one is based on "**BURLINGTON**", which is a city located in county "**DES MOINES**", the second one is based on "**IOWA**" as there is also a county called "**IOWA**" in state Iowa. Such a record will be flagged for further manual checking. In contrast, records such as "**COOK CNTY ILL CMNTY COLLEGE CITY COLLEGES CHICAGO**" will not be flagged as both of the matches "**COOK**" and "**CHICAGO**" are associated with "**COOK**" county.

we go through all the observations within each step priority. Most of the conflicts can be easily resolved with human reading, using less than 10 lines of code (for each state), although we had to spend more time on some of the complicated cases.

Table 1.20 presents descriptive statistics. We have approximately 2.5m unique bonds with 20m bond*month observations. The value-weighted average time to maturity at the trading time is about 18 years (221 months). The difference between maturity and the ratio of observations to bonds suggests that most bonds in our sample are only sparsely traded, and we must take care of this (with fixed effects) in a later section to make sure our results are not simply driven by trading on different classes of bonds during different political alignment. The overall matching rating is 0.80, which is pretty high given that a substantial fraction of municipal bonds are issued by the state government or its affiliates, for which no county should be matched by definition. There is non-negligible variation across states in matching rate, though states with low matching rate⁵⁸ issue smaller number of municipal bonds and thus they will be naturally downward weighted in our regressions.

As a validation, Fig. 1.13 plots debt outstanding in 2016 (from the annual survey) and total bond value matched at the county level. As we can see, the density of our matching results, shown in the last map, closely match each other, alleviating the concern of systematic bias of our matching procedure. Similar patterns also apply for other related measures such as total fiscal expenditure, fiscal deficit, and county GDP. In addition, we calculate the changes in debt for adjacent years based on government census data and compare with the changes in debt in the same period based on our matched sample, taking into account new issuance and retirement. These two measures are again highly correlated.

58. Note that Alaska, one of the states with the lowest matching rate, only has voting records at the electoral district level. Thus all observations will be dropped in the regression due to missing of explanatory variable.

1.8.6 Option Adjusted Yield Spread

Roughly half of the municipal bonds in the market are callable,⁵⁹ and we need to adjust the yield of the bond accordingly. Following the standard of the literature (Longstaff et al. [2005], Gao et al. [2019b], Novy-Marx and Rauh [2012]), we use the Black [1976] model for pricing forward commodity contracts to calculate the value of the embedded call option. One problem is that most of the callable bonds are exotic in the sense that they specify a collection of (Expiration date, Strike Price) at issuance (typically at a monthly/quarterly/yearly frequency), and the issuer can call back all or part of the bond according to any of the date and price. We calculate the value of the embedded call option that expires on the nearest call date relative to the first day of the trading month, similar to Gao et al. [2019b], in our baseline analysis and also try two alternative methods, including calculating the maximum of all non-expired options and only focusing on the option-free bonds.

We first discount the coupon and principal payment between the trading date and the call option expiration date using the zero coupon U.S. Treasury yield curve, calculated based on the method proposed in Gürkaynak et al. [2007].⁶⁰ We then calculate the difference between the trading price and the sum of the present value of future cash flow, discounting to call option expiration date to get the forward price of the municipal bond (F_B). Then the value of the call option is given by the Black [1976] pricing formula:

$$C = e^{-rfT}[F_B N(d_1) - KN(d_2)]$$
$$d_1 = \frac{\log(F_B/K) + \sigma_F^2 T/2}{\sigma_F \sqrt{T}}$$
$$d_2 = d_1 - \sigma_F \sqrt{T}$$

59. Less than 0.1% of bonds are puttable.

60. Since in its nature yield curve can only be observed discretely, Gürkaynak et al. [2007] does the interpolation using the Nelson and Siegel [1987], Svensson [1994] form function with four parameters. In the current analysis, we use polynomial splines for simplicity but the results are quantitatively similar.

Where K is the strike price of the call option, T is the time to the expiration date of the call option, r_f is the risk-free rate for the U.S. treasury bond with T maturity, and $N(\cdot)$ is the CDF of standard normal distribution. The volatility of the forward bond price σ_F is calculated using the 60-day ahead volatility in daily returns for corresponding contracts where the variation comes from variations in the yield curve and accrued interest.

The call option adjusted trading price of the bond is given by the observed trading price plus the price of the embedded call option. The call-option-adjusted yield spread is defined as the difference between the call-option-adjusted yield and the risk-free yield of a synthetic risk-free bond with the same payoff structure, following the methodology of Longstaff et al. [2005].

The last step is to adjust for the tax rate for municipal bonds as the majority is tax-free.⁶¹ A small literature studies the marginal tax rate implied by municipal bond prices. Kueng [2014] find that financial markets forecast future tax rates well in both the short and long run. The short-term implied tax rates are slightly below the top statutory bucket and long-term implied rates are significantly lower. Due to data limitations and the scope of this paper, we do not plan to estimate the marginal tax rate ourselves. Instead, in line with the estimates in literature [Longstaff, 2011, Kueng, 2014, Cestau et al., 2019], we assume that the marginal tax rate for tax-exempt bonds is in the top income tax bucket. However, as we directly add bond fixed effects. The impact of tax rate on our main results is, however, rather minimal as it is largely absorbed by bond fixed effects.

61. Only tax-exempt bonds are included in the main analysis.

CHAPTER 2

SHADES AND TRACES OF ESG IN PUBLIC FINANCE: EVIDENCE FROM 120,000 MUNICIPAL OFFICIAL DISCLOSURES

2.1 Introduction

Valued at over \$4 trillion, the municipal bond market finances critical public infrastructure and services across the United States. Issued by state and local governments and various agencies, these bonds are commonly viewed by practitioners, investors, and regulators as aligned with environmental, social, and governance principles, often characterized as “de facto ESG” investments. They frequently fund projects dedicated to clean water, affordable housing, education, and community resilience (Susterra [n.d.], Nelson and Greer [2023], O’Reilly et al. [2021], Nuveen [2024], Municipal Securities Rulemaking Board [2021]). This perception thus arises naturally from their core purpose: financing essential public goods that promote sustainability, equity, and responsible governance.

Despite this perception, explicit ESG labeling in the municipal bond market lags. As illustrated in Fig. 2.1, ESG labeled issuance accounts for only a small fraction of total municipal debt, even as global sustainable finance continues to surge. This discrepancy raises fundamental questions about the alignment between perception and practice. Are municipal bonds genuinely “de facto ESG,” or does this characterization overlook important nuances? Do the underlying projects and their official disclosures adequately reflect established ESG standards, such as those articulated by the Government Finance Officers Association (GFOA)? To what extent do issuers explicitly emphasize ESG factors in their primary market offering documents? And, importantly, does the gap between ESG perception and formal labeling, if it exists, influence municipal bond pricing, particularly the existence and magnitude of a “greenium” in primary market issuance?

These questions sit at the heart of the "values versus value" debate in public finance. On the values side, emphasizing ESG factors could enable issuers to tap into a growing pool of socially conscious investors (Flammer [2021], Tang and Zhang [2020]), who increasingly prioritize sustainable and equitable projects in their portfolios. This alignment might not only broaden market access but also potentially reduce borrowing costs through a greenium, a yield concession reflecting heightened demand. However, such explicit signaling carries risks, including political backlash in polarized environments where ESG initiatives are often critiqued as ideologically driven or overly regulatory. This concern is amplified in the municipal bond market, which is highly segmented due to tax exemptions that favor local investors (Chang et al. [2024]); issuers in conservative-leaning jurisdictions may face voter or stakeholder resistance, deterring proactive ESG promotion. On the value side, even if a greenium exists, its magnitude may be insufficient to offset the upfront costs of labeling, such as third-party certifications, enhanced reporting, or legal reviews, expenses that disproportionately burden smaller issuers with limited resources (Baker et al. [2022], Larcker and Watts [2020], Municipal Securities Rulemaking Board [2021], Bunch et al. [2025]). Furthermore, the subjective nature of ESG materiality (Marlowe [2023], Davidson and Cooper [2025]) adds another layer of uncertainty: without clear, standardized definitions, issuers may hesitate to highlight ESG elements, fearing misinterpretation or liability, leading to under-disclosure despite robust underlying fundamentals.

To bridge this labeling gap and provide empirical clarity, this paper introduces a novel measure leveraging large language models (LLMs) to quantify both the *potential* ESG alignment of municipal bonds, rooted in underlying project fundamentals, and the *actual* ESG emphasis embedded within official disclosures. Using the complete universe of over 120,000 primary market official statements issued between 2012 and 2023, sourced from the Electronic Municipal Market Access (EMMA) system, we deploy state-of-the-art (SOTA)¹

1. At the time of writing (April 2025). Given the rapid evolution of large language models, characterizing any model as SOTA is inherently risky.

LLMs such as Gemma-3 and DeepSeek-V3 to systematically score municipal bonds across environmental (E), social (S), and governance (G) dimensions. Guided by GFOA criteria and foundational ESG principles, our *potential* ESG score assesses the intrinsic alignment of financed projects with ESG objectives, independently of promotional rhetoric. For instance, the LLM evaluates whether a project’s outcomes inherently advance environmental or social goals, irrespective of any ESG labeling or promotional language. In contrast, our *actual* ESG score captures the extent of ESG signaling explicitly or implicitly emphasized within disclosure texts, including formal designations (e.g., "green bond" labels or certifications) and subtler references (e.g., discussions of sustainability impacts, community equity, or governance safeguards).

This LLM-based measure constitutes the chapter’s central methodological contribution, offering a scalable and objective framework for ESG assessment in the often-opaque muni market. Traditional ESG ratings from different agencies frequently exhibit substantial disagreement (Christensen et al. [2022], Berg et al. [2022]), suffer from limited coverage, methodological shifts over time, and inherent subjectivity in rating processes. These limitations are particularly pronounced in the decentralized municipal bond space, characterized by unstandardized disclosure practices. By employing unified, standardized prompts grounded in transparent guidelines from GFOA, our LLM-driven approach addresses these challenges directly, analyzing primary market disclosures that capture issuer intent, project specifics, and initial risk assessments. Consequently, our method reveals substantive ESG elements often overlooked by traditional metrics, providing a valuable complementary lens alongside existing provider-generated labels such as Bloomberg’s sustainable debt tags.

We first validate the scores in Section 2.3. Cross-model agreement is high and distributions are stable across LLM runs. Existing Bloomberg-labeled bonds score higher on both *Potential* and *Actual*, confirming face validity, while many unlabeled bonds with strong fundamentals also surface, precisely the under-promoted cases our measure is designed to detect.

The labeling gap (Potential–Actual) is *persistent* and *widens after 2020*. Figure 2.18 shows positive gaps for every pillar throughout the sample, with a clear post–2020 drift in *Environmental* and the *Composite*. Figure 2.19 documents broad positive gaps across all states and meaningful cross–state dispersion. Within documents, gaps co–move but are far from collinear, pointing to distinct disclosure shortfalls by pillar rather than one common “ESG factor” in OS text.

Aggregating to the county level and using flexible tree ensembles, we summarize drivers via SHAP. Out–of–sample R^2 is modest on the full county sample (≈ 0.10 – 0.18) and larger in the top–500 issuance counties (e.g., Social ≈ 0.34 – 0.37 , Composite ≈ 0.32 – 0.36). Across pillars, three clusters are consistently important: *Prosperity/Cost*, *Demographics*, and *Health/Environment*; signed SHAP often indicates these factors widen the gap. Pillar salience aligns with intuition (e.g., Health/Environment for Social; Prosperity/Cost and Geo–climate/scale for Environmental). Political leaning is comparatively weak once fundamentals are in the model.

Finally, using the Baker et al. [2022] specification with our preferred set of controls and fixed effects (Issuer, Rating, Year–Month), the Bloomberg label’s “greenium” is fragile and often imprecise (Table 2.6, col. (5): -1.361 bps, s.e. 1.807). Replacing the label with our *Composite* scores is more informative. Table 2.7 shows both *Potential* and *Actual* load negatively and are statistically indistinguishable (Wald $F = 0.04$; $p = 0.843$). Interpreted in levels, a 10–point improvement in either composite score is associated with roughly a 4.5–5 bps lower offering yield. Pillar estimates (cols. (3)–(5)) highlight realized *Environmental* content and *Governance* as the clearest contributors; *Social* is small and imprecise. In full horse races (cols. (6)–(7)), pillar scores absorb the informative variation and the Bloomberg label adds little incremental power once text–based scores are present. The pricing takeaway is simple: the market rewards bonds whose OS text signals *capacity* to deliver ESG outcomes and those that *actually* do—at essentially the same marginal rate per unit of information. For issuers, closing disclosure gaps can matter at the margin even without formal labels. For

investors, text-based scoring complements existing vendor tags by surfacing unlabeled bonds with substantive ESG content.

The remainder proceeds as follows. Section 2.1.1 reviews related work and our contributions. Section 2.2 details data curation and the LLM scoring pipeline. Section 2.3 validates the score measures. Section 2.4 characterizes time-series, geography, and drivers of the labeling gap and then reassesses the primary-market greenium. Section 2.5 concludes.

2.1.1 Literature

Our paper contributes primarily to three strands of literature: (i) ESG measurement via textual analysis in finance, (ii) municipal bond pricing and the greenium, and (iii) broader implications of ESG in asset pricing.

First, substantial research highlights critical limitations of traditional ESG scores provided by rating agencies, including inconsistent coverage, subjectivity, and considerable divergence. Berg et al. [2022] quantify this "aggregate confusion," attributing rating disagreements to differences in measurement methods and scope of ESG factors considered. These challenges are particularly pronounced in municipal finance, where disclosure standards are decentralized, resulting in sparse and inconsistent ESG coverage (Marlowe [2023]). Recent qualitative studies further underscore this issue; for instance, Davidson and Cooper [2025] document frequent omissions of material climate risks from official municipal bond disclosures.

Motivated by these concerns, a growing literature leverages natural language processing (NLP) to systematically extract ESG information directly from textual disclosures. Foundational techniques for textual analysis in economics were introduced by Gentzkow et al. [2019], subsequently adapted to ESG contexts. For instance, Engle et al. [2020] pioneered a market-level textual indicator by constructing a "climate news" index from newspaper coverage, widely used as a proxy for aggregate climate sentiment. Similarly, Sautner et al. [2023] apply NLP methods to measure firm-level climate exposure from earnings calls, finding strong

correlations with actual carbon emissions and regulatory risks. Other recent advancements include NLP-based models developed by Schimanski et al. [2024], which quantify corporate ESG disclosure content across specific domains; Birti et al. [2025], who demonstrate that fine-tuned large language models (LLMs) can reliably detect ESG-related content in financial disclosures; and Wood et al. [2025], who use generative AI to assess mutual funds’ stated ESG commitments from prospectus text.

Our chapter extends this emerging NLP literature specifically to public finance and municipal bonds. To the best of our knowledge, we are the first to systematically apply SOTA generative AI models and leverage zero-shot chain-of-thought prompt engineering to comprehensively evaluate ESG content in municipal primary market disclosures. By benchmarking disclosures against transparent ESG guidelines, such as those recommended by the Government Finance Officers Association (GFOA), our novel approach provides objective measures of ESG substance and reveals persistent disclosure gaps. In doing so, we directly address critical shortcomings of conventional ESG scoring methodologies in municipal finance.

Second, our paper contributes to research on municipal bond pricing, specifically examining whether ESG or “green”-labeled bonds command a pricing premium (the greenium). A greenium exists if investors accept lower yields (higher prices) for sustainability-labeled bonds, presumably due to non-pecuniary preferences or perceived reductions in risk.

Prior evidence regarding the municipal greenium is mixed, as summarized in detail by Partridge and Medda [2020b]. Early studies typically found little evidence of a greenium. For instance, Larcker and Watts [2020] matched municipal green bonds with nearly identical conventional bonds, detecting no significant yield difference. Similarly, Karpf and Mandel [2018] found that early municipal green bonds sometimes experienced yield penalties rather than premia. Using an international sample, Zerbib [2019] identified only a minimal greenium across U.S. and European bond markets.

However, recent research suggests that a municipal greenium has emerged. Baker et al.

[2022], analyzing a broad sample of U.S. green municipal bonds, document yields several basis points lower than comparable conventional bonds, with premiums concentrated in bonds backed by third-party certifications or verifications. Similarly, Partridge and Medda [2020a] identify a small but growing greenium in matched bond pairs, correlating its rise with the expansion of ESG-focused investing. Complementary evidence from corporate bonds further supports this trend: Flammer [2021] finds positive stock-price reactions and improved subsequent environmental performance following corporate green-bond issuance, suggesting credible ESG signals strengthen investor trust and demand.

Our study advances this debate by explicitly differentiating ESG labels from substantive ESG disclosure quality. Few prior studies, such as Benincasa et al. [2022], have directly linked textual ESG substance to the municipal greenium, and none have employed advanced generative AI methodologies. Our chapter fills this gap, using SOTA LLM to systematically quantify ESG disclosure from official bond statements, offering new insights into greenium determinants aligned closely with the "value vs. values" framework by Starks [2023].

Lastly, our paper relates broadly to literature examining ESG's impact on asset pricing and public policy. Theoretical models by Pástor et al. [2021, 2022] and Pedersen et al. [2021] demonstrate how investor preferences for ESG can generate equilibrium pricing effects, such as lower expected returns on green assets irrespective of fundamental differences. Empirical evidence confirms these theoretical predictions: Hartzmark and Sussman [2019] show mutual fund flows respond significantly to sustainability rankings, while Avramov et al. [2022] highlight how ESG rating uncertainty affects portfolio outcomes. In fixed income, Bolton and Kacperczyk [2021] document a carbon premium, reflecting higher yields required by investors for carbon-intensive ("brown") firms. Recent studies further illustrate policy-driven ESG impacts; anti-ESG legislation in states like Texas has increased municipal borrowing costs by reducing competition among underwriters and discouraging ESG disclosures (Garrett and Ivanov [2024], Mullin et al. [2023]). We contribute to this literature by demonstrating

that municipal ESG pricing can depend on substantive issuer disclosures in addition to mere labels, and by documenting that local political ideology correlates with, and potentially drives, issuers’ ESG labeling decisions, leading to possible mispricing in public debt markets.

2.2 Data

This section describes data sources, detailed processing steps, and large language model configurations used to generate ESG scores for our empirical analysis. Section 2.2.1 outlines our primary datasets and sources, Section 2.2.2 summarizes cleaning procedures for the primary market disclosures, and Section 2.2.3 details LLM configurations, including prompt engineering and parameter selection.

2.2.1 Data Sources

Our analysis leverages multiple datasets to comprehensively evaluate ESG alignment in municipal bonds, with the core data consisting of primary market disclosures. These disclosures, containing official statements issued at bond origination, are sourced from the MSRB Primary Market Disclosure Historical Data Product accessed through UChicago Booth’s Fama-Miller Center. Although publicly hosted on Electronic Municipal Market Access (EMMA), direct scraping is strictly prohibited, necessitating licensed access to historical data dumps, which also include continuing disclosures not used in this analysis.

To benchmark our ESG scores, we use muni ESG labels from Bloomberg. A detailed, step-by-step collection procedure is provided in Section 2.7.1. Additionally, we gather ESG disclosure guidelines from the Government Finance Officers Association (GFOA)², which serve as foundational references to align our prompt-engineering with muni industry best practices.

2. Available here.

We primarily utilize Gemma-3-27B-IT, introduced by Google (Team et al. [2025]), as our principal LLM for ESG scoring, supplemented by DeepSeek-V3-0324 (Liu et al. [2024]) for verification exercises. We experimented extensively with official APIs, local computational resources (single H100 GPU), and third-party API providers. Ultimately, Nebius AI Studio³ was selected as the cost-efficient solution for our scoring tasks.

For analyzing drivers of ESG labeling gaps, we compile a rich dataset of county-level socioeconomic, demographic, and political information from multiple sources: internal migration (IRS Statistics of Income), labor market data (Bureau of Labor Statistics), local economic conditions (Bureau of Economic Analysis), public health statistics (CDC), election outcomes (CQ voting data), demographics (U.S. Census), COVID policies (USAFACTS), industry structure (County Business Patterns), weather data (NOAA), and educational attainment and poverty rates (U.S. Department of Agriculture). We further augment this county-level dataset with health indicators, crime statistics, shooting incidents, and mobility data from a publicly available repository⁴.

Finally, to study the muni greenium, we rely on standard primary market bond issuance data from Mergent, covering bond issuances up to July 29, 2022. Additionally, we use Atlas Munis GIS-based geolocation, an improvement over the string-based method introduced in Chapter 1, to accurately map municipal bond issuers to their respective counties.

2.2.2 Cleaning Procedures for Primary Market Disclosures

The principal dataset for this study is the historical MSRB Primary Market Disclosure data dumps. Fig. 2.2 illustrates the information available on EMMA for a given CUSIP9. Although the site is publicly accessible, systematic scraping is prohibited. Official Statements (OS) are distributed as PDFs packaged in dated ZIP archives, and companion XML index files provide

3. Accessible here.

4. Available here.

metadata linking issues and securities to those PDFs. Despite this relatively structured delivery, substantial cleaning is required before the texts can be supplied to LLM APIs.

Because we view the cleaning pipeline itself as a contribution, we document a reproducible procedure to identify, select, and extract the relevant OS for each CUSIP.

From XML to a CUSIP–OS map. Working directly with CUSIPs as they appear inside PDFs is unreliable. Although all CUSIPs in a serial muni issue are present, their appearances are unstandardized across documents. We therefore begin with the XML index files. As shown in Fig. 2.3, the XML `UnderlyingFiles` nodes link CUSIPs to OS PDFs, allowing us to avoid scanning entire PDFs for unstructured CUSIP mentions.⁵ Our parser, detailed in Section 2.7.2, establishes these links for the 2012–2023 period.

Initial filters. Starting from the XML-based links, we remove test and obviously erroneous records (e.g., CUSIP9 beginning with 999, maturities set to 2099, issuer names clearly marked as tests), and focus on new-issue CUSIPs when `IssueType` indicates a new issue.⁶ Table 2.1 reports counts of security-level observations, unique CUSIPs, unique XMLs, and ultimately mapped OS PDFs. The initial mapping contains more rows than unique CUSIPs, reflecting OS updates posted over time; a small number of XMLs have no linked documents. These filters have limited impact on sample size.

Deduplication when multiple OS are linked. One-to-many mappings occur both across and within XML files (Fig. 2.4). Our two-stage rule (Section 2.7.3) first prioritizes `DocumentType = OfficialStatement` over `PreliminaryOfficialStatement`. This single stage collapses 90% of CUSIPs with any mapped OS—1,377,043 of 1,526,317—to exactly

5. Many PDFs in the dumps do not resemble bona fide official statements; querying them wastes compute and introduces noise.

6. This step relies on the accuracy of `IssueType` in the XML; spot checks suggest it is imperfect.

one OS.⁷ We then apply deterministic posting-date and file-size rules to finalize a one-to-one CUSIP–OS mapping. For consistency and verification, we manually reviewed all residual $n \rightarrow 1$ linkages, opening more than 12,000 browser sessions to apply occasional corrections. The “IF OS Available” block of Table 2.1 summarizes the before/after counts.

CUSIPs with XMLs but no OS. As reported in Table 2.1, **30,028** CUSIPs have XML links but no mapped OS. Using a Selenium-assisted browsing utility (Section 2.7.4), we verified that approximately **77%** genuinely lacked an OS on EMMA and manually filled the remaining **23%** by locating the correct `FileIdentifier` in the dumps.⁸ We then restrict to posting dates between 2012 and 2023. The resulting sample comprises **1,523,533** unique CUSIPs mapped to **126,430** OS PDFs (Table 2.1).

Text extraction and token constraints. The CUSIP–OS mapping is only the first step. We then extract text with PyMuPDF and validate a subsample manually. Because LLMs operate on tokens and have bounded context windows, we count tokens with the Gemma-3 tokenizers and enforce truncation to remain within the context limit.⁹ Our TOC-guided heuristic (Section 2.7.5) trims appendices and exhibits, yielding comparable main texts. We present distributions of extracted tokens, pages, and file sizes in Fig. 2.5a. Some older PDFs are image-only, and we do not apply OCR to avoid additional noise. Therefore, such PDFs have 0 tokens and cannot be parsed. To eliminate such cases, we further require at least 1,000 tokens per extracted OS. Distributions for the finalized sample also appear in Fig. 2.5b and Table 2.1.

Fig. 2.5b also shows document length varies substantially; some OS exceed 100 pages or

7. One could reasonably stop here under a “20–80” principle.

8. Specifically, 6,995 of 30,028 receive a valid OS `FileIdentifier` from the data dumps; these cases reflect omissions in the XML rather than true absences.

9. APIs differ in their handling of over-length inputs; we truncate at the input stage to avoid unexpected behavior.

100,000 tokens, which stresses context limits. With a working window of 128,000 tokens, we cap extracted texts at 120,000 tokens to preserve headroom for prompts. With these steps, we obtain a cleaned corpus of main-text extracts from mapped OS PDFs, with token counts suitable for efficient LLM inference.

2.2.3 LLM Setup and Prompt Engineering

In this subsection, we outline the LLM setup and prompt-engineering steps used to generate ESG scores.

Model choice and rationale. We chose Gemma-3 as the main LLM scorer and used DeepSeek-V3-0324 for validation on a random subsample. Gemma-3 is a large open-source multimodal model introduced by Google on 2025/03/12 (Team et al. [2025]). We selected it for cost-efficiency and for its competitive performance in *Chatbot Arena* (Chiang et al. [2024]) relative to high-performing "thinking" models (e.g., DeepSeek R1, o1-2024-12-17) at the time we performed scoring. Given budget constraints, processing the full universe of 126k mapped OS with the most capable "thinking" models was infeasible.

Context length and truncation. As noted in Section 2.2.2, we truncated all extracted main-body texts at 120k tokens. A useful rule of thumb is that 1 token \approx 0.75 English words; the cap ensures we remain within Gemma-3's 128k context window. The context window can be viewed as the model's working memory: tokens within the window are available to condition the output. Even with truncation, appendix text may still be included (e.g., due to buffer pages in our TOC method; see Section 2.7.5). We further explicitly instruct the model to focus on the main-body content to mitigate partial coverage and maintain fairness across disclosures. With all 126k OS PDFs truncated in this way, plus a 7k random subsample for later verification, the total cost of a full run was about \$900 (see Fig. 2.6). In total, roughly 7 billion tokens were processed, equivalent to \sim 90 years of continuous reading for a single

analyst at 8 hours/day.

Execution infrastructure. Although these models can run locally, end-to-end processing at our scale is impractical without a dedicated cluster. Conversely, the official APIs do not efficiently support high-throughput batch scoring for the entire OS corpus. We therefore used the third-party Nebius AI Studio platform, which offers a customized, easy-to-deploy API with favorable cost dynamics for mass calls. To respect rate limits in practice, we operated multiple accounts and executed calls in parallel.

Model behavior and sizing experiments. Modern LLMs are robust to irregular input formatting, which is helpful for our extracted and truncated texts. We used Gemma-3-27B-IT (the instruction-tuned, largest model in the family). To understand scaling effects, we designed a simple prompt to compare performance across both model sizes and temperatures in Table 2.2. All models handled the message correctly, while larger variants produced richer, more calibrated responses. In the same experiment, we also recorded runtime under different compute settings.

Prompt engineering. Because both models are “non-thinking,” we adopt a step-by-step prompt layout (chain-of-thought style) that guides the model through a logical sequence of tasks. The full prompt appears in Section 2.7.6 and draws explicitly on GFOA ESG guidelines (Section 2.7.7). The most important component is the score-generation scheme: *potential* ESG scores emphasize inherent alignment with ESG principles and recognized best practices, the nature of the project, and consistency with GFOA criteria; *actual* scores focus on promotional language and implicit cues (e.g., explicit branding/labeling such as “green,” “sustainable,” or “social”; implicit ESG cues when labels are absent; and the scope/depth of ESG mentions). Explicit marketing/labels are *ignored* when generating the potential score. Each E, S, and G dimension is evaluated separately and then combined into composite scores.

Reasoning is constrained to ~ 150 words per field for concision, and outputs are returned in JSON. The prompt also directs the model to focus on the main steps and to act as an ESG expert.

Zero-shot rationale. We intentionally do not provide labeled examples. The only normative guide is the GFOA ESG principles. This zero-shot setup avoids injecting dataset-specific labeling standards that could bias the outputs and instead grounds the scoring in an industry best-practice framework. This design helps correct potential misinterpretations and reduces reliance on superficial labels.

Parameters and batching. Finally, we set `temperature` = 0.3 for balanced determinism, `top_p` = 0.95 for controlled diversity, `presence_penalty` = 0.5 to reduce repetition, and `top_k` = 40. Intuitively, a lower temperature reduces randomness; `top_p` and `top_k` restrict the next-token candidate set. These values are standard in practice. We process documents in batches using multi-threaded execution across API keys to manage rate limits.

2.3 Labeling Gap and Score Validation

In this section we first document the distributions of the ESG scores introduced in Section 2.2 and the Potential-Actual labeling gap. We then validate the measures in three steps: (i) qualitative spot checks of model rationales against the underlying OS on EMMA; (ii) a robustness exercise on a random subsample of $\sim 6,800$ OS comparing our original Gemma-3 run to a fresh Gemma-3 run and a DeepSeek-V3 run; and (iii) a benchmark against Bloomberg’s muni ESG labels.

2.3.1 *Distribution of Scores and the Labeling Gap*

Distributions. Figure 2.7 shows Potential scores systematically right-shifted relative to Actual across all pillars, largest for *Environmental* and *Social*, smallest for *Governance*; the composite mirrors these patterns. This implies a pervasive "labeling gap": OS text undersignals ESG content present in project fundamentals (e.g., purpose, use of proceeds). The smaller governance gap is consistent with routine disclosure of legal/covenant material to establish creditworthiness and tax-exempt status.

The labeling gap. Figure 2.8 plots the distribution of Potential-Actual scores within each OS. Mean gaps are positive and statistically different from zero in every pillar, indicating a broad pattern rather than outliers. Rank correlation between Potential and Actual is strongest for *Social*, moderate for *Environmental* and *Governance*, and weakest for the *Composite*. Issuers tend to get the *ordering* right, but labels understate levels. Because absolute levels can be model-specific, we emphasize the within-document gap as our main object and test its robustness below.

2.3.2 *Qualitative Review of Scoring Rationales*

Across the examples in Table 2.3, Gemma-3's rationales track the OS: when pillar content is explicit (e.g., Qualified Energy Conservation Bonds; boards/committees/covenants), both Potential and Actual are high and the cited text matches the reasoning; where disclosures are transactional/legal and omit pillar content, both scores are low. The clearest under-labeling is *Social* (e.g., student housing, income-limited programs): fundamentals imply benefits (high Potential) but the OS rarely frames them (low Actual). These checks support face validity and echo the aggregate patterns.

2.3.3 Robustness Across Runs and Models

Same model, same inputs. On the $\sim 6,800$ -OS subsample, Figure 2.9 presents (i) score distributions, (ii) original–validation score differences, and (iii) jittered scatter of validation vs original scores. Distributions overlap closely, differences center on zero, and points lie near the 45° line with high rank correlation, confirming that Gemma-3 is stable when inputs and decoding are held fixed.

Different model, same inputs. Figure 2.10 repeats the comparison with scores generated by DeepSeek-V3. Level distributions are broadly similar but shifted upward for DeepSeek, with the largest shift in *Social*. This provides strong evidence that score levels are model-dependent.

Gap vs. gap (main robustness). Crucially, Figure 2.13 compares the labeling gaps themselves across models: (i) gap distributions by pillar, (ii) the gap difference (Gemma-3 gap – DeepSeek gap), and (iii) jittered scatter of DeepSeek gap vs. Gemma-3 gap. Gemma-3 tends to produce larger gaps on *Environmental* and *Social*, but the composite score gaps are similar across both models. The positive correlation further indicates that documents with larger under-labeling under Gemma-3 tend to do so under DeepSeek as well. Together with Figures 2.11 and 2.12, which show the existence of a labeling gap under the DeepSeek scores, this demonstrates the robustness of the labeling gap.

2.3.4 Benchmark Against Bloomberg Muni ESG Labels

We conclude the validation with an external benchmark against Bloomberg’s municipal ESG labels. We treat a bond as *Bloomberg Green* if Bloomberg flags either “Green Instrument” or “Self-Reported Green”; as *Bloomberg Social* if it carries “Social Bond” or “Self-Reported Social.” A *Bloomberg ESG* bond is one that carries all of the above pillar tags and, in addition, “Sustainable Debt Instrument” and “Self-Reported Sustainable Debt Instrument.”

Figures 2.14 to 2.16 assemble, respectively, counts by score, density distributions, and

maturity-amount-weighted means (with 95% CIs) for Bloomberg ESG-, Green-, and Social-labeled issues versus non-labeled peers. First, the labeled sample is small: only 2,078 ESG-labeled OS, 1,440 Green, and 424 Social, consistent with the scarcity documented earlier in Fig. 2.1. Despite this imbalance, a clear pattern emerges: Bloomberg-labeled bonds exhibit *high Potential and high Actual* in the corresponding pillar, which translates into higher composite scores. The selectivity is also sharp. For Bloomberg *Social* bonds, the Social Potential/Actual distributions shift markedly to the right, while Environmental and Governance overlap closely with non-Social issues; conversely, Bloomberg *Green* issues show pronounced shifts in Environmental but little movement in Governance. For the combined *Bloomberg ESG* label, both the *Environmental* and *Social* Potential/Actual distributions shift materially to the right, driving a higher composite, while *Governance* remains comparatively stable and overlaps strongly with non-ESG issues. This robustness in Governance is consistent with our broader evidence that governance content is routinely disclosed across OS and exhibits a smaller labeling gap, whereas E and especially S provide the discriminating signal captured by Bloomberg's ESG designation.

These results support two points. First, our LLM scores align with how Bloomberg labels are assigned: when a reviewer sees pillar-relevant substance in the OS and project fundamentals, she acts on it, and the Bloomberg-labeled bonds show both higher Potential and Actual scores in that pillar. Second, our scores add granularity beyond Bloomberg's binary tag: they recover degrees of "ESG-ness" within and across pillars and, crucially, flag cases where substance is present but labeling lags (high Potential, low Actual). These are plausible under-labeling candidates (i.e., bonds that look "missed" by the vendor) and we illustrate them with model rationales in Table 2.4.

Finally, Figure 2.17 shows the labeling gap persists even among Bloomberg-labeled issues, but its size depends on the designation. For Social-labeled bonds the gap collapses on the Social pillar (mean 0.6 vs 3.3 for non-Social) and is notably smaller in the composite

score, consistent with reviewers explicitly labeling social substance when they see it. In contrast, Green-labeled (and combined ESG) bonds typically retain larger gaps, especially in Environmental (e.g., Green mean 2.4 vs 2.1 for non-Green) and in the composite, suggesting environmental substance is often under-sold in the text (or labels are applied more liberally), leaving residual under-labeling. Governance gaps remain comparatively small and stable throughout.

2.4 Labeling Gap Analysis

With scores validated in Section 2.3, we now analyze their behavior. We begin with time-series and geographic patterns of the labeling gap (Potential–Actual), then examine cross-pillar correlations. We next collapse the gap to the county level to study its drivers, and finally revisit the primary-market greenium using our measures.

2.4.1 Time-Series and Geographic Patterns of the Labeling Gap

Figure 2.18 plots monthly gaps for each pillar and the composite, showing both simple averages (blue) and maturity-amount-weighted averages (orange), with raw series in light tones and 6-month smooths in dark tones. Three features stand out. First, the gap is *persistent*: all pillars exhibit positive gaps throughout the sample. Second, the gap *drifts upward* over time, most visibly in *Environmental* and the *Composite*; the post-2020 period shows a clear widening, consistent with heightened salience of ESG topics in public debate and changes in issuance mix.¹⁰ Third, weighted and simple series track closely but occasionally diverge during issuance booms, revealing the known seasonality in muni issuance.

Figure 2.19 maps the maturity-amount-weighted *Composite* gap by state (top) and ranks states by weighted gaps across pillars (bottom). Two observations emerge. (i) Under-labeling is *ubiquitous*: every state exhibits a positive composite gap. (ii) The *level* of under-labeling

10. We refrain from causal interpretation here; Section 2.4.2 examines observables related to this pattern.

varies meaningfully across states, with lower gaps concentrated in parts of New England and higher gaps in several traditionally conservative states. These patterns are consistent with—though not proof of—political and institutional differences that we test directly using county-level covariates in Section 2.4.2.

Finally, Figure 2.20 summarizes cross-pillar comovement of within-document gaps. All pairwise correlations are positive but far from collinear: Environmental–Social ≈ 0.43 , Environmental–Governance ≈ 0.31 , Social–Governance ≈ 0.26 , and each pillar correlates most strongly with the *Composite*. This indicates that the gap reflects *distinct disclosure shortfalls* across pillars, especially in Environmental and Social, rather than a single common factor embedded uniformly in OS text.

2.4.2 Gap Drivers

Motivated by the persistence, recent widening, and spatial dispersion of the labeling gap, we aggregate scores to the county level and relate them to economically motivated clusters of covariates (issuance/market depth; geo–climate; demographics; prosperity/cost of living; health & environment; crime & mortality; labor market; industry structure; political leaning; COVID impact; and education). The full variable list and clustering are in Table 2.5; their correlation structure is shown in Figure 2.21.

Univariate screening. Figure 2.22 reports the top-20 *absolute* Spearman correlations between each pillar’s county-level gap and individual covariates.

Environmental. The top-20 list is dominated by scale/prosperity and cost-of-living measures (e.g., population, issuance, housing/medical costs), mortality/accident rates (vehicle, homicides, suicides, alcohol-impaired driving), and demographic composition (higher Asian/Hispanic shares positively related; higher White share negatively related). GOP vote shares (2016/2020) appear with *modest* negative associations. As plotted, no NOAA weather

variables enter the top-20.

Social. Health burdens and behaviors lead: teen birth, physically/mentally unhealthy days, fair/poor health, and smoking are among the strongest positive correlates. Higher life expectancy and income tend to be negatively related. Cost-of-living and education shares also feature prominently.

Governance. Vaccination rates are negatively related; several health/behavior measures, education shares, and cost-of-living items are positively related.

Composite. The pattern mirrors Environmental/Social: population/issuance scale, cost-of-living, mortality/accident indicators, and demographics are most prominent; the signs line up with the corresponding pillar components.

These single-covariate patterns are informative but limited: many covariates co-move (Figure 2.21), and relationships are plausibly non-linear and interactive. We therefore turn to flexible multivariate models.

Multivariate, non-linear models. We fit two complementary tree ensembles on the county cross-section using the pre-defined clusters in Table 2.5: a *Random Forest* (bagging) and *LightGBM* (gradient boosting). For each pillar, we report cluster-level importance via the mean *absolute* SHAP value and cluster direction via the mean *signed* SHAP value (positive = widens the gap; negative = shrinks it). Results are visualized in Figures 2.23 and 2.24 for the full county sample and for the top-500 issuance counties.

Interpreting model contributions (SHAP). To summarize “what matters” in the non-linear tree ensembles, we use SHAP values, which decompose each prediction into additive, observation-level contributions of the inputs and aggregate cleanly to groups of variables. For a given county i , the model prediction can be written as a baseline plus feature contributions, $\hat{y}_i = \phi_0 + \sum_j \phi_{ij}$, where ϕ_{ij} is the SHAP value for feature j . We report *mean absolute SHAP* at the pre-defined cluster level (our importance metric), which answers “how much

does this cluster move predictions, on average, regardless of sign?”, and *mean signed SHAP* (our direction metric), which answers “on net, does this cluster widen (+) or shrink (–) the gap?”. SHAP is well-suited here because TreeSHAP provides exact Shapley attributions for tree ensembles, accommodates non-linearities and interactions, and yields additive local attributions that can be summed to variable clusters and compared across Random Forest and LightGBM (on the same outcome scale and background). Compared with permutation importance or linear coefficients, SHAP yields *local* attributions that aggregate transparently to policy-relevant clusters. Two caveats apply: SHAP reflects associations *within* the fitted model and can be attenuated by collinearity inside clusters; hence we report out-of-sample R^2 alongside SHAP summaries and interpret effects as descriptive, not causal.

Model fit. Out-of-sample performance is assessed with a 20% holdout; the corresponding R^2 is printed in each panel title. On the full sample, fit is modest but meaningful (about 0.10–0.18 across pillars and models). Restricting to the top-500 issuance counties increases explanatory power substantially (e.g., Social \approx 0.34–0.37, Composite \approx 0.32–0.36, Environmental \approx 0.17–0.25, Governance \approx 0.13–0.23). Random Forest and LightGBM deliver similar out-of-sample R^2 and broadly consistent cluster rankings.

What survives multivariate controls? Three robust patterns emerge from the SHAP aggregations:

1. **Prosperity/Cost, Demographics, and Health/Environment** are consistently among the most important clusters for the *Composite* gap in both samples; mean signed SHAP often indicates these factors *widen* the gap.
2. Pillar-specific salience lines up with intuition: *Health/Environment* is especially important for the *Social* gap; *Prosperity/Cost* and *Geo-climate/scale* feature prominently for *Environmental*; *Governance* draws on a mix of Health/Environment and Pros-

perity/Cost. COVID-related variables appear more clearly in the top-500 sample for Environmental and Governance.

3. **Political leaning** is comparatively weak once fundamentals are in the model—small on average and, where present (e.g., Environmental in the top-500 sample), secondary to the clusters above.

We interpret these as associations, not causal effects. The cross-sectional aggregation helps reveal stable covariates of under-labeling, while the time-series patterns in Figure 2.18 suggest a promising extension: augment the county panel with time-varying covariates to study within-place dynamics of the gap.

2.4.3 Primary Market Greenium

We estimate primary-market pricing regressions on a security-level panel that merges our LLM scores, Bloomberg ESG labels, and Mergent primary-market fundamentals. Our specification follows Baker et al. [2022]:

$$OfferingYield_{it} = \alpha + \beta ESGValue_i + \gamma' \mathbf{X}_{it} + \mu_{\text{issuer}} + \mu_{\text{rating}} + \mu_{\text{ym}} + \varepsilon_{it},$$

where *ESGValue* is either the Bloomberg ESG-label indicator or our Potential and Actual scores (pillar-level and composite). \mathbf{X}_{it} collects standard bond-characteristic controls: years to maturity and its inverse (duration proxy), log bond size and log deal size, taxability, bank-qualified and insurance indicators, call/put flags, and fixed effects for capital-purpose categories and use-of-proceeds buckets. We further include issue Year-Month fixed effects, rating fixed effects where ratings are sourced from all three major rating agencies, and issuer fixed effects. Standard errors are clustered at the issuer level.

Benchmark with Bloomberg labels. Table 2.6 shows that the Bloomberg-label “greenium” is fragile. Depending on the set of controls, the coefficient sometimes flips sign: with only Year–Month fixed effects, the Bloomberg ESG label is associated with a higher offering yield (an “ESG penalty”). Under our preferred specification in column (5) with the full set of controls and Issuer, Rating, and Year–Month fixed effects, the estimate is small and imprecise (−1.361 bps, s.e. 1.807), echoing the mixed “label greenium” results in prior work.

Results with our ESG scores. Replacing the label with *only* our Composite *Potential* and *Actual* scores and estimating the preferred specification, both coefficients are negative and economically similar (Table 2.7, col. (2)). A Wald test cannot reject equality ($F = 0.04$; $p = 0.843$). Interpreted in levels, a 10-point improvement in either composite score is associated with roughly a 4.5–5 bps lower offering yield under the preferred specification. The equality result suggests the primary market prices *capacity to be ESG* (Potential) and *realized ESG-ness* (Actual) at essentially the same marginal rate. In other words, underwriters/buy-side appear to synthesize both signals into a similar pricing belief at issuance.

Columns (3)–(5) of Table 2.7 replace the composite with pillar scores. *Environmental Actual* and both *Governance* scores load negatively and significantly in the preferred specification, while *Social* scores are small and imprecise. In the full horse race (cols. (6)–(7)), adding all scores causes the composite coefficients to lose precision, consistent with pillar scores absorbing the informative variation given their high correlations. The Bloomberg label adds little incremental pricing power once our scores are included. Full regression results for such scores are provided in Table 2.8, Table 2.9, Table 2.10, Table 2.11, Table 2.12, and Table 2.13.

Using the Baker et al. [2022] specification, we thus find a modest but economically meaningful primary-market concession associated with better ESG fundamentals and disclosures: both *Potential* and *Actual* composite scores load negatively and are statistically indistinguishable. The market rewards issuers that *look able* to deliver ESG outcomes and those that

actually do at roughly the same price per unit of information.

2.5 Conclusion

This chapter asks how much *values* (stated ESG intent) and *value* (priced fundamentals) show up in public finance, and what OS text can add when labels are thin. We build a scalable pipeline that parses more than 120,000 official statements, benchmarks disclosure against GFOA guidance with state-of-the-art LLMs, and delivers document-level *Potential* and *Actual* scores by pillar and composite. We validate the measures, then trace their behavior across time and space. Three facts emerge.

First, the *labeling gap* (Potential–Actual) is persistent and widens notably after 2020, with broad positive gaps nationwide and meaningful cross-state dispersion. Second, county-level drivers are systematic: prosperity/cost, demographics, and health/environment consistently matter in flexible models, while political leaning is comparatively weak once other potential drivers are in the mix. Third, the primary market places a modest but economically meaningful concession on ESG content when measured from text. In our preferred specification, both composite *Potential* and *Actual* scores load negatively and are statistically indistinguishable, implying that the market rewards issuers that *look able* to deliver ESG outcomes and those that *actually* do at essentially the same price per unit of information. Pillar results point to realized *Environmental* content and *Governance* as the clearest contributors; existing Bloomberg labels add little once text-based scores are present.

Methodologically, the chapter contributes a transparent data curation and wrangling pipeline: OS–CUSIP mapping, TOC-guided text extraction, and zero-shot scoring, that can be reused to study other disclosure domains within muni OS. Substantively, we show where ESG lives in public finance: in persistent disclosure shortfalls that vary with fundamentals, and in a pricing relation that values both capacity and realization rather than labels alone.

2.6 Figures and Tables from Chapter 2

2.6.1 Figures

Figure 2.1: Bloomberg ESG-Labeled Issuance

Note: This figure illustrates the volume of ESG-labeled municipal bond issuance from 2012 to 2023, based on Bloomberg classifications. An issue is considered ESG-labeled if tagged as "Sustainable Debt Instrument", "Self-Reported Sustainable Debt Instrument", "Self-Reported Green", "Green Instrument", "Social Bond", or "Self-Reported Social". Issuance amounts and years are derived from primary-market official statements.

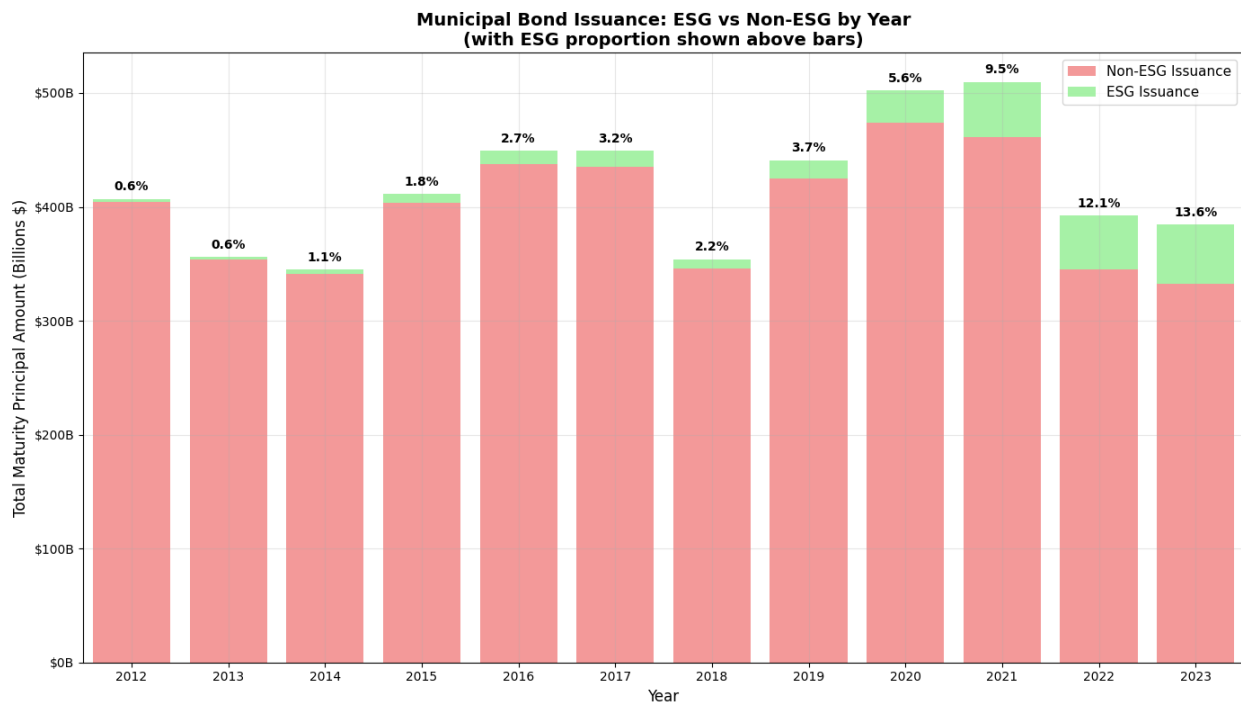



Figure 2.2: EMMA Website Example

Note: This figure provides an example of the detailed information available for a given CUSIP on the EMMA website. The MSRB Primary Market Disclosures dataset consists of zipped files containing all documents listed under the "Official Statements" section, as shown in the screenshot.



CUSIP: 57582RTQ9*
THE COMMONWEALTH OF MASSACHUSETTS GENERAL OBLIGATION REVENUE ANTICIPATION NOTES SERIES C (MA)
 MASSACHUSETTS ST GO RAN 2018 C (MA)*

Coupon: 4 %

Maturity Date: 06/20/2019

Dated Date: 08/28/2018

Initial Offering Price/Yield: 101.839% / 1.7%

Principal Amount at Issuance: \$500,000,000

Time of Formal Award: 08/23/2018 11:46 AM

Time of First Execution: 08/23/2018 04:00 PM

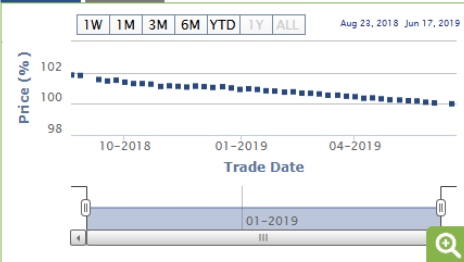
Closing Date: 08/28/2018

Fiscal Year End Date: 06/30/2024

Price
Yield

1W 1M 3M 6M YTD 1Y ALL

Aug 23, 2018 Jun 17, 2019



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Ratings
Disclosure Documents
Final Scale
Compare

View the official statement – similar to a prospectus – for information about the features and risks of this security. View available continuing disclosures for updated financial and other information.

Official Statement(s)

Documents	Posted Date
Official Statement - 2018 Commonwealth of Massachusetts RANs Final OS (1.4 MB)	08/24/2018
Official Statement - OS for Comm Mass Tran (1.4 MB)	08/24/2018
Official Statement - MA RANs Final (1.4 MB)	08/24/2018
Official Statement - FINAL OS (1.4 MB)	08/24/2018
Official Statement - Final OS (1.4 MB)	08/24/2018
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- [Fact Sheet: Understanding Official Statements](#)
- [Fact Sheet: Investor's Guide to Financial Disclosures](#)
- [Learn More: Monitoring Bonds](#)
- [Using EMMA® to Identify the Timing of Financial Disclosures](#)

Figure 2.3: XML Index File Example

Note: This figure illustrates an example of the XML index file included in the MSRB Primary Market Disclosure dataset. The XML file provides structured information for each issue, including key details such as CUSIP, maturity amount, and initial offering yield. Each entry can be directly linked to its corresponding primary market disclosure PDF file stored within the UnderlyingFiles node.

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              <DisclosureFilingSchedule ScheduleBasisForFiling="FiscalYearEnd" FiscalYearEndMonth="6" FiscalYearEndDay="30" MonthOrDayCountAfterFiscalYearEndWhenFilingExpected="270" MonthOrDayAfterFiscalYearEndWhenFilingExpected="Day"/>
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          <UnderlyingFiles>
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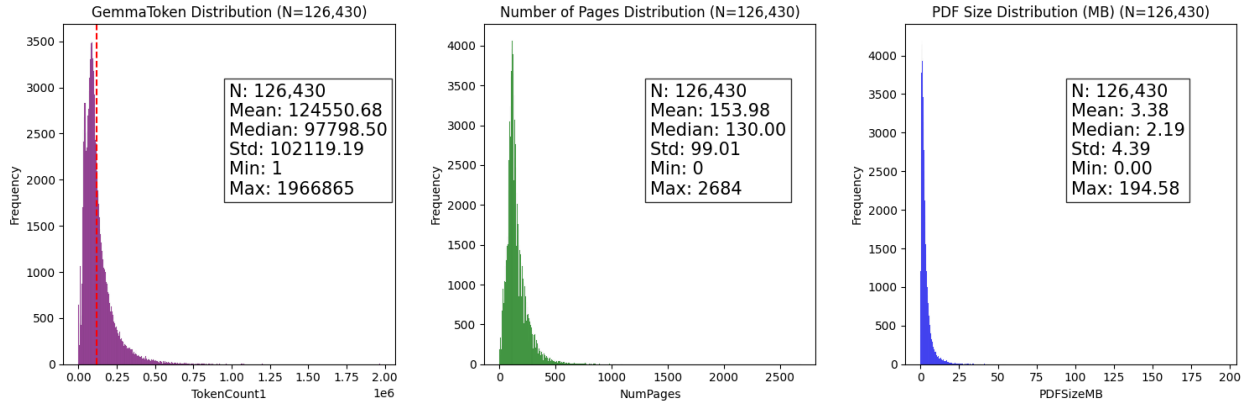
Figure 2.4: Multiple XML-CUSIP Example

Note: This figure illustrates a scenario where a single CUSIP is associated with multiple XML index files. This one-to-many mapping complicates the data linkage process, likely due to the creation of new XML files each time primary market information is updated or amended.

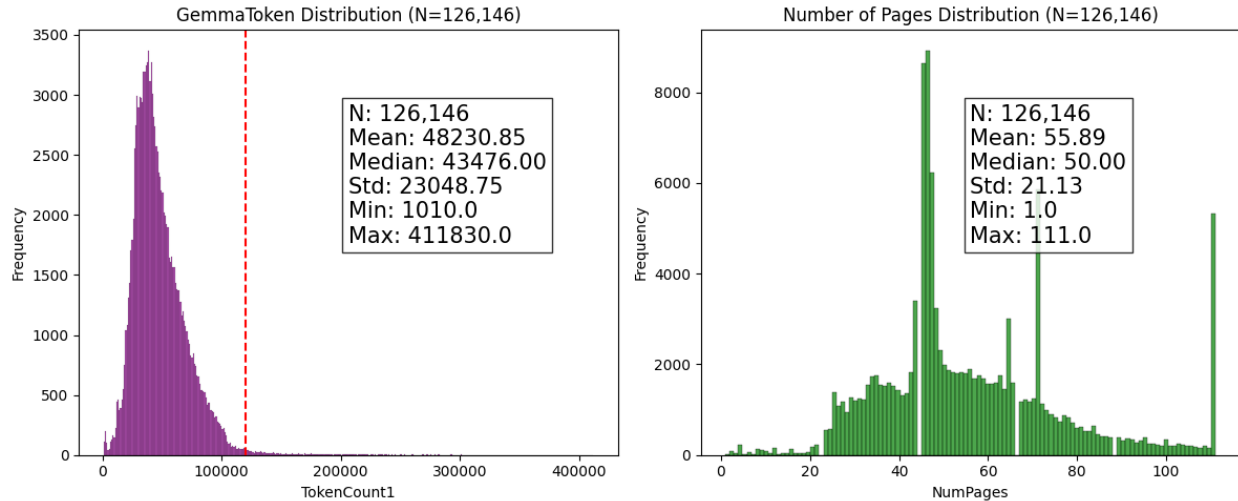
FolderName	XML	DocumentType	DocumentPostingDate	DocumentDescription	FileIdentifierList	FilePostingDateList	OfferingType	CUSIP9	InitialOfferingPrice
1956902	PM.2018.08.23.IndexData.zip	ES1193237.xml					Bond	57582RTQ9	101.872
1957036	PM.2018.08.23.IndexData.zip	ES1193300.xml					Bond	57582RTQ9	101.872
1957201	PM.2018.08.23.IndexData.zip	ES1193366.xml					Bond	57582RTQ9	None
1957264	PM.2018.08.23.IndexData.zip	ES1193382.xml					Bond	57582RTQ9	101.856
1958025	PM.2018.08.24.IndexData.zip	ER1145733.xml					Bond	57582RTQ9	101.856
1958026	PM.2018.08.24.IndexData.zip	ER1145734.xml					Bond	57582RTQ9	101.856
1958072	PM.2018.08.24.IndexData.zip	ER1145751.xml	[2018-08-24]	[Final OS]	[[ER1297024]]	[[2018-08-24]]	Bond	57582RTQ9	101.856
1958075	PM.2018.08.24.IndexData.zip	ER1145757.xml	[2018-08-24]	[FINAL OS]	[[ER1297029]]	[[2018-08-24]]	Bond	57582RTQ9	101.856
1958077	PM.2018.08.24.IndexData.zip	ER1145758.xml	[2018-08-24]	[MA RANs Final]	[[ER1297030]]	[[2018-08-24]]	Bond	57582RTQ9	101.856
1958079	PM.2018.08.24.IndexData.zip	ER1145759.xml	[2018-08-24]	[OS for Comm Mass Tran]	[[ER1297031]]	[[2018-08-24]]	Bond	57582RTQ9	101.856
1958130	PM.2018.08.24.IndexData.zip	ER1145816.xml	[2018-08-24]	[2018 Commonwealth of Massachusetts RANs Final...]	[[ER1297083]]	[[2018-08-24]]	Bond	57582RTQ9	101.839
1958146	PM.2018.08.24.IndexData.zip	ER1145825.xml	[2018-08-24]	[2018 Commonwealth of Massachusetts RANs Final...]	[[ER1297083]]	[[2018-08-24]]	Bond	57582RTQ9	101.839

Figure 2.5: OS PDF distributions of Token, Page and Size

Note: Each panel shows frequency histograms (counts). In-panel stat boxes report the number of OS (N) and the mean, median, standard deviation, minimum, and maximum of the plotted metric (GemmaToken, pages, or PDF size). The red dashed line marks the 120k-token cap. The *All OS PDFs* panel uses the full sample; the *Cleaned OS PDFs* panel restricts to OS with at least 1,000 tokens.



(a) All OS PDFs: Token, Page, and Size Distributions



(b) Cleaned OS PDFs: Token & Page Distributions

Figure 2.6: Total Costs and Processed Tokens

Note: This figure summarizes usage and costs on Nebius AI Studio for Gemma-3-27b-it and DeepSeek-V3-0324. To bypass the platform’s per-minute token limit, we used three separate accounts, each with multiple API keys; this is why the same model appears multiple times in the cost/usage entries.

Product	SKU ID	Price	Usage	Cost
DeepSeek-V3-0324	Input	\$0.50 per 1M tokens	170,578,274 tokens	\$85.29
DeepSeek-V3-0324	Output	\$1.50 per 1M tokens	3,038,479 tokens	\$4.56
Gemma-3-27b-it	Input	\$0.10 per 1M tokens	2,505,583,912 tokens	\$250.56
Gemma-3-27b-it	Output	\$0.30 per 1M tokens	36,919,182 tokens	\$11.08
DeepSeek-V3-0324	Input	\$0.50 per 1M tokens	149,000,542 tokens	\$74.50
DeepSeek-V3-0324	Output	\$1.50 per 1M tokens	2,077,121 tokens	\$3.12
Gemma-3-27b-it-fast	Input	\$0.20 per 1M tokens	5,873 tokens	<\$0.01
Gemma-3-27b-it-fast	Output	\$0.60 per 1M tokens	1,025 tokens	<\$0.01
Gemma-3-27b-it	Input	\$0.10 per 1M tokens	2,246,198,871 tokens	\$224.62
Gemma-3-27b-it	Output	\$0.30 per 1M tokens	33,300,926 tokens	\$9.99
Gemma-3-27b-it	Input	\$0.10 per 1M tokens	2,358,657,118 tokens	\$235.87
Gemma-3-27b-it	Output	\$0.30 per 1M tokens	35,226,271 tokens	\$10.57

Figure 2.7: Potential vs. Actual ESG Scores by Pillar

Note: Histograms for Environmental, Social, Governance, and composite scores across all 126k mapped OS scored by Gemma-3. Potential distributions are consistently right-shifted, most pronounced for E and S, modest for G, with the composite mirroring these pillar patterns, indicating that many issues appear ESG-aligned even when disclosures do not label them as such.

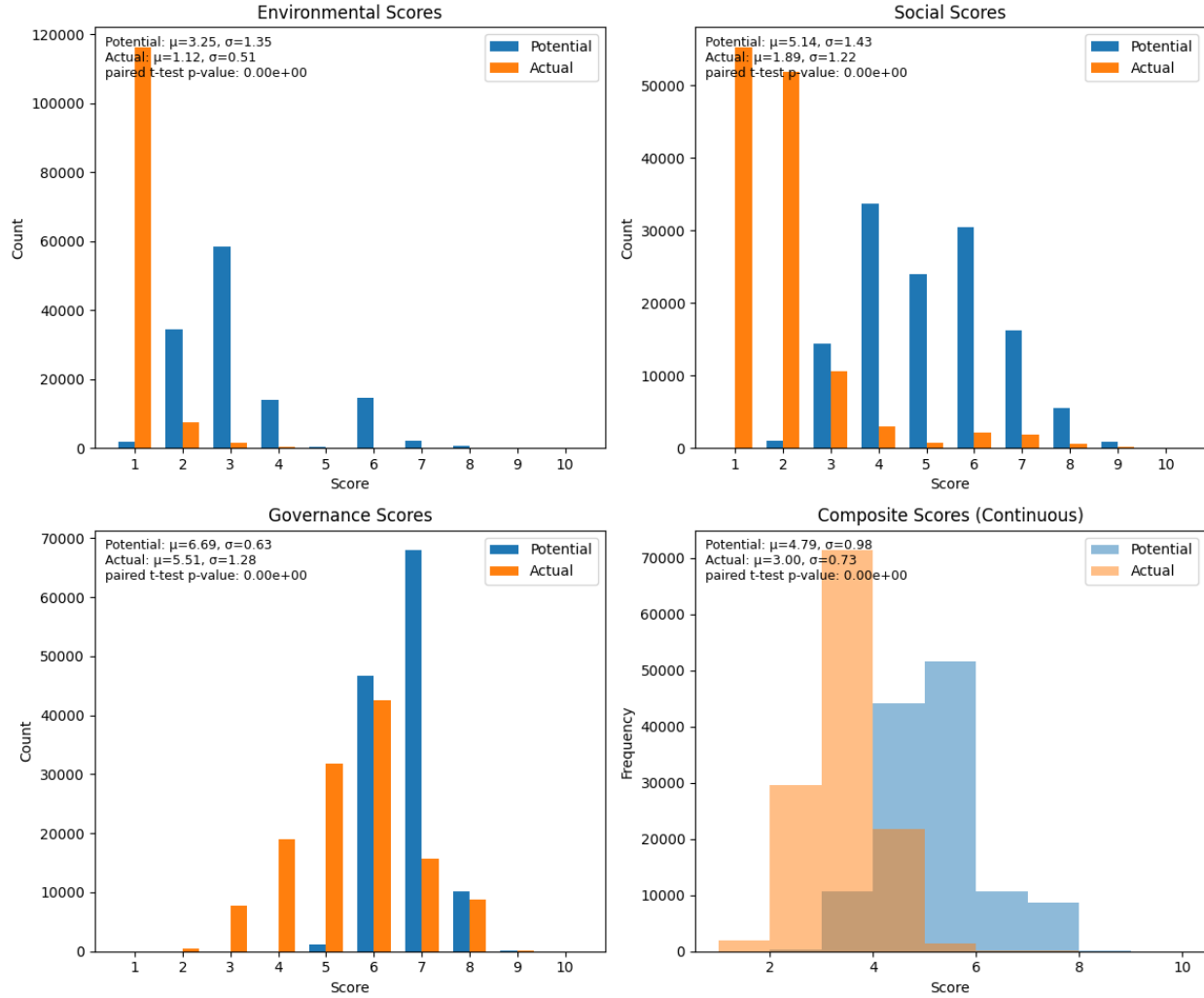


Figure 2.8: Potential vs. Actual ESG Scores by Pillar

Note: Histograms of Potential minus Actual scores for Environmental, Social, Governance, and the composite across all 126k mapped OS scored by Gemma-3. The dashed vertical line marks zero. Each panel reports N , mean and s.d. of the gap, a t -test of mean= 0, and rank correlations (Spearman ρ and Kendall τ_b) between Potential and Actual. The mass to the right of zero indicates systematic under-labeling in disclosures.

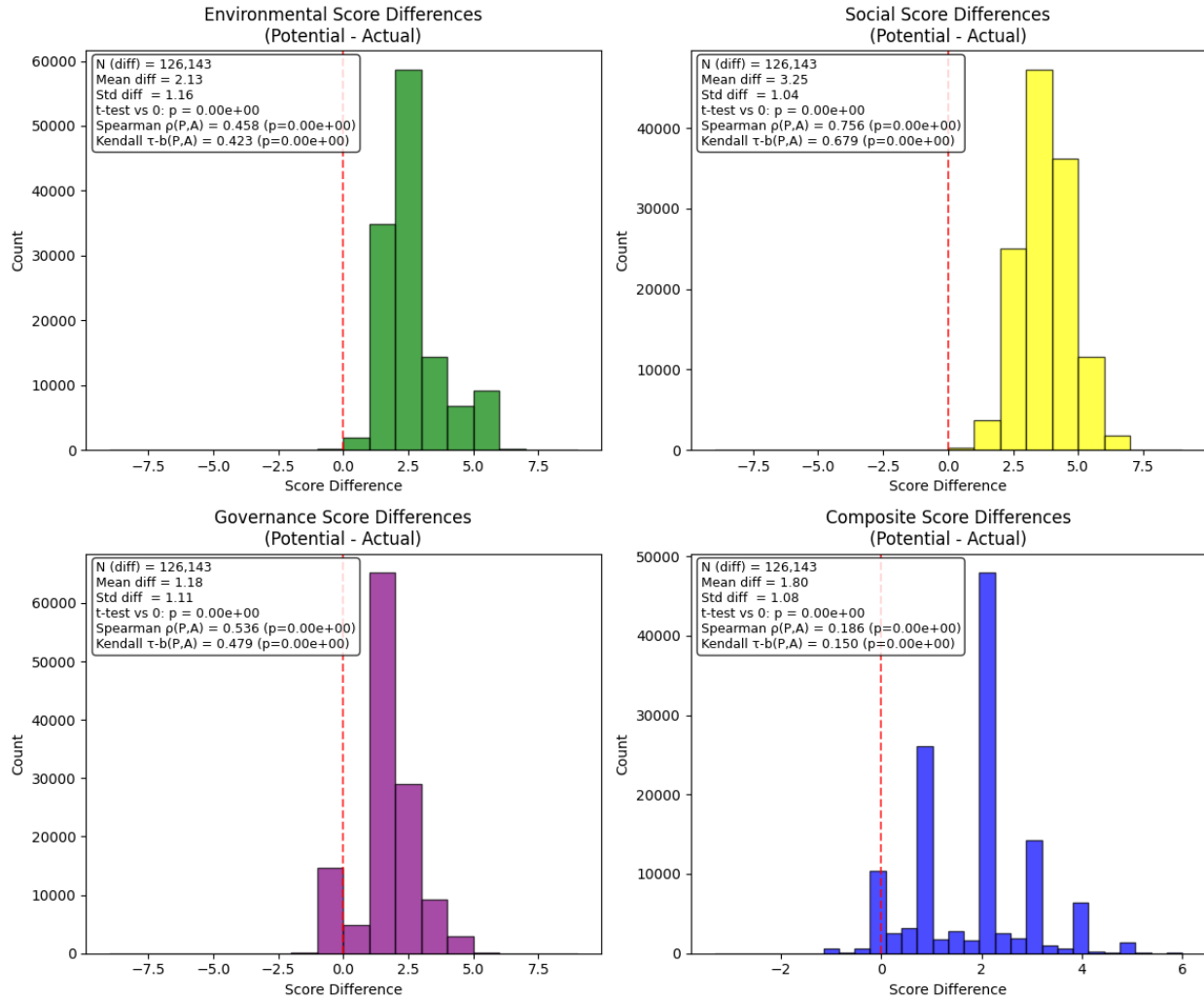
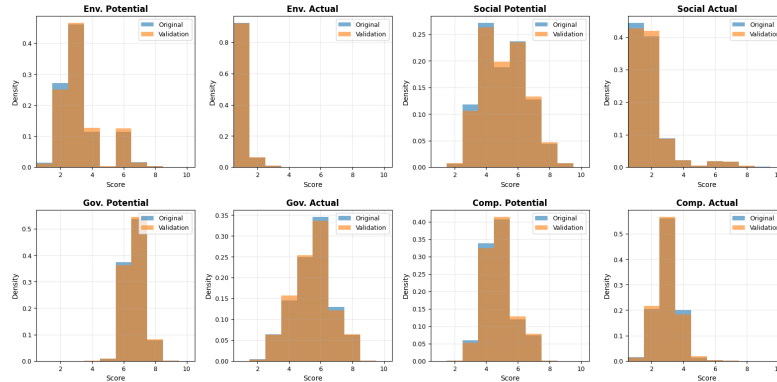
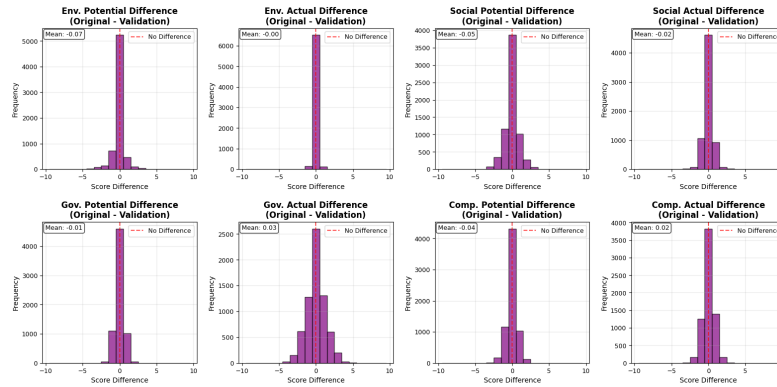


Figure 2.9: Original vs Validation (Gemma-3 vs Gemma-3): Distributions, Differences, and Jittered Scatter

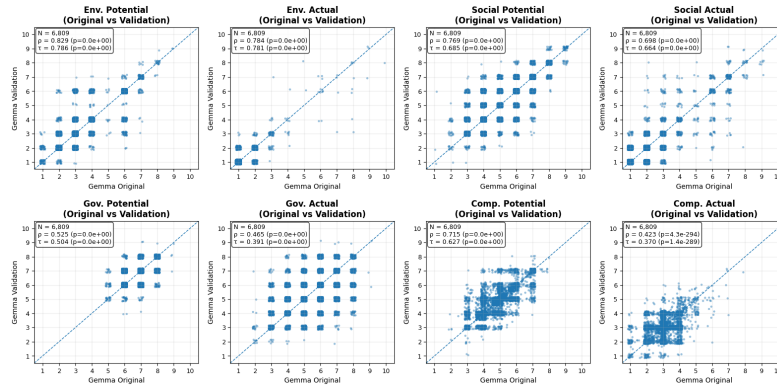
Note: Same $\sim 6,800$ OS subsample scored twice by Gemma-3. Top: density histograms of Potential/Actual (blue = original, orange = validation). Middle: histograms of original – validation with zero line. Bottom: jittered scatter of validation vs original with 45° line; panel boxes report N , Spearman’s ρ , and Kendall’s τ . Overlap and near-zero means indicate high within-model stability.



(a) Distributions



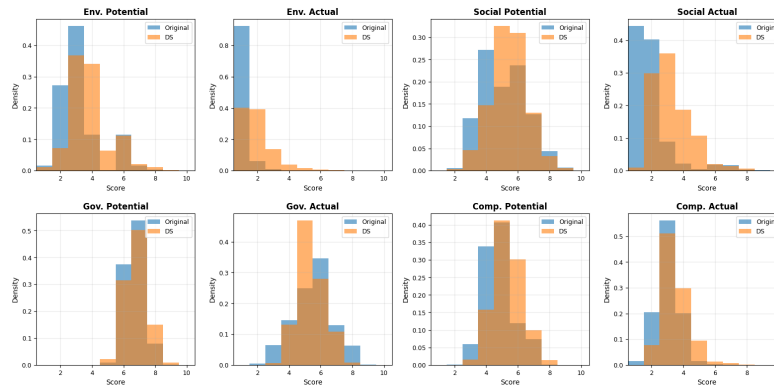
(b) Differences (Original – Validation)



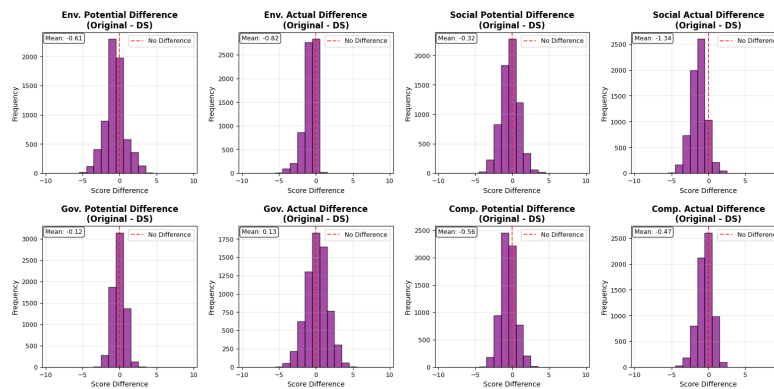
(c) Jittered scatter

Figure 2.10: Original vs Validation (Gemma-3 vs DeepSeek-V3): Distributions, Differences, and Jittered Scatter

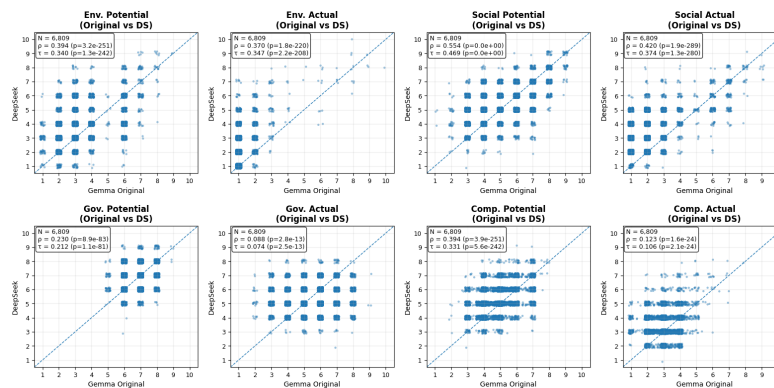
Note: Same subsample scored by Gemma-3 (original) and DeepSeek-V3. Top: distributions (blue = Gemma-3, orange = DeepSeek). Middle: histograms of Gemma-3 – DeepSeek with zero line. Bottom: jittered scatter of DeepSeek vs Gemma-3 with 45° line; panels report N , ρ , and τ . DeepSeek tends to score higher on average (largest in *Social* and composite) with moderate rank agreement.



(a) Distributions



(b) Differences (Gemma-3 – DeepSeek)



(c) Jittered scatter

Figure 2.11: Potential vs. Actual ESG Scores by Pillar (DeepSeek-V3)

Note: Histograms for Environmental, Social, Governance, and composite scores on the same ~6,809 OS subsample scored by DeepSeek-V3. Potential distributions are consistently right-shifted—most pronounced for *E* and *S*, modest for *G*—with the composite mirroring these pillar patterns, indicating that many issues appear ESG-aligned even when disclosures do not label them as such.

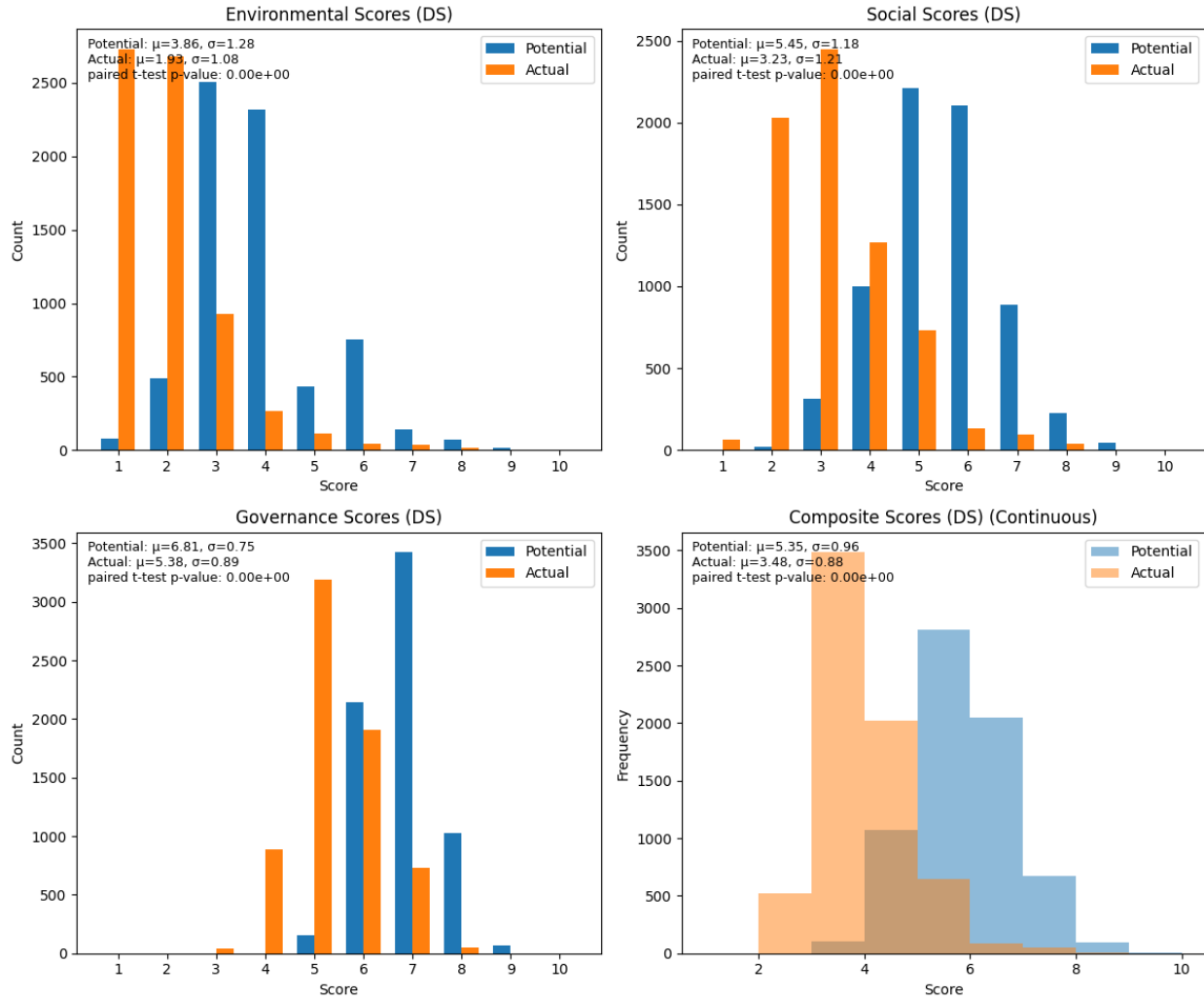


Figure 2.12: Score Differences (Potential–Actual) by Pillar (DeepSeek–V3)

Note: Histograms of Potential minus Actual scores for Environmental, Social, Governance, and the composite on the same ~6,809–OS subsample scored by DeepSeek–V3. The dashed vertical line marks zero. Each panel reports N , mean and s.d. of the gap, a t -test of mean = 0, and rank correlations (Spearman ρ and Kendall τ_b) between Potential and Actual. Mass to the right of zero indicates systematic under-labeling in disclosures.

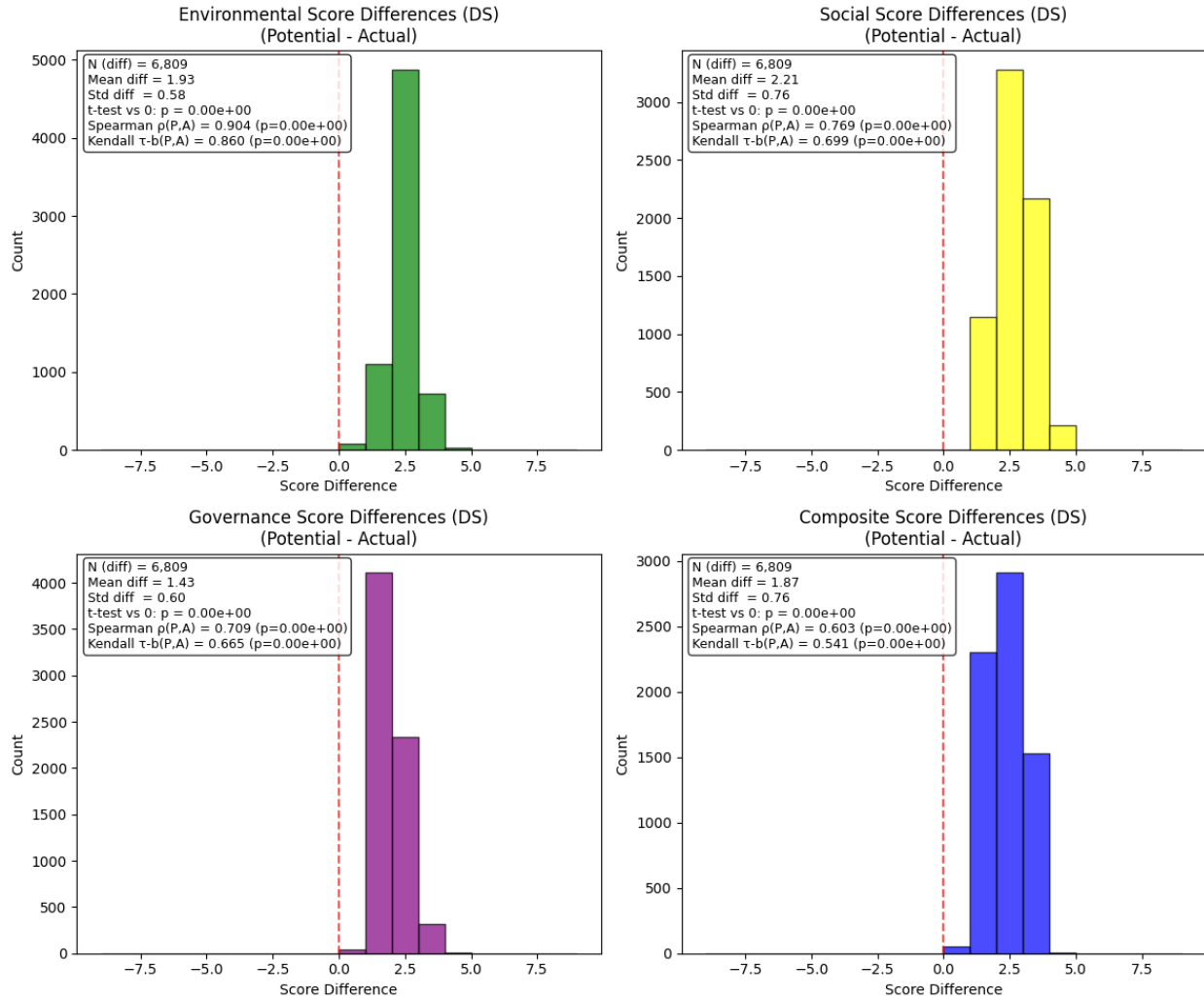
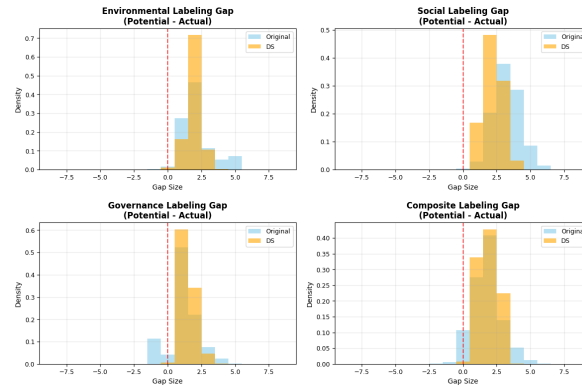
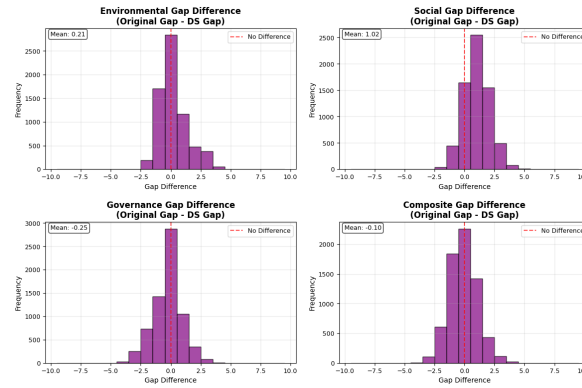


Figure 2.13: Original vs Validation Labeling Gaps (Gemma-3 vs DeepSeek-V3): Distributions, Differences, and Jittered Scatter

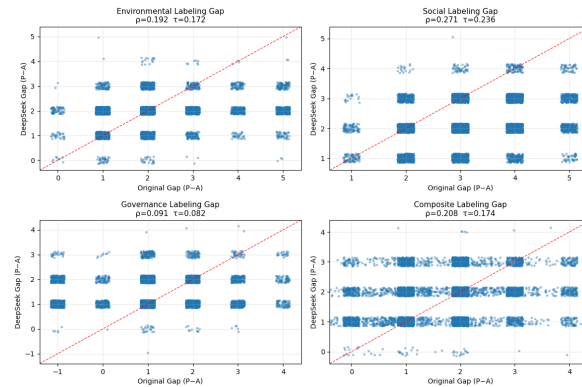
Note: Same $\sim 6,800$ OS subsample. We compare the labeling gap (Potential–Actual) for Gemma-3 and DeepSeek-V3. Top: density histograms of the gap for each model (blue = Gemma-3, orange = DeepSeek). Middle: histograms of the gap difference (Gemma-3 gap – DeepSeek gap) with a zero reference line. Bottom: jittered scatter of DeepSeek gap vs Gemma-3 gap with a 45° reference; panel boxes report N , Spearman’s ρ , and Kendall’s τ .



(a) Gap distributions (P–A): Gemma-3 vs DeepSeek



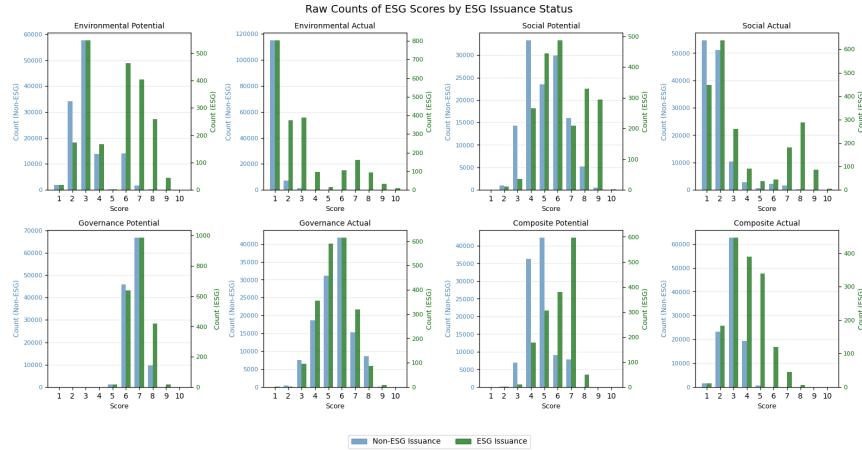
(b) Gap differences: Gemma-3 gap – DeepSeek gap



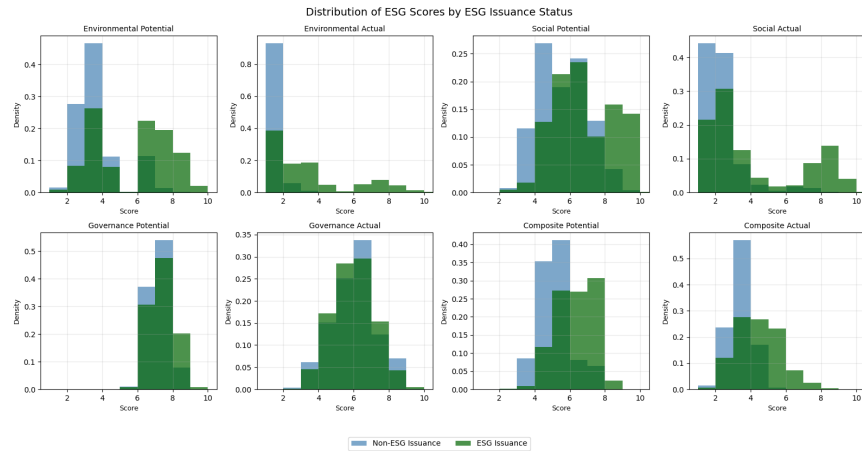
(c) Jittered scatter: DeepSeek gap vs Gemma-3 gap

Figure 2.14: Bloomberg Benchmark by ESG Issuance Status: Counts, Distributions, and Weighted Means

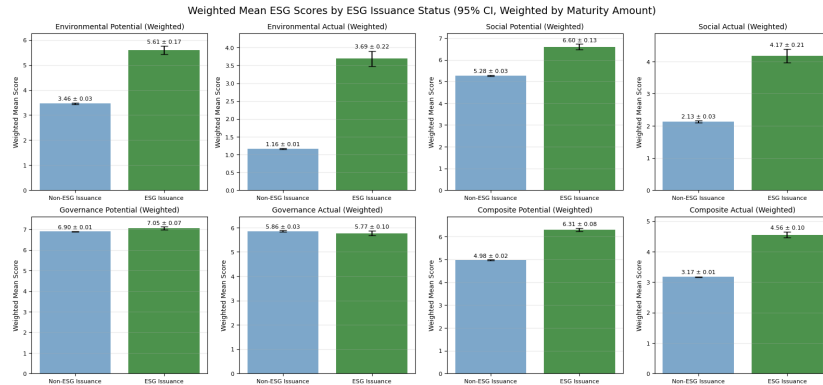
Note: Blue = non-Bloomberg ESG issuance; green = Bloomberg ESG issuance. Top: raw counts by score. Middle: density histograms. Bottom: weighted mean scores with 95% CIs (weighted by maturity amount).



(a) Counts by score



(b) Distributions (density)

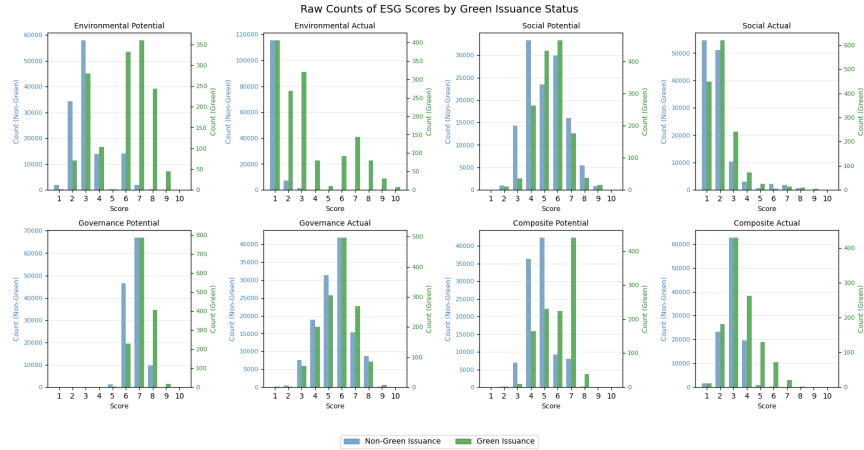


(c) Weighted means (95% CI)

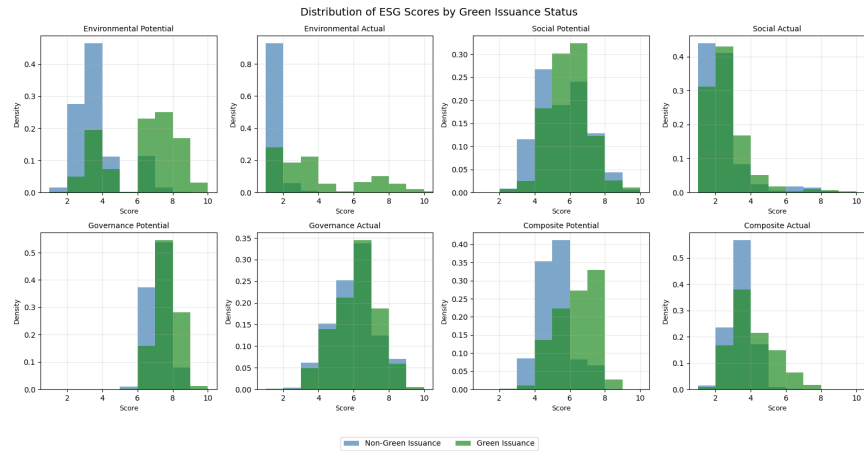
Figure 2.15: Bloomberg Benchmark by *Green* Issuance Status: Counts, Distributions, and Weighted Means

Note: Blue = non-Bloomberg Green issuance; green = Bloomberg Green issuance. Top: raw counts by score.

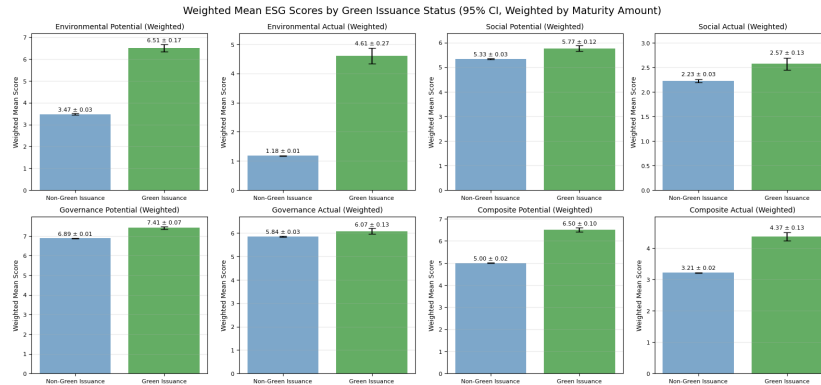
Middle: density histograms. Bottom: weighted mean scores with 95% CIs (weighted by maturity amount).



(a) Counts by score



(b) Distributions (density)

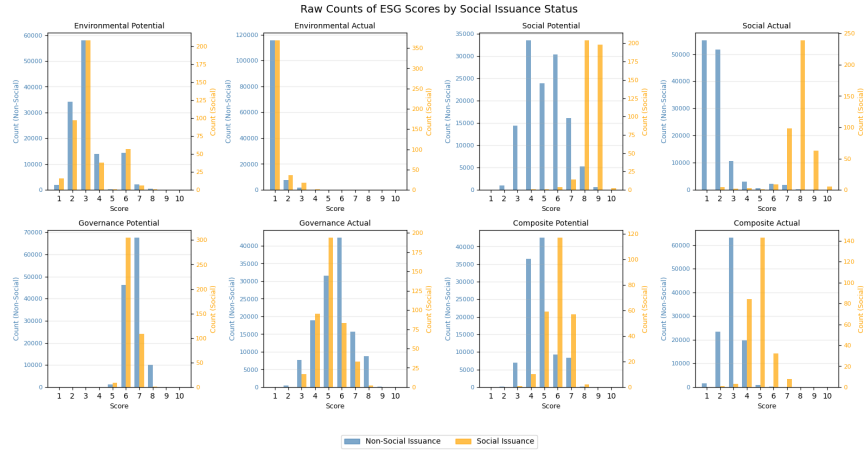


(c) Weighted means (95% CI)

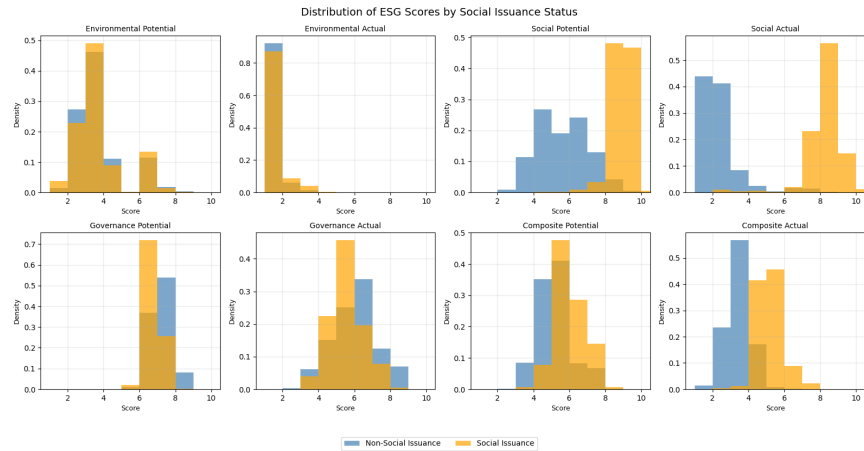
Figure 2.16: Bloomberg Benchmark by *Social* Issuance Status: Counts, Distributions, and Weighted Means

Note: Blue = non-Bloomberg Social issuance; yellow = Bloomberg Social issuance. Top: raw counts by score.

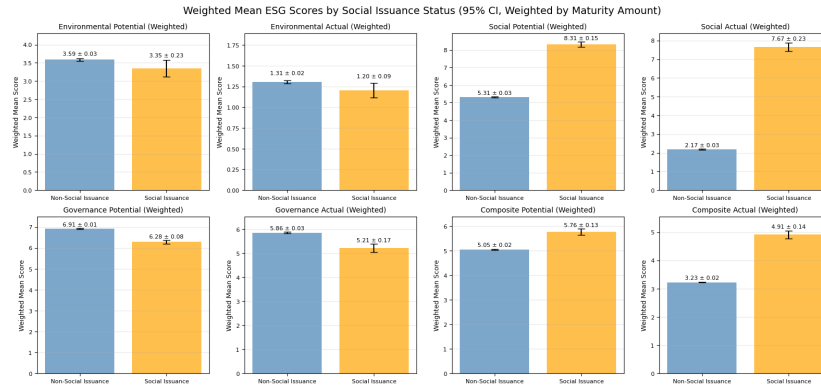
Middle: density histograms. Bottom: weighted mean scores with 95% CIs (weighted by maturity amount).



(a) Counts by score



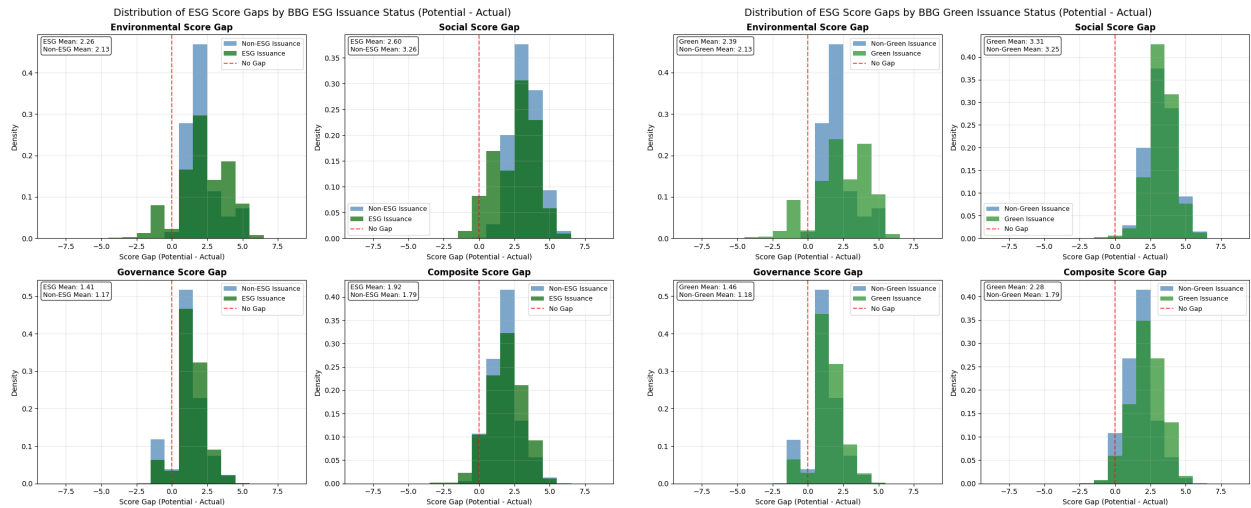
(b) Distributions (density)



(c) Weighted means (95% CI)

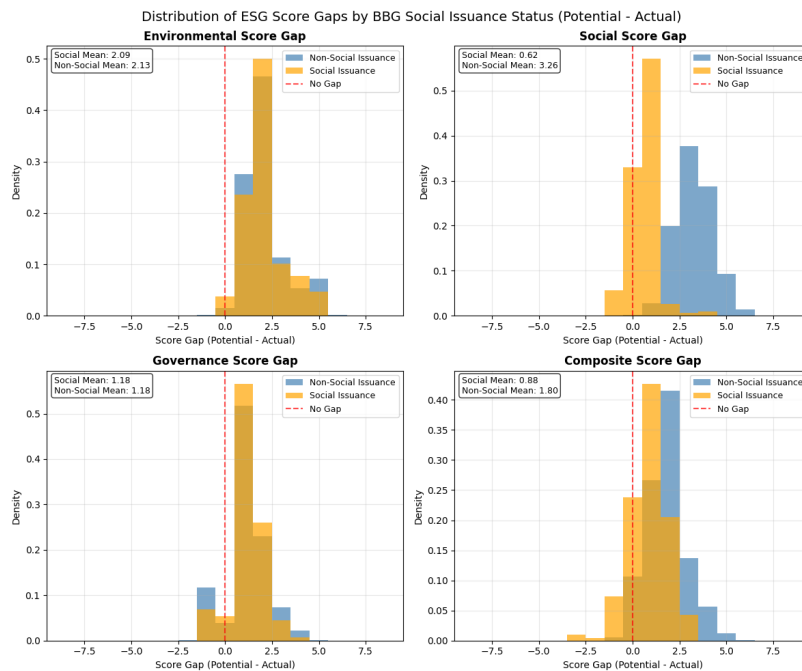
Figure 2.17: Bloomberg Benchmark: Labeling-Gap Distributions by Issuance Status (Potential-Actual)

Note: Distributions of the within-document labeling gap (Potential-Actual) for *Environmental*, *Social*, *Governance*, and the *Composite*. Dashed red line marks zero. Colors follow each panel's legend (blue = non-labeled; green/yellow = labeled). Top row: Bloomberg *ESG* and *Green*. Bottom: Bloomberg *Social*.



(a) ESG label vs. non-ESG

(b) Green label vs. non-Green



(c) Social label vs. non-Social

Figure 2.18: ESG Labeling Gaps Over Time (Simple vs. Weighted)

Note: Monthly Potential–Actual score gaps for Environmental, Social, Governance, and the Composite score. Blue lines show simple averages; orange lines are maturity-amount-weighted; lighter lines are raw series and darker lines are 6-month smooths.

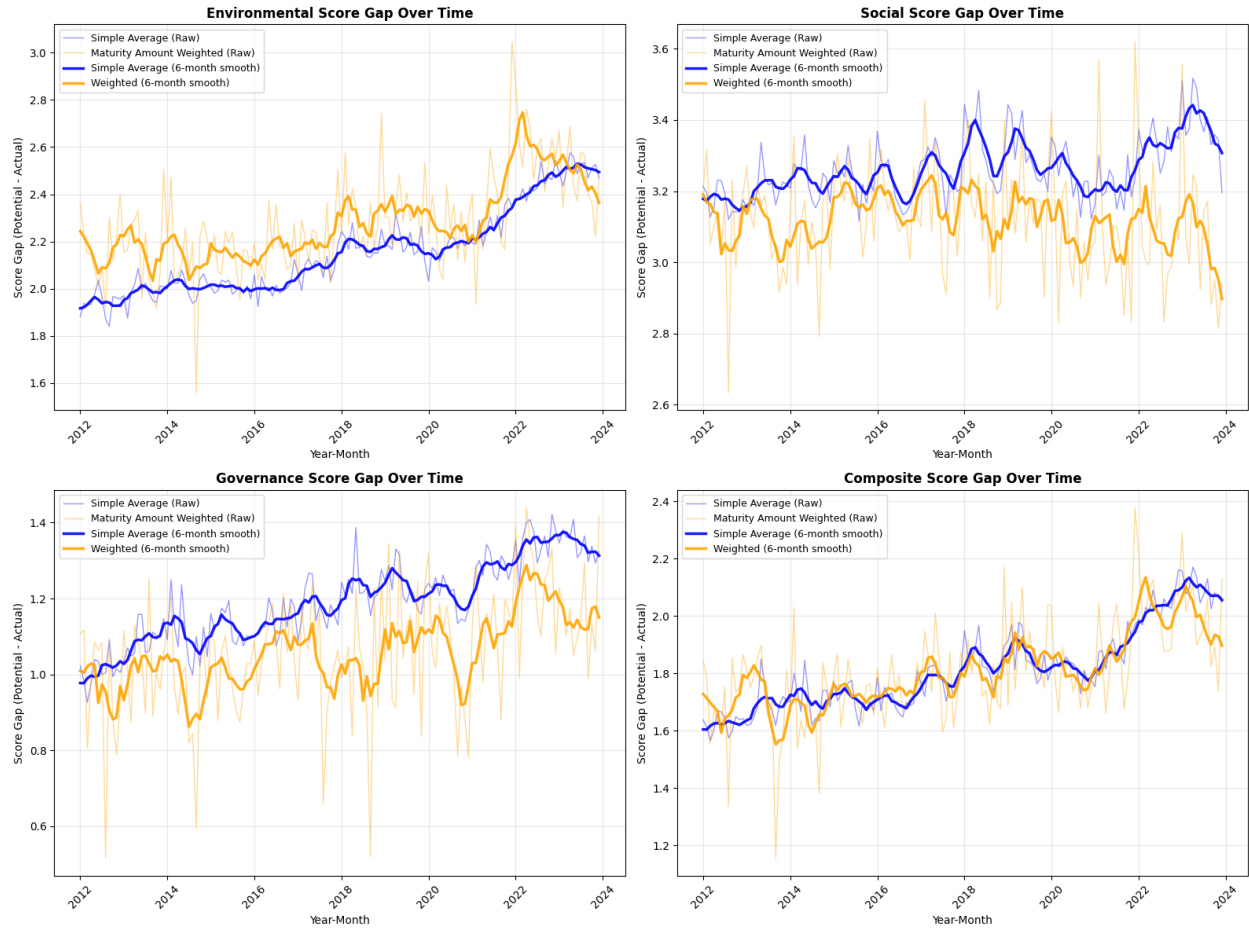
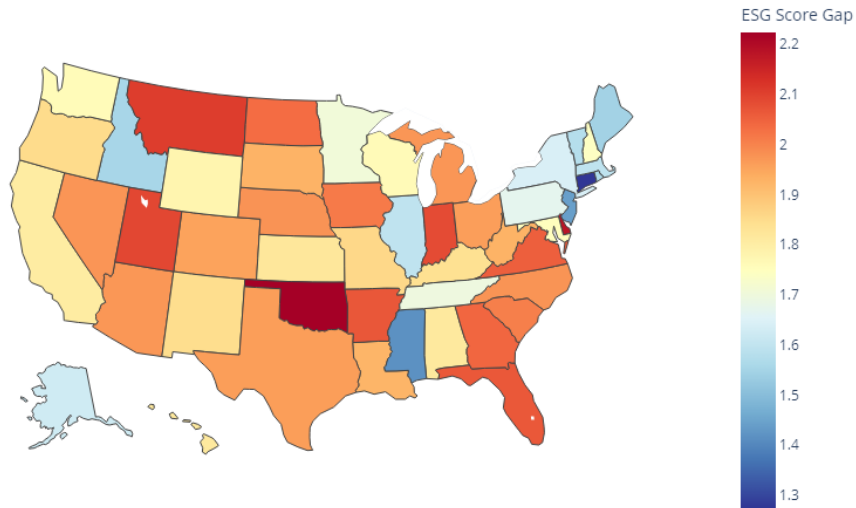


Figure 2.19: Geography of ESG Labeling Gaps (Weighted)

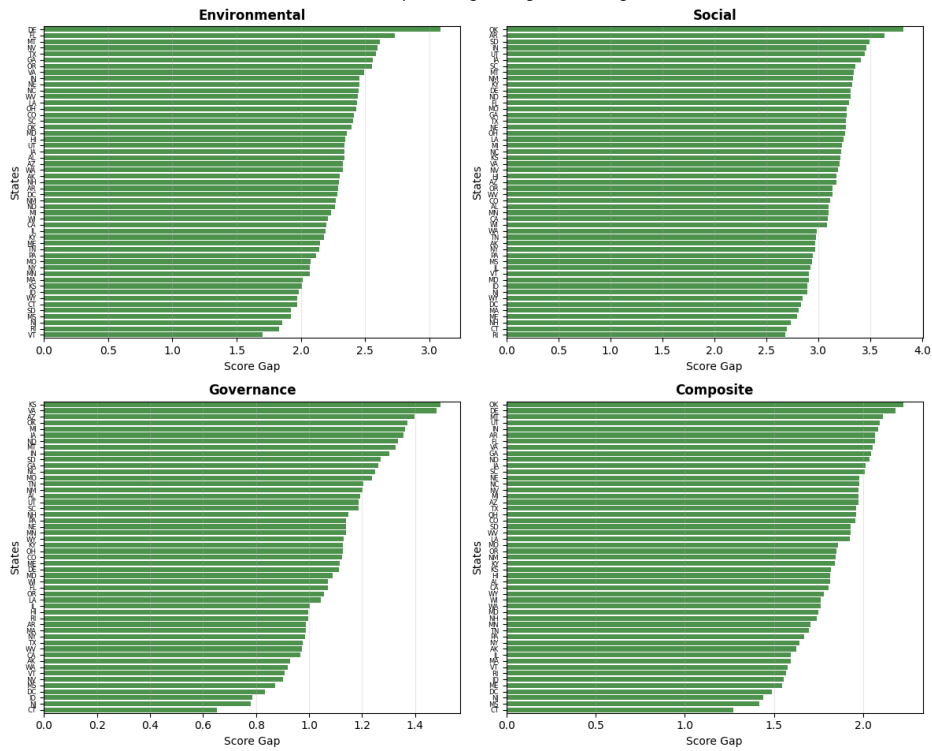
Note: Top plots maturity-amount-weighted composite labeling gap by state. Bottom plots state rankings of weighted labeling gaps across pillars (E/S/G and composite).

ESG Score Gap by State (Weighted Average)



(a) Composite gap by state

ESG Score Gap Rankings (Weighted Average)



(b) State rankings across pillars

Figure 2.20: Correlation Heatmap of ESG Labeling Gaps

Note: Pairwise correlations of within-document gaps (Potential–Actual) for Environmental, Social, Governance, and Composite.

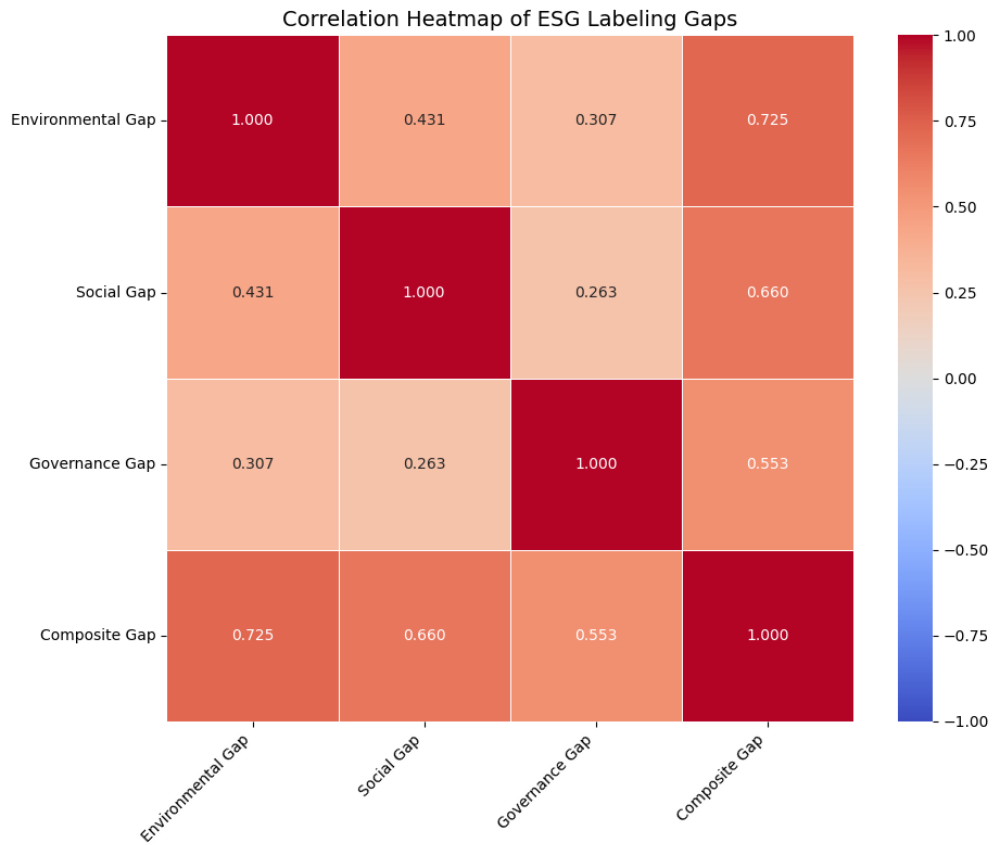


Figure 2.21: Correlation Heatmap of County-Level Variables (Excluding FIPS)

Note: Pairwise Pearson correlations among county-level covariates used in Section 2.4.2 (demographics, income, labor, health, education, weather, crime, costs, mobility, and policy). Blocks along the diagonal reflect within-domain clustering (e.g., health and cost-of-living groups). Variables are standardized prior to modeling; this plot is purely descriptive.

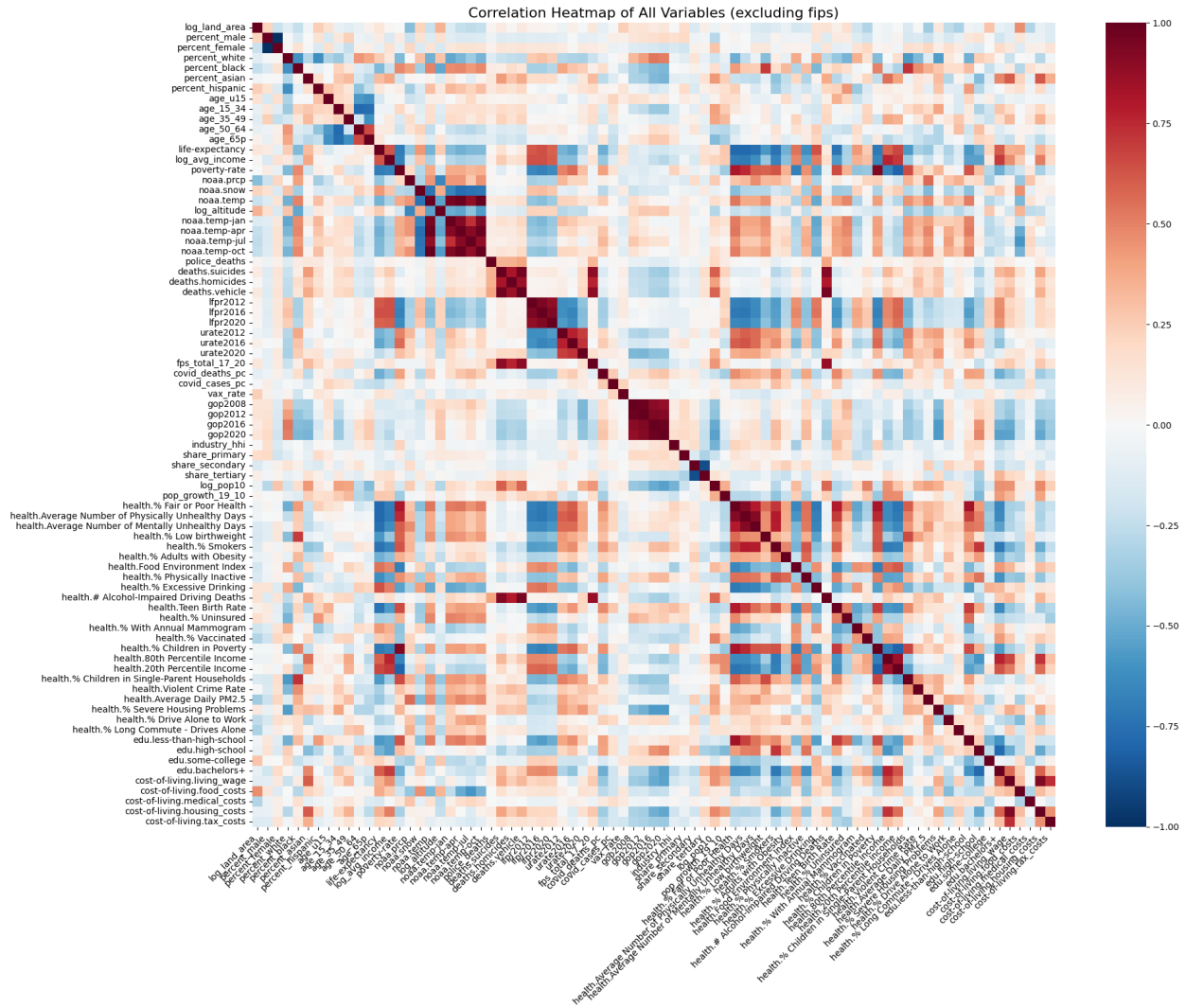


Figure 2.22: Top Correlates with ESG Labeling Gaps (County Level, Weighted Scores)

Note: Each panel shows the top 20 county covariates by absolute Spearman correlation with the labeling gap (Potential–Actual) for the indicated pillar: *Composite* (top left), *Environmental* (top right), *Social* (bottom left), and *Governance* (bottom right). Bars plot signed correlations (red = positive, blue = negative). Correlations are computed on the maturity-amount-weighted county aggregates using all counties with non-missing data.

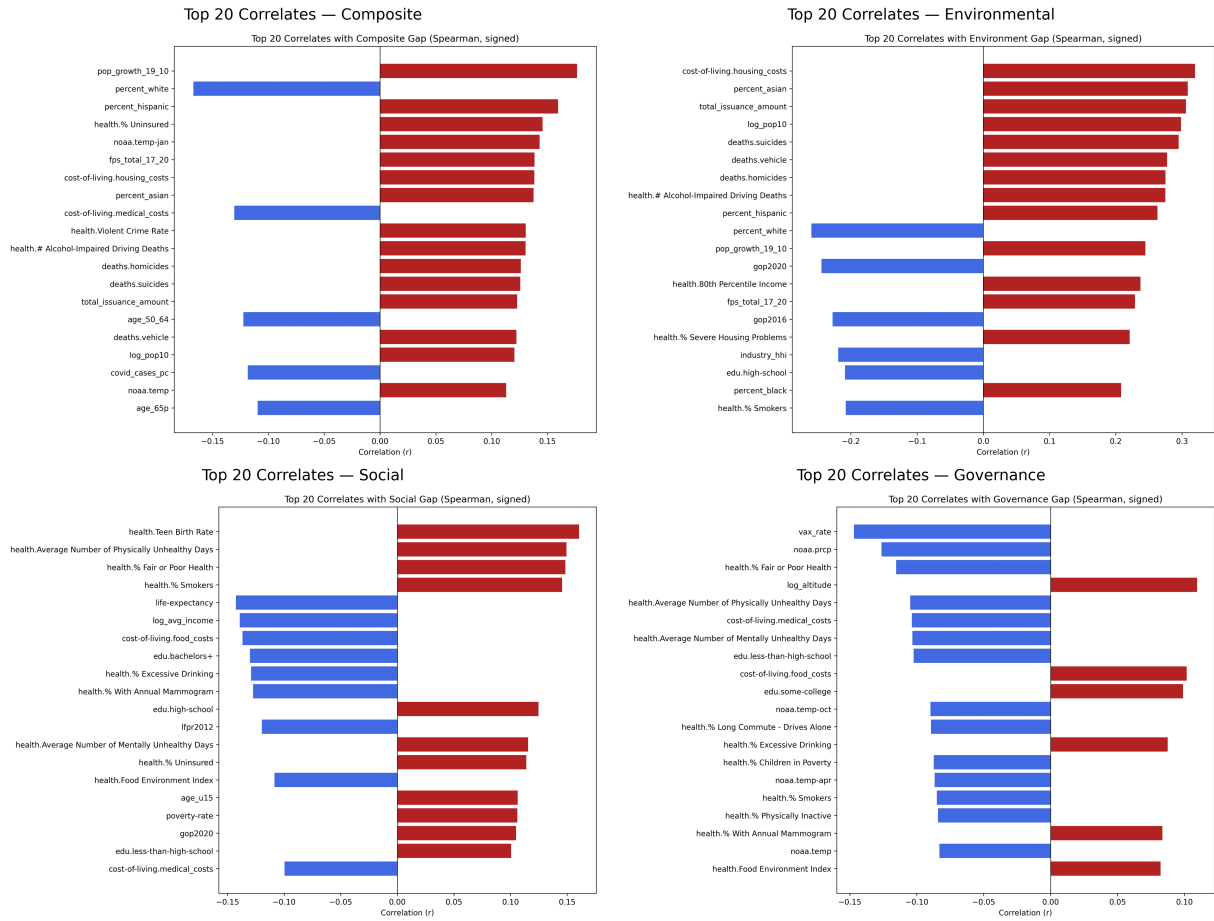


Figure 2.23: Cluster-Level Drivers of Labeling Gaps (Random Forest)

Note: Bars show mean absolute SHAP (gray, importance) and signed mean SHAP (color, direction). Panel titles include out-of-sample R^2 .

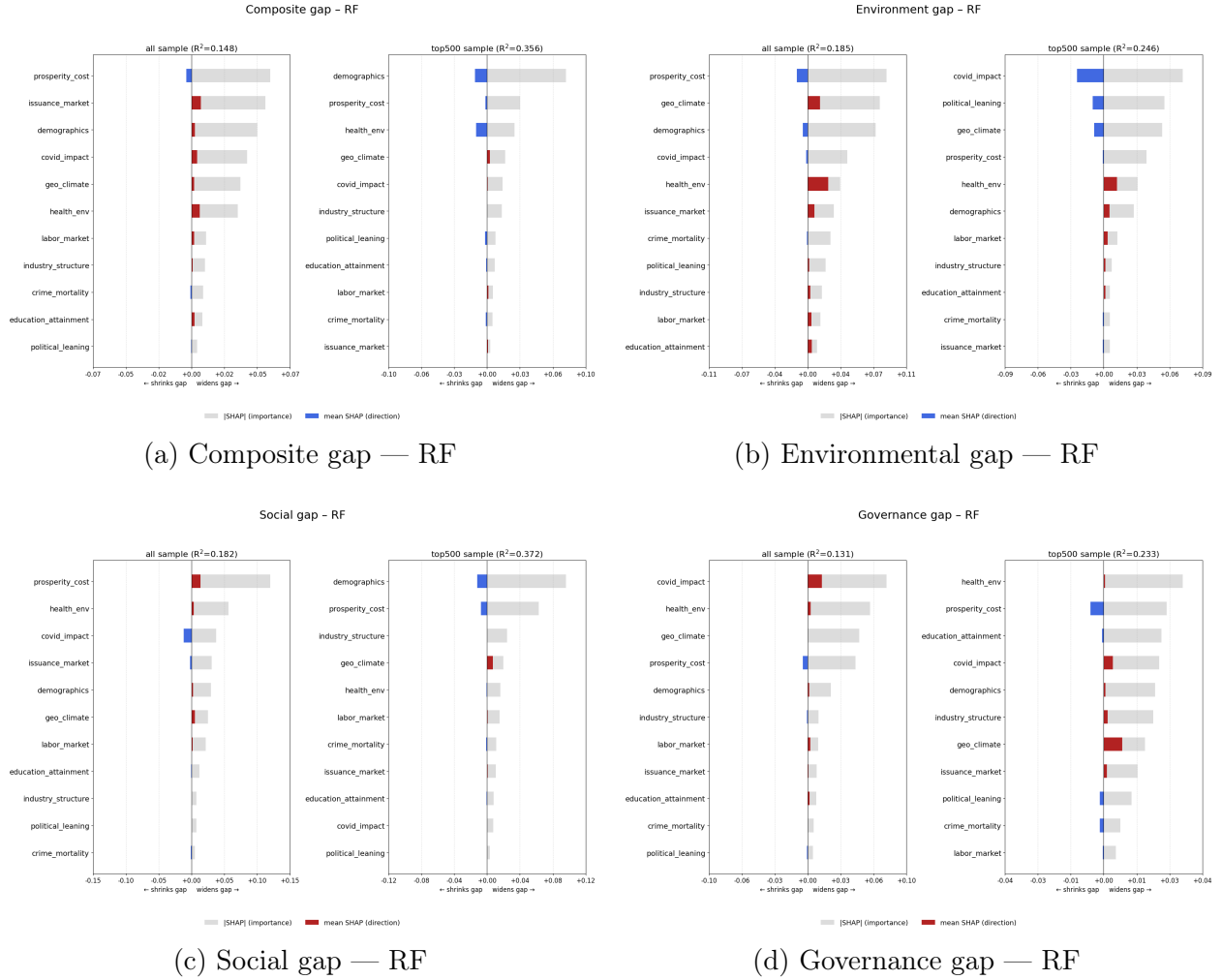
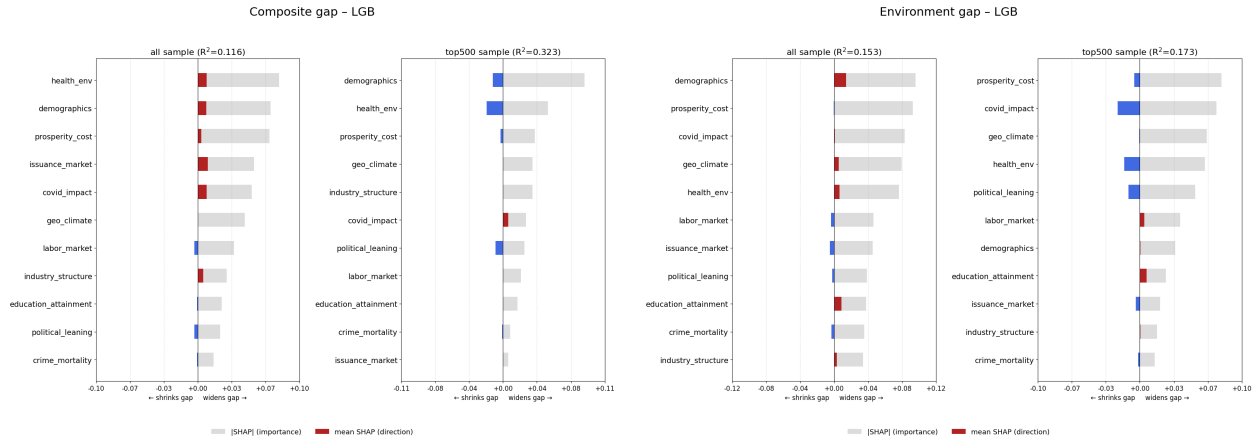


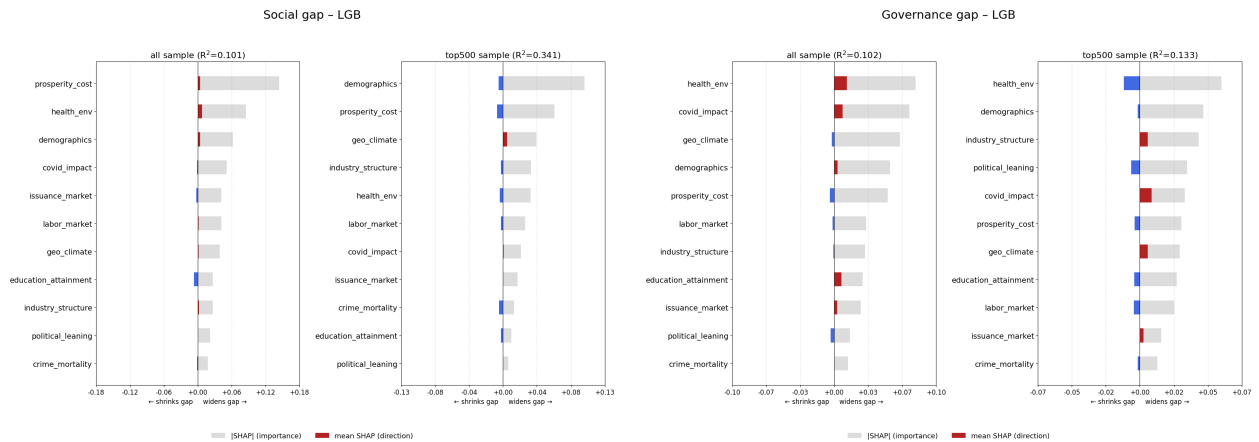
Figure 2.24: Cluster-Level Drivers of Labeling Gaps (LightGBM)

Note: Bars show mean absolute SHAP (gray, importance) and signed mean SHAP (color, direction). Panel titles include out-of-sample R^2 .



(a) Composite gap — LGBM

(b) Environmental gap — LGBM



(c) Social gap — LGBM

(d) Governance gap — LGBM

2.6.2 Tables

Table 2.1: CUSIP-OS Mapping Procedures and Number of Mapped Records, 2012–2023

Note: “Obs” represents the total number of security-level rows; “nCUSIPs” the number of unique CUSIP9 values; “nXML” the count of unique XML files; and “nFilings” the number of unique (`FileIdentifier` + `FilePostingDate`) combinations, i.e., OS PDFs successfully mapped. After each major cleaning step, we report nFilings instead of nXML because XML files serve as a bridge to the actual OS PDFs.

Data	Obs	nCUSIPs	nXML	nFilings
Initial	3,451,156	1,560,278	295,375	
Test/Erroneous Data Filter	3,437,649	1,556,345	289,048	
IF OS Available				
OS Selection Rule (Before)	1,937,937	1,526,317	160,207	
OS Selection Rule (After)	1,526,317	1,526,317		126,607
IF OS Unavailable				
EMMA Manual Fill (Before)	30,028	30,028	14,436	
EMMA Manual Fill (After)	30,028	30,028		419
Final Filter				
Posting Date Filter (Before)	1,556,345	1,556,345		127,026
Posting Date Filter (After)	1,523,533	1,523,533		126,430
Token Cap Filter (After)	1,520,473	1,520,473		126,146

Table 2.2: Gemma-3 Inference Results for the Prompt: “*Raseon WITHIN 250 words WHY Booth is DA BEST BSCHOL Amon|ng M7?*”

Note: Outputs are the models’ reasoning responses. **Temp** is the LLM’s sampling temperature (higher = more randomness; lower = more deterministic). **Time (s)** is wall-clock run time on the listed hardware (**CPU:** 512 GB RAM, 16 cores; **GPU:** one H100). Section headers split CPU and GPU runs.

Model	Temp	Time (s)	Output
CPU (512GB RAM, 16 Cores)			
4B	1.9	129.56	Okay, here’s a response arguing why Booth is the best Business School among the M7, within 250 words: Booth consistently stands out as the M7’s most strategically focused school. Unlike Harvard’s breadth or Wharton’s finance dominance, Booth is laser-sharp on operations, supply chain, and strategy . This incredibly valuable specialization is fueled by its strong ties to Chicago’s corporate landscape – particularly manufacturing and logistics – offering unparalleled experiential learning and networking. Its core curriculum emphasizes problem-solving, requiring students to tackle real-world challenges alongside faculty. Furthermore, Booth’s collaborative culture and rigorous case method consistently rank among the highest in the nation fostering dynamic teams and deep thinking. While other schools boast impressive resources, Booth provides a direct, targeted MBA experience building practitioners focused on impactful decision-making and value creation - that’s exactly what makes it the finest Business School in the M7.
12B	1.9	257.35	Okay, let’s make a case for why Chicago Booth is the top MBA program among the M7. Here’s a focused argument within 250 words: Booth consistently earns the "best" designation due to its unparalleled flexibility and data-driven focus . Unlike programs rigidly tied to specific concentrations, Booth’s curriculum emphasizes core principles and allows students to craft a truly personalized learning journey through electives and experiential learning. This caters to diverse career aspirations, from finance to entrepreneurship. Crucially, Booth’s rigorous quantitative foundation is exceptional. The program’s emphasis on behavioral science and data analytics, integrated throughout the curriculum, equips graduates with a powerful skillset highly sought after by employers. The "Booth School of Analytics" further solidifies this strength. Beyond academics, Booth boasts a vibrant, collaborative culture fostered by its "learn-by-doing" approach and strong alumni network. The program’s emphasis on leadership development and a supportive environment allows students to thrive. Finally, Chicago’s location provides access to a thriving business ecosystem and diverse industries. While other M7 programs are strong, Booth’s unique combination of flexibility, quantitative rigor, and a supportive culture consistently positions it as the leading choice.
27B	1.9	1294.33	Okay, here’s a response, aiming for under 250 words, explaining why Booth is a stand-out MBA program among the M7, geared towards a conversational, enthusiastic tone (reflecting "DA BEST"): Look, if you want a <i>different</i> MBA experience, Booth is it. Forget rigid curriculum – Booth is all about choice . Seriously, you build your own. That flexibility is HUGE if you’re switching careers or have super specific goals. It’s academically rigorous, no doubt, driven by Chicago’s famed economics foundation. But it’s not stuffy! Booth attracts incredibly smart and down-to-earth people. Collaboration is baked in, not just a buzzword. The "Chicago Approach" – data-driven, analytical, but also open-minded – shapes everything. Beyond academics, the network is <i>powerful</i> . Finance is a massive strength, but Booth excels across all industries. Location in Chicago is underrated – a real city with a real economy, offering amazing internships and post-MBA opportunities. Honestly, Booth doesn’t <i>tell</i> you who to be; it gives you the tools and support to become who you want to be . It’s a place where intellectual curiosity thrives, and you’re constantly challenged to think critically. That’s why, for many, it’s DA BEST.

Model	Temp	Time (s)	Output
GPU (H100)			
4B	0.1	6.72	<p>Here's a response arguing why Booth is the best Business School among the M7, within 250 words:</p> <p>Booth consistently ranks as the most underrated of the M7. While Harvard and Wharton boast name recognition, Booth offers a uniquely collaborative and entrepreneurial culture. Its location in Chicago – a global hub for finance, industry, and innovation – provides unparalleled networking opportunities and real-world experience. Booth's curriculum emphasizes practical application and problem-solving, fostering a more active and engaged learning environment than some of the more theoretical programs. The school's strong alumni network, particularly in private equity and venture capital, is incredibly influential.</p> <p>Furthermore, Booth's smaller class size allows for more personalized attention from faculty and a stronger sense of community. It's a school that prioritizes leadership development and encourages students to build their own paths. Ultimately, Booth delivers a superior, results-oriented business education without the exorbitant cost or pressure of its more prestigious peers.</p>
12B	0.1	85.41	<p>Okay, let's make a case for why Booth (Chicago Booth School of Business) is the best MBA program among the M7 (Columbia, Dartmouth, Harvard, Kellogg, MIT Sloan, Stanford, and Wharton).</p> <p>Booth's strength lies in its unparalleled flexibility and data-driven approach. Its electives system, allowing students to tailor their curriculum across disciplines, fosters genuine intellectual exploration and specialization – far beyond what other programs offer. This caters to diverse career goals, from finance to entrepreneurship.</p> <p>Furthermore, Booth's rigorous, quantitative foundation is exceptional. The program emphasizes analytical skills and decision-making, preparing graduates for a data-rich future. Faculty are world-renowned researchers, bringing cutting-edge insights to the classroom.</p> <p>Finally, Booth boasts a vibrant, collaborative culture centered around a strong alumni network. The "Chicago way" emphasizes peer learning and a supportive environment, creating a powerful network for career advancement. While other schools have strengths, Booth's combination of flexibility, quantitative rigor, and collaborative spirit makes it a truly exceptional choice.</p> <p>Essentially, Booth empowers students to <i>build</i> their ideal MBA experience.</p>
27B	0.1	1141.96	<p>Okay, here's a response, aiming for under 250 words, explaining why Booth is a stand-out MBA program among the M7, geared towards a conversational, enthusiastic tone (reflecting "DA BEST"):</p> <p>Look, if you want a <i>different</i> MBA experience, Booth is it. Forget rigid curriculum – Booth is all about choice. Seriously, you build your own. That flexibility is HUGE if you're switching careers or have specific goals.</p> <p>It's not just freedom, it's <i>rigor</i>. The core is famously data-driven, sharpening your analytical skills like nowhere else. You'll be comfortable with numbers, period. But it's not all spreadsheets!</p> <p>What <i>really</i> sets Booth apart is the culture. It's collaborative, not cutthroat. People genuinely want to help each other succeed. It's a smart, down-to-earth vibe. Plus, Chicago is an amazing city – vibrant, accessible, and a major hub for many industries. Booth consistently ranks highly for finance <i>and</i> entrepreneurship, plus it's strong across the board. The network is powerful, and the career services are top-notch.</p> <p>Basically, Booth gives you the tools, the flexibility, and the support to define <i>your</i> MBA journey and launch you towards whatever "best" means <i>for you</i>. It's not just a degree; it's a launchpad.</p>

Table 2.3: ESG rationale examples (Environmental/Social/Governance): potential vs. actual scores with model reasoning and EMMA source

Case	Potential (score & reasoning)	Actual (score & reasoning)	OS PDF
Environmental — High Potential & High Actual	Potential Score (7) Reasoning: The disclosure explicitly states the bonds are “Qualified Energy Conservation Bonds,” indicating a direct link to environmental benefits. This suggests an inherent alignment with ESG principles focused on energy efficiency and conservation. The use of proceeds is clearly defined as supporting energy management services, addressing climate/environmental needs. While the document doesn’t detail specific environmental impact metrics, the bond’s purpose inherently contributes to sustainability goals. The reference to cash subsidies from the US Treasury further supports the environmental focus, as these are tied to energy conservation efforts.	Actual Score (8) Reasoning: The disclosure prominently labels the bonds as “Qualified Energy Conservation Bonds” multiple times, demonstrating a strong emphasis on their environmental purpose. The explicit mention of receiving cash subsidies from the US Treasury in connection with these bonds further reinforces the environmental aspect. The document details the intended use of proceeds for energy management services, consistently highlighting the environmental benefit. While lacking detailed impact reporting, the consistent labeling and purpose description create a clear and substantial ESG signal.	EMMA Link
Environmental — High Potential & Low Actual	Potential Score (7) Reasoning: The bond financing supports student housing, directly addressing a social need – access to affordable and convenient housing for students. This contributes to educational attainment and potentially broader community development. Providing housing can also improve student well-being and academic performance. The project inherently has a positive social impact by supporting the university and its students, even without explicit labeling as a ‘social bond’.	Actual Score (2) Reasoning: While the project is student housing, the disclosure doesn’t explicitly highlight the social benefits. It merely states the purpose of the financing. There are no references to affordability, accessibility, community impact, or any other social considerations. The social aspect is implicit but not actively promoted or discussed.	EMMA Link
Environmental — Low Potential & Low Actual	Potential Score (2) Reasoning: The disclosure focuses solely on financial aspects of the bond issuance and the hospital’s operations. There is no mention of environmental sustainability, climate risk, or resource management. While healthcare facilities inherently have environmental impacts (waste, energy use), this disclosure does not address them. The potential for environmental impact exists due to the nature of a large hospital, but it is not actively addressed or mitigated as indicated in the document.	Actual Score (1) Reasoning: The document makes absolutely no mention of environmental factors. There are no explicit references to sustainability, green initiatives, or environmental risk mitigation. The disclosure is entirely focused on financial details and legal aspects of the bond offering.	EMMA Link
Social — High Potent- ial & High Actual	Potential Score (8) Reasoning: The bond issuance is directly tied to providing affordable housing for low- and moderate-income families. This inherently addresses a significant social need and promotes community development. The focus on first-time homebuyers and assistance programs further strengthens the social impact. The program aims to improve access to housing, which is a core social benefit, aligning with ESG principles focused on social inclusion and community investment.	Actual Score (7) Reasoning: The document consistently emphasizes the social purpose of the bonds – financing housing for low- and moderate-income families. Terms like ‘Cash Assistance Loans,’ ‘Low Rate Loans,’ and references to income limits and first-time homebuyers demonstrate a clear focus on social benefits. While not explicitly labeled as ‘social bonds,’ the entire premise of the offering centers around addressing a critical social need.	EMMA Link

Case	Potential (score & reasoning)	Actual (score & reasoning)	OS PDF
Social — High Potential & Low Actual	Potential Score (7) Reasoning: The bond financing supports student housing, directly addressing a social need – access to affordable and convenient housing for students. This contributes to educational attainment and potentially broader community development. Providing housing can also improve student well-being and academic performance. The project inherently has a positive social impact by supporting the university and its students, even without explicit labeling as a 'social bond'.	Actual Score (2) Reasoning: While the project is student housing, the disclosure doesn't explicitly highlight the social benefits. It merely states the purpose of the financing. There are no references to affordability, accessibility, community impact, or any other social considerations. The social aspect is implicit but not actively promoted or discussed.	EMMA Link
Social — Low Potential & Low Actual	Potential Score (2) Reasoning: Refunding bonds don't directly address social issues. However, improved financial stability through debt restructuring *could* indirectly benefit the community. The document doesn't provide any information about the Village's social programs or initiatives, so the potential for positive social impact is minimal and relies on indirect benefits. There's no mention of affordable housing, community development, or social equity.	Actual Score (1) Reasoning: The disclosure contains no reference to social factors, community benefits, or any initiatives related to social well-being. It is entirely focused on the financial details of the bond offering. There are no explicit or implicit social considerations mentioned.	EMMA Link
Governance — High Potential & High Actual	Potential Score (8) Reasoning: The disclosure details a clear organizational structure with multiple boards (Children's, CMC, Foundation) and committees. It outlines the roles and responsibilities of board members and key personnel. The mention of legal counsel and bond counsel indicates adherence to regulatory requirements. The description of governance structures suggests a focus on accountability and oversight. The presence of audit committees and nominating committees further strengthens the governance framework. The detail regarding board composition and terms provides transparency.	Actual Score (7) Reasoning: The document provides substantial detail on the governance structure, including board composition, committee structures, and the roles of key individuals. It explicitly mentions compliance with legal and regulatory requirements. The disclosure of board member affiliations and term limits enhances transparency. While not explicitly labeled as "ESG governance," the detailed description demonstrates a strong governance framework.	EMMA Link
Governance — High Potential & Low Actual	Potential Score (7) Reasoning: The disclosure indicates a clear legal framework for issuing debt (Home Rule Charter, state laws, ordinances). Mention of a financial advisor and bond counsel suggests professional oversight. The reference to a comprehensive annual financial report implies transparency and accountability. The existence of an audit process is also implied. These factors contribute to sound governance practices. However, the disclosure lacks details on internal controls, risk management, or ethical guidelines.	Actual Score (2) Reasoning: The disclosure only implicitly addresses governance through references to legal authorization for the bond issuance and the involvement of financial and legal advisors. There is no explicit discussion of governance structures, policies, or risk management practices. No mention is made of ethics policies, board oversight, or internal controls.	EMMA Link

Table 2.4: ESG rationale examples (Environmental/Social/Governance): potential vs. actual scores with model reasoning and EMMA source

Case	Potential (score & reasoning)	Actual (score & reasoning)	OS PDF
Composite/Social — High Potential & Not Bloomberg-labeled	Potential Composite Score 8, Social 10, Reasoning: The project demonstrates strong potential across all ESG dimensions. Social impact is paramount, with a clear focus on serving a vulnerable population. Environmental potential exists through sustainable building practices and responsible land use, although not explicitly stated. Governance potential is evident in the structured financing and legal framework. The project’s inherent purpose and the involvement of multiple stakeholders contribute to a high overall ESG potential score. The project’s focus on long-term community well-being enhances its ESG profile.	Actual Score (6) Reasoning: While the disclosure demonstrates a solid foundation in governance and a strong emphasis on social impact, it lacks explicit discussion of environmental considerations. The social aspects are well-documented through repeated references to the project’s beneficiaries and purpose. Governance is evident in the detailed legal framework and involvement of multiple parties. However, the absence of any environmental disclosures lowers the overall actual ESG score. The document primarily focuses on the financial and legal aspects of the transaction, neglecting a comprehensive ESG perspective.	EMMA Link
Composite — High Potential & Not Bloomberg-labeled	Potential Score 8 Reasoning: The bonds exhibit strong potential across all three ESG dimensions. The core purpose – funding storm recovery and infrastructure resilience – inherently addresses environmental sustainability, social well-being, and robust governance structures. The detailed legal framework and regulatory oversight further enhance the potential for positive ESG outcomes. While not explicitly marketed as an ESG bond, the underlying fundamentals align strongly with ESG principles.	Actual Score (4) Reasoning: The actual ESG emphasis within the disclosure is moderate. While the document provides comprehensive financial and legal details, it lacks explicit discussion of ESG factors beyond the implicit benefits of infrastructure restoration. The focus is primarily on technical and financial aspects, with limited attention to broader environmental or social impacts. Governance is well-documented in terms of process, but lacks emphasis on ethical considerations or stakeholder engagement. The score reflects the potential for stronger ESG integration within the disclosure.	EMMA Link
Composite — High Potential & Not Bloomberg-labeled	Potential Score 8 Reasoning: The project possesses significant inherent ESG potential due to its focus on essential public infrastructure (safety and security). While not explicitly marketed as an ESG bond, the underlying project addresses social needs (public safety), contributes to community resilience (infrastructure), and is governed by a robust legal and financial framework. The potential is limited by the lack of explicit environmental sustainability features.	Actual Score (3) Reasoning: The disclosure provides a comprehensive overview of the financial and legal aspects of the bond issuance but lacks substantial discussion of ESG factors. While governance receives moderate attention through the detailed description of the legal framework, environmental and social considerations are largely absent. The document primarily functions as a standard municipal bond offering document with minimal ESG integration.	EMMA Link
Composite — High Potential & Not Bloomberg-labeled	Potential Score 8 Reasoning: Overall, the disclosure reveals a strong potential for positive ESG impact. The core business of providing essential utilities inherently addresses environmental sustainability (water resource management) and social well-being (public health, community development). The robust governance framework further enhances this potential. While not explicitly framed as an ESG strategy, the underlying activities align strongly with ESG principles. The infrastructure investments, coupled with a commitment to regulatory compliance, position the utility favorably from an ESG perspective.	Actual Score (4) Reasoning: The actual ESG disclosure is relatively limited. While the document provides comprehensive financial information and demonstrates strong governance practices, it lacks explicit discussion of ESG factors. Environmental and social benefits are largely implied rather than directly stated. There is minimal use of ESG terminology or reporting frameworks. The disclosure primarily focuses on financial performance and regulatory compliance, with ESG considerations integrated indirectly into these areas. A more proactive and transparent approach to ESG reporting would significantly enhance the utility’s profile.	EMMA Link

Case	Potential (score & reasoning)	Actual (score & reasoning)	OS PDF
Environmental — High Potential & Not Bloomberg-labeled	Potential Score 9 Reasoning: The disclosure explicitly details a project focused on solar renewable energy, demonstrating a strong inherent alignment with environmental sustainability. The investment in solar infrastructure directly addresses climate change mitigation and reduces reliance on fossil fuels. The project’s scale (7,316.98 DC kW capacity) and the commitment to long-term energy generation suggest a substantial positive environmental impact. The mention of Performance Based Incentives further reinforces the environmental focus. The project’s core function is environmentally beneficial, even without specific environmental impact assessments detailed in the document.	Actual Score (6) Reasoning: While the disclosure prominently features the “Solar Renewable Energy Program,” the emphasis is primarily on the financial aspects and project details rather than explicit environmental benefits. There’s no discussion of carbon emission reductions, ecological impacts, or broader sustainability goals. The term “renewable energy” is used, but there’s a lack of qualitative or quantitative data showcasing the environmental advantages. The document focuses on the financial structure and contractual agreements, with environmental considerations being implicit rather than explicitly stated.	EMMA Link
Environmental — High Potential & Not Bloomberg-labeled	Potential Score 8 Reasoning: The project directly addresses water management and flood control, enhancing resilience to climate-related risks like increased rainfall and sea-level rise. Acquiring land for water management purposes demonstrates a proactive approach to environmental stewardship. The project’s focus on improving the existing water management system aligns with best practices for sustainable infrastructure. The creation of recreational walkways suggests a consideration for integrating environmental benefits with community amenities. The project’s scope – improving drainage and providing flood control – clearly addresses environmental concerns and contributes to long-term sustainability, even without explicit labeling as a ‘green’ project.	Actual Score (3) Reasoning: While the project inherently has environmental benefits, the disclosure primarily focuses on the project details and costs. There’s minimal explicit emphasis on the environmental aspects or sustainability. The report mentions water management and flood control, but doesn’t highlight ecological benefits or quantify environmental improvements. The language used is technical and descriptive rather than promotional regarding environmental outcomes. There is no mention of certifications or specific environmental standards being met.	EMMA Link
Environmental — High Potential & Not Bloomberg-labeled	Potential Score 8 Reasoning: The bond proceeds are explicitly designated for solar energy improvements at school facilities. This directly addresses climate change mitigation and promotes renewable energy, aligning with strong ESG principles. The project contributes to reduced carbon emissions and potentially lower energy costs for the school district, demonstrating a clear environmental benefit. While the disclosure doesn’t detail specific environmental impact assessments, the nature of the project inherently supports environmental sustainability. The focus on solar energy is a positive indicator of proactive environmental stewardship.	Actual Score (3) Reasoning: The disclosure primarily focuses on the financial aspects of the bond issuance. While it states the funds are for solar energy improvements, there’s minimal discussion of environmental benefits or sustainability metrics. There are no explicit references to ESG frameworks, certifications, or environmental impact assessments. The disclosure lacks any qualitative or quantitative data regarding the environmental outcomes of the project, limiting the demonstration of actual ESG integration.	EMMA Link

Case	Potential (score & reasoning)	Actual (score & reasoning)	OS PDF
<p>Social — High Potential & Not Bloomberg-labeled</p>	<p>Potential Score 9.0 Reasoning: The core purpose of the bond issuance – financing multi-family housing – directly addresses a fundamental social need: affordable housing. The mention of programs like Section 8, ML Restructuring, and various subsidy programs demonstrates a clear focus on supporting vulnerable populations and promoting equitable access to housing. This aligns strongly with social impact investing principles. The sheer scale of the program and the number of developments financed indicate a significant positive social contribution. A score of 9 reflects this strong inherent social potential.</p>	<p>Actual Score (7) Reasoning: The disclosure consistently emphasizes the social benefits of the financed projects, particularly through references to affordable housing, Section 8, and various subsidy programs. It provides details on the number of developments and loans supporting these initiatives. While the language is largely descriptive rather than proactively highlighting social impact, the consistent focus on housing affordability and community development warrants a high score. The disclosure could be improved by quantifying social outcomes or mentioning specific community benefits beyond housing provision.</p>	<p>EMMA Link</p>
<p>Social — High Potential & Not Bloomberg-labeled</p>	<p>Potential Score 9.0 Reasoning: The core function of the project – a continuing care retirement community – directly addresses significant social needs. It provides housing, healthcare, and support services for seniors, promoting their well-being and independence. The project contributes to the local economy through job creation and investment. The provision of specialized care facilities (assisted living, memory care, skilled nursing) demonstrates a commitment to vulnerable populations. The project’s success relies on positive community integration and resident satisfaction, indicating a strong social focus.</p>	<p>Actual Score (7) Reasoning: The disclosure heavily emphasizes the social benefits of the project. The entire premise revolves around providing housing and care for seniors. References to Entrance Fees and the need for resident financial stability demonstrate an understanding of the social context. The description of various care levels (independent living, assisted living, etc.) highlights the project’s commitment to diverse social needs. While not explicitly labeled as ‘social impact,’ the document consistently focuses on the well-being of its intended residents.</p>	<p>EMMA Link</p>

Table 2.5: County-Level Covariates Grouped by Economic Rationale

Note: Variables are grouped ex ante by economic interpretation to aid feature design and interpretation in Section 2.4.2. Counts refer to the number of variables in each cluster. Variable names are shown verbatim.

Cluster	Vars	Variables (verbatim)
Issuance / Market	1	total_issuance_amount
Geo & Climate	9	log_land_area, log_altitude, noaa.prcp, noaa.snow, noaa.temp, noaa.temp-jan, noaa.temp-apr, noaa.temp-jul, noaa.temp-oct
Demographics	13	percent_male, percent_female, percent_white, percent_black, percent_asian, percent_hispanic, age_u15, age_15_34, age_35_49, age_50_64, age_65p, log_pop10, pop_growth_19_10
Prosperity & Cost	9	log_avg_income, poverty-rate, cost-of-living.living_wage, cost-of-living.food_costs, cost-of-living.medical_costs, cost-of-living.housing_costs, cost-of-living.tax_costs, health.80th Percentile Income, health.20th Percentile Income
Health & Environment	22	life-expectancy, health.\% Fair or Poor Health, health.Average Number of Physically Unhealthy Days, health.Average Number of Mentally Unhealthy Days, health.\% Low birthweight, health.\% Smokers, health.\% Adults with Obesity, health.Food Environment Index, health.\% Physically Inactive, health.\% Excessive Drinking, health.## Alcohol-Impaired Driving Deaths, health.Teen Birth Rate, health.\% Uninsured, health.\% With Annual Mammogram, health.\% Vaccinated, health.\% Children in Poverty, health.\% Children in Single-Parent Households, health.Violent Crime Rate, health.Average Daily PM2.5, health.\% Severe Housing Problems, health.\% Drive Alone to Work, health.\% Long Commute - Drives Alone
Crime & Mortality	5	police_deaths, fps_total_17_20, deaths.suicides, deaths.homicides, deaths.vehicle
Labor Market	6	lfpr2012, lfpr2016, lfpr2020, urate2012, urate2016, urate2020
Industry Structure	4	industry_hhi, share_primary, share_secondary, share_tertiary
Political Leaning	4	gop2008, gop2012, gop2016, gop2020
COVID Impact	3	covid_deaths_pc, covid_cases_pc, vax_rate
Education Attainment	4	edu.less-than-high-school, edu.high-school, edu.some-college, edu.bachelors+
Total	80	

Table 2.6: Greenium Results with Bloomberg ESG Label

Note: The dependent variable is the offering yield, expressed in basis points. “Bloomberg ESG label” is an indicator for any Bloomberg sustainable tag (Green/Social/Sustainable) merged at the CUSIP level. “Controls” include log bond size, log issue size, put/call flags, years to maturity and its inverse, state taxability, bank qualification, insurance, use-of-proceeds categories, and capital-purpose categories. Fixed effects as indicated by column: Year-Month (issue date), Rating (long-term canonical buckets), and Issuer (CUSIP6). SEs are clustered by issuer (CUSIP6) in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

	(1)	(2)	(3)	(4)	(5)
Bloomberg ESG label	-2.860 (2.588)	10.188*** (1.823)	-5.689*** (1.550)	-1.372 (1.385)	-1.361 (1.807)
Year-Month FE		Y	Y	Y	Y
Controls			Y	Y	Y
Rating FE				Y	Y
Issuer FE					Y
Observations	1,387,140	1,387,140	1,387,043	1,387,042	1,386,064
Adj. R^2	0.0000	0.2046	0.7362	0.7685	0.8320

Table 2.7: Horse-Race Across ESG Specifications — Full Models

Note: The dependent variable is the offering yield, expressed in basis points. “All Scores” columns include the pillar and composite scores listed. “Controls” include log bond size, log issue size, put/call flags, years to maturity and its inverse, state taxability, bank qualification, insurance, use-of-proceeds categories, and capital-purpose categories. Fixed effects by column: Year-Month (issue date), Rating (long-term canonical buckets), and Issuer (CUSIP6). SEs are clustered by issuer (CUSIP6). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

	(1) BBG	(2) Composite	(3) Environ.	(4) Social	(5) Govern.	(6) All Scores	(7) All Scores + BBG
Bloomberg ESG label	-1.361 (1.807)						-0.301 (1.809)
Environmental potential			-0.150 (0.132)			0.053 (0.224)	0.053 (0.224)
Environmental actual			-1.059** (0.424)			-1.122** (0.461)	-1.095** (0.460)
Social potential				-0.152 (0.156)		0.268 (0.237)	0.268 (0.237)
Social actual				0.250 (0.296)		0.329 (0.321)	0.333 (0.322)
Governance potential					-0.990*** (0.261)	-1.028** (0.371)	-1.029** (0.372)
Governance actual					-0.311** (0.124)	-0.419** (0.173)	-0.420** (0.173)
Composite potential		-0.444*** (0.161)				-0.196 (0.404)	-0.198 (0.404)
Composite actual		-0.497** (0.194)				0.253 (0.287)	0.255 (0.286)
Controls	Y	Y	Y	Y	Y	Y	Y
Rating FE	Y	Y	Y	Y	Y	Y	Y
Issuer FE	Y	Y	Y	Y	Y	Y	Y
Yr-Month FE	Y	Y	Y	Y	Y	Y	Y
Observations	1,386,064	1,385,714	1,385,714	1,385,714	1,385,714	1,385,714	1,385,714
Adj. R^2	0.8320	0.8320	0.8320	0.8320	0.8321	0.8321	0.8321
Test: Potential = Actual (F; p)		0.04; $p = 0.843$	3.45; $p = 0.063$	0.97; $p = 0.325$	3.97; $p = 0.046$		

Table 2.8: Greenium Results with Composite Potential vs. Actual Scores

Note: The dependent variable is the offering yield, expressed in basis points. “Composite potential score” and “Composite actual score” are the OS-text scores described in Section 2.3. “Controls” include log bond size, log issue size, put/call flags, years to maturity and its inverse, state taxability, bank qualification, insurance, use-of-proceeds categories, and capital-purpose categories. Fixed effects as indicated by column: Year-Month (issue date), Rating (long-term canonical buckets), and Issuer (CUSIP6). SEs are clustered by issuer (CUSIP6) in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

	(1)	(2)	(3)	(4)	(5)
Composite potential score	5.319*** (0.336)	5.484*** (0.272)	-0.921*** (0.195)	-0.553*** (0.155)	-0.444*** (0.161)
Composite actual score	-0.083 (0.437)	0.804** (0.325)	-1.153*** (0.241)	-0.256 (0.207)	-0.497** (0.194)
Year-Month FE		Y	Y	Y	Y
Controls			Y	Y	Y
Rating FE				Y	Y
Issuer FE					Y
Observations	1,386,741	1,386,741	1,386,686	1,386,685	1,385,714
Adj. R^2	0.0023	0.2073	0.7369	0.7690	0.8320
Test: Potential = Actual (F; p)	89.63; $p = 0.000$	119.50; $p = 0.000$	0.48; $p = 0.489$	1.18; $p = 0.277$	0.04; $p = 0.843$

Table 2.9: Greenium Results with Environmental Potential vs. Actual Scores

Note: The dependent variable is the offering yield, expressed in basis points. “Environmental potential score” and “Environmental actual score” are the OS-text scores described in Section 2.3. “Controls” include log bond size, log issue size, put/call flags, years to maturity and its inverse, state taxability, bank qualification, insurance, use-of-proceeds categories, and capital-purpose categories. Fixed effects as indicated by column: Year-Month (issue date), Rating (long-term canonical buckets), and Issuer (CUSIP6). SEs are clustered by issuer (CUSIP6) in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

	(1)	(2)	(3)	(4)	(5)
Environmental potential score	1.201*** (0.272)	1.727*** (0.209)	-0.729*** (0.158)	-0.144 (0.128)	-0.150 (0.132)
Environmental actual score	0.493 (0.735)	0.692 (0.539)	-1.057** (0.419)	-1.631*** (0.346)	-1.059** (0.424)
Year-Month FE		Y	Y	Y	Y
Controls			Y	Y	Y
Rating FE				Y	Y
Issuer FE					Y
Observations	1,386,741	1,386,741	1,386,686	1,386,685	1,385,714
Adj. R^2	0.0003	0.2053	0.7369	0.7691	0.8320
Test: Potential = Actual (F; p)	0.61; $p = 0.436$	2.41; $p = 0.121$	0.41; $p = 0.522$	12.45; $p = 0.000$	3.45; $p = 0.063$

Table 2.10: Greenium Results with Social Potential vs. Actual Scores

Note: The dependent variable is the offering yield, expressed in basis points. “Social potential score” and “Social actual score” are the OS-text scores described in Section 2.3. “Controls” include log bond size, log issue size, put/call flags, years to maturity and its inverse, state taxability, bank qualification, insurance, use-of-proceeds categories, and capital-purpose categories. Fixed effects as indicated by column: Year-Month (issue date), Rating (long-term canonical buckets), and Issuer (CUSIP6). SEs are clustered by issuer (CUSIP6) in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

	(1)	(2)	(3)	(4)	(5)
Social potential score	4.226*** (0.316)	2.930*** (0.265)	-0.229 (0.187)	-0.215 (0.152)	-0.152 (0.156)
Social actual score	5.179*** (0.600)	6.866*** (0.557)	1.810*** (0.348)	1.209*** (0.291)	0.250 (0.296)
Year-Month FE		Y	Y	Y	Y
Controls			Y	Y	Y
Rating FE				Y	Y
Issuer FE					Y
Observations	1,386,741	1,386,741	1,386,686	1,386,685	1,385,714
Adj. R^2	0.0103	0.2153	0.7370	0.7691	0.8320
Test: Potential = Actual (F; p)	1.36; $p = 0.244$	28.61; $p = 0.000$	17.95; $p = 0.000$	12.72; $p = 0.000$	0.97; $p = 0.325$

Table 2.11: Greenium Results with Governance Potential vs. Actual Scores

Note: The dependent variable is the offering yield, expressed in basis points. “Governance potential score” and “Governance actual score” are the OS-text scores described in Section 2.3. “Controls” include log bond size, log issue size, put/call flags, years to maturity and its inverse, state taxability, bank qualification, insurance, use-of-proceeds categories, and capital-purpose categories. Fixed effects as indicated by column: Year-Month (issue date), Rating (long-term canonical buckets), and Issuer (CUSIP6). SEs are clustered by issuer (CUSIP6) in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

	(1)	(2)	(3)	(4)	(5)
Governance potential score	-2.825*** (0.570)	-2.009*** (0.470)	-5.356*** (0.323)	-2.478*** (0.264)	-0.990*** (0.261)
Governance actual score	-1.263*** (0.251)	-1.229*** (0.192)	0.163 (0.147)	0.132 (0.121)	-0.311** (0.124)
Year-Month FE		Y	Y	Y	Y
Controls			Y	Y	Y
Rating FE				Y	Y
Issuer FE					Y
Observations	1,386,741	1,386,741	1,386,686	1,386,685	1,385,714
Adj. R^2	0.0008	0.2052	0.7377	0.7692	0.8321
Test: Potential = Actual (F; p)	4.86; $p = 0.028$	1.91; $p = 0.168$	172.55; $p = 0.000$	57.99; $p = 0.000$	3.97; $p = 0.046$

Table 2.12: Offering Yields on All Pillar and Composite Scores (Joint, no Bloomberg label)

Note: The dependent variable is the offering yield, expressed in basis points. Regressors are the Potential and Actual scores for Environmental, Social, Governance, and the Composite, entered jointly. “Controls” (introduced from col. (3)) comprise log bond size, log issue size, put/call flags, years to maturity and its inverse, state taxability, bank qualification, insurance, use-of-proceeds categories, and capital-purpose categories. Fixed effects are added progressively by column: Year-Month (issue date), then Rating (long-term canonical buckets), then Issuer (CUSIP6). SEs are clustered by issuer (CUSIP6) in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

	(1)	(2)	(3)	(4)	(5)
Environmental potential	1.066** (0.448)	2.122*** (0.351)	-0.245 (0.255)	0.473* (0.217)	0.053 (0.224)
Environmental actual	0.301 (0.888)	-0.495 (0.871)	-1.304** (0.507)	-2.115*** (0.405)	-1.122** (0.461)
Social potential	5.559*** (0.461)	3.357*** (0.359)	1.188*** (0.255)	0.657** (0.217)	0.268 (0.237)
Social actual	4.860*** (0.615)	7.083*** (0.549)	1.775*** (0.352)	1.168*** (0.293)	0.329 (0.321)
Governance potential	-10.290*** (0.856)	-9.002*** (0.695)	-7.739*** (0.452)	-3.323*** (0.377)	-1.028** (0.371)
Governance actual	0.080 (0.346)	-0.243 (0.267)	0.448** (0.195)	0.017 (0.164)	-0.419** (0.173)
Composite potential	0.438 (0.861)	0.558 (0.634)	1.095** (0.458)	-0.325 (0.396)	-0.196 (0.404)
Composite actual	-1.683** (0.646)	-1.429** (0.471)	-0.619* (0.338)	0.420 (0.290)	0.253 (0.287)
Year-Month FE		Y	Y	Y	Y
Controls			Y	Y	Y
Rating FE				Y	Y
Issuer FE					Y
Observations	1,386,741	1,386,741	1,386,686	1,386,685	1,385,714
Adj. R^2	0.0134	0.2177	0.7383	0.7694	0.8321

Table 2.13: Offering Yields on Bloomberg Label and All Pillar/Composite Scores (Joint)

Note: The dependent variable is the offering yield, expressed in basis points. “Bloomberg ESG label” indicates any Bloomberg sustainable tag (Green/Social/Sustainable) at the CUSIP level. Regressors include the Potential and Actual scores for Environmental, Social, Governance, and the Composite (all entered jointly). “Controls” (introduced from col. (3)) comprise log bond size, log issue size, put/call flags, years to maturity and its inverse, state taxability, bank qualification, insurance, use-of-proceeds categories, and capital-purpose categories. Fixed effects are added progressively by column: Year–Month (issue date), then Rating (long–term canonical buckets), then Issuer (CUSIP6). SEs are clustered by issuer (CUSIP6) in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

	(1)	(2)	(3)	(4)	(5)
Bloomberg ESG label	−25.809*** (3.166)	−10.723*** (2.323)	−7.358*** (1.593)	−0.214 (1.404)	−0.301 (1.809)
Environmental potential	1.029** (0.446)	2.097*** (0.351)	−0.267 (0.255)	0.472* (0.217)	0.053 (0.224)
Environmental actual	3.097*** (0.909)	0.666 (0.914)	−0.520 (0.526)	−2.092*** (0.430)	−1.095** (0.460)
Social potential	5.533*** (0.458)	3.348*** (0.358)	1.194*** (0.255)	0.658*** (0.217)	0.268 (0.237)
Social actual	5.301*** (0.588)	7.256*** (0.545)	1.862*** (0.354)	1.171*** (0.294)	0.333 (0.322)
Governance potential	−10.412*** (0.853)	−9.066*** (0.694)	−7.776*** (0.452)	−3.325*** (0.377)	−1.029*** (0.372)
Governance actual	−0.128 (0.341)	−0.323 (0.267)	0.398** (0.195)	0.015 (0.165)	−0.420** (0.173)
Composite potential	0.277 (0.857)	0.496 (0.634)	1.044** (0.457)	−0.326 (0.395)	−0.198 (0.404)
Composite actual	−1.403** (0.636)	−1.316** (0.470)	−0.547 (0.338)	0.422 (0.290)	0.255 (0.286)
Year–Month FE		Y	Y	Y	Y
Controls			Y	Y	Y
Rating FE				Y	Y
Issuer FE					Y
Observations	1,386,741	1,386,741	1,386,686	1,386,685	1,385,714
Adj. R^2	0.0141	0.2179	0.7384	0.7694	0.8321

Table 2.14: TOC Heuristic-based Flags and Text Extraction Window

Note: The table reports counts and shares of OS PDFs by TOC flag and the corresponding extraction window. Flags are: 1 = TOC found within the first 30 pages; 0 = no TOC found within the first 30 pages; -1 = PDF has fewer than 30 pages and no TOC. For 1, we extract from the first page after the TOC to $\min(\text{toc_offset} + \text{candidate_last} + 10, 110, \text{total} - 1)$. For 0, we extract up to $\min(70, \text{total} - 1)$ pages from the start. For -1, we extract the full document.

TOC Flag	Obs	% of total
TOC found (1)	119,636	94.6%
No TOC within 30 pages (0)	5,243	4.1%
<30 pages, no TOC (-1)	1,551	1.2%
Total	126,430	100%

2.7 Appendix from Chapter 2

2.7.1 Bloomberg Muni ESG Data Extraction Details

We retrieve ESG-labeled municipal bond data from Bloomberg as of December 31, 2024. Below is a concise overview of the extraction process:

- **Initial Filters:** We consolidate duplicate bonds and select municipal instruments across all security statuses ("Active", "Matured", and "N.A."), resulting in 5,698,062 initial instruments. We also include the CUSIP field to facilitate matching with other datasets.
- **ESG Fields:** We query six Bloomberg fields capturing both self-reported and derived labels, including "Green", "Social", and a general "Sustainable Debt Instrument Indicator". Applying these criteria returns 41,755 records.
- **Further Exclusions:** We exclude derivative munis (i.e., entries flagged as "Muni Is Derivative") and remarketed issues (i.e., Muni Sale Method is "Remarketed"). This step yields a final set of 40,136 unique instruments.
- **Terminal Query Process:** Because Bloomberg's Excel add-in supports batches of up to 5,000 queries at a time, we divide the 40,136-instrument list into multiple state-based groups. Each group is further split into 500-instrument segments to remain within daily BQL request limits. Queries are then executed over the course of one week to collect the full dataset.

2.7.2 XML Parser

We begin by processing the XML files published by the MSRB for municipal securities data. For each ZIP archive, the parser performs the following steps:

- **Reading and Preparing XML Files:**

Each XML file inside the ZIP archive is opened and parsed into an `ElementTree`. If an XML fails to parse or lacks any `<Security>` element with a `CUSIP9`, it is skipped. We remove XML namespaces to simplify subsequent element lookups.

- **Collecting Document-Level Information:**

Rather than focusing on a single "best" file identifier, the parser gathers information from all `<Document>` elements whose `DocumentStatus` is "Current." For each such document, attributes including `DocumentType`, `DocumentPostingDate`, and `DocumentDescription` are stored in parallel lists. Within each document, the parser further collects all `<File>` elements with `FileStatus="Current"`, extracting their `FileIdentifier` and `FilePostingDate` into corresponding *lists-of-lists*. These document- and file-level attributes are intentionally preserved as parallel lists and attached downstream.

- **Parsing `<Offering>` and `<Issue>` Elements:**

If an `<Offering>` element exists, its core attributes (`OfferingType`, etc.) are mapped into standardized columns. If multiple `<Offering>` elements exist, we use the first. Similarly, each `<Issue>` node is parsed for fields such as `IssueType`, `IssuerName`, and date/time details (e.g., from `<FormalAwardDateTime>` and `<FirstTradeExecutionDateTime>`). In addition, the parser collects all `<ObligatedPerson>` entries under each issue as parallel lists (e.g., `ObligatedPersonType` and `NameOfObligatedPersonForContinuingDisclosureFiling`), preserving the *nth-type/nth-name* correspondence.

- **Capturing Security-Level Details:**

Under every `<Issue>`, there can be multiple `<Security>` nodes, each typically representing an individual maturity from a serial municipal bond. For each security, the parser extracts attributes such as `CUSIP9`, `MaturityDate`, and `InterestRate`. Fields are then combined with document-, offering-, and issue-level attributes to create one

row per security.

2.7.3 CUSIP–OS De-duplication Procedure

We deduplicate CUSIP–OS mappings by prioritizing linked `OfficialStatement` types with the following two-step rule:

- **Within-XML selection.** For each row (mapped XML), we inspect all `Current` documents and examine their `DocumentType`:
 1. If any `OfficialStatement` exists, we keep *all* such documents as candidates.
 2. Else, if any `PreliminaryOfficialStatement` exists, we keep *all* such documents as candidates.
 3. Otherwise, no candidates are kept (e.g., types such as `RemarketingSupplement` or `AdvancedRefundingDocument` alone yield none).

Candidate attributes (`DocumentType`, `DocumentPostingDate`, `FileIdentifierList`, `FilePostingDateList`) are preserved as parallel lists; no recency tiebreaker is applied at this stage.

- **CUSIP-level filtering.** For each CUSIP9, we look across all linked rows (i.e., across all of its mapped XMLs). If any linked row has an `OfficialStatement` among its candidates, we drop rows whose candidates are only `PreliminaryOfficialStatement`. If no `OfficialStatement` exists for that CUSIP, we retain the preliminary candidates.

After restricting to desired `DocumentTypes`, we further deduplicate to a unique CUSIP–OS as follows.

- **Working heuristic.** Select the OS with the *earliest* posting date. This aligns with our primary-market focus, as later updates rarely alter the substance of the original version for pricing analyses.

- **Systematic rule (size/date).** To make the procedure more systematic, we incorporate file size for candidate OS PDFs. When a CUSIP maps to multiple OSs, we focus on the two largest files among the candidates and compute the ratio $R = \frac{\text{larger size}}{\text{smaller size}}$. If $R \leq 1.2$, a number we believe reasonably captures updates’ impacts on file sizes, we select the OS with the *earlier* posting date (if the dates coincide, we pick the *larger* file). If $R > 1.2$, we select the *larger* file. This rule extends to cases with any number of mapped candidate OSs by restricting attention to the two largest files.
- **Final consistency pass.** File-size and posting-date rules do not eliminate all mis-specifications. We therefore perform a final manual review of *ALL* such one-to-many linkages via scripted EMMA lookups and make consistency-preserving choices.¹¹

2.7.4 EMMA Browsing Tool

We identified **30,028** CUSIPs that were unmapped to a primary-market disclosure via XML links. The absence of an OS can be legitimate (e.g., certain remarketings/reoffers, or simply regulatory or practical reasons) rather than a data error. To verify absence and facilitate targeted manual fills, we built a Selenium-assisted *browsing* utility. This tool only opens and normalizes EMMA pages; **selection and fixes are manual**.

Specifically, for each CUSIP that appears to lack a disclosure record, we open its corresponding EMMA page and check whether any official statements are available. If official statements are found, we manually locate the exact PDF in the data dump and record its identifier. The procedure is outlined below:

- **Accessing EMMA URLs.** For each CUSIP, the tool constructs

<https://emma.msrb.org/Security/Details/CUSIP9>

11. Consistency corrections are available upon request. We opened roughly 12,000 browser sessions to conduct these checks.

then loads the page in Chrome and dismisses disclaimer/cookie prompts.

- **Checking for missing records.** If EMMA displays "no records exist for this CUSIP," the CUSIP is flagged as having no official statement; otherwise, the page is parsed for available disclosures.
- **Handling multiple official statements.** The `officialStatementContainer` typically lists one row per statement, with a hyperlink (`<a>`) and a date cell (`<td>`) indicating the posting date and the unique file identifier. We manually collect all listed statements and select the one with the most recent posting date. The PDF link has the form

P#####-P#####-P#####

and the trailing token (after the final hyphen, without the `.pdf` suffix) is used as the `FileIdentifier` to match the exact file in the data dump.

2.7.5 TOC-Guided Text Extraction from OS PDFs

We convert EMMA OS PDFs to plain text using a table-of-contents (TOC) heuristic that truncates appendices/exhibits to keep texts comparable across issuers.

- **Detection.** Using PyMuPDF, we scan the first 30 pages for "Table of Contents" (case-insensitive). We assign a flag: 1 = TOC found; 0 = no TOC within 30 pages; -1 = PDF has fewer than 30 pages and no TOC.
- **When TOC is found.** Starting from the TOC page, we examine up to four subsequent pages (stopping early if "Appendix/Appendices/Exhibit" appears). From these pages we collect numeric targets (page numbers), discard spurious jumps (first gap > 50), and take the largest retained number as the candidate last page of the main text. We

then extract from the first page after the TOC through

$$\min(\text{toc_offset} + \text{candidate_last} + 10, 110, \text{total_pages} - 1),$$

i.e., a 10-page buffer, capped at 110 pages and by the document length.

- **When TOC is not found.** If no TOC is detected within 30 pages:
 1. If the PDF has fewer than 30 pages (-1), extract the full document.
 2. Otherwise (0), extract up to $\min(70, \text{total_pages} - 1)$ pages from the start.
- Table 2.14 shows the distribution of TOC flags and that the majority of the mapped OS PDFs have a TOC flag.

2.7.6 LLM Scoring Prompt (Full Text)

We score each OS using the following prompt (system + user messages), shown verbatim for reproducibility.

```
messages = [  
  {  
    "role": "system",  
    "content": """"You are an ESG analysis expert tasked with evaluating  
municipal bond disclosures based on: 1) The Government Finance Officers  
Association (GFOA) ESG disclosure guidelines; 2) General ESG best practices.  
Your job is to assess whether the disclosure is a valid municipal bond primary  
market disclosure and, if valid, produce two types of scores-"Potential ESG"  
and "Actual ESG"-across Environmental (E), Social (S), and Governance (G)  
dimensions. Follow all instructions below carefully. At the end, output only a  
single JSON object containing your analysis.""",  
  },  
]
```

```

{
  "role": "user",
  "content": f"""
    ---
    1. VALIDITY CHECK
    ---
    1.1 Read the provided text. Decide if it appears to be a genuine
    municipal bond primary market disclosure.
    - If it is not a valid primary market disclosure, set:
      "disclosure_validity": "This does not look like a primary
    market disclosure."
      And set all other JSON fields to "N/A".
      Then end your output.
    - If it is a valid primary market disclosure, set:
      "disclosure_validity": "Valid disclosure"
      And proceed with scoring.
    ---
    2. INSTRUCTIONS FOR SCORING
    ---
    You will assign two scores per dimension (Environmental, Social
    , Governance):
    ---
    2.1 POTENTIAL ESG SCORE
    ---
    - Definition
      Reflects the bond's inherent ESG potential if the issuer or
    underwriter were to fully adopt GFOA's ESG guidelines and general ESG best
    practices.
  """
}

```

- **Ignore** explicit marketing or labeling.

- **Focus** on the underlying project/fundamentals: Does it address climate/environmental needs, social benefits, or robust governance structures in line with standard ESG principles?

- **Scoring Considerations**

1. Alignment with recognized environmental, social, or governance best practices.

2. Nature of the project (e.g., infrastructure resilience, community health, educational improvements).

3. Potential to meet GFOA's criteria if the issuer clearly documented and followed established ESG guidelines.

- **Range**: 1-10

- **1** = Minimal or no inherent alignment with ESG principles.

- **10** = Strong, clear alignment with recognized ESG frameworks, even absent explicit labeling.

- **Potential Reasoning** (~150 words)

- Summarize why you assigned the chosen score.

- Reference relevant guidelines or fundamental ESG benefits from the main text.

- **Exclude** any marketing language (focus only on actual project merits, existing policies, or structural strengths).

2.2 ACTUAL ESG SCORE

- **Definition**

Reflects how strongly the issuer emphasizes or promotes ESG factors -either **explicitly** (e.g., labeling the bond as "green" or "social," citing certifications) or **implicitly** (e.g., referencing sustainability initiatives

, equity programs, governance improvements) within the disclosure text.

- **Scoring Considerations**

1. **Explicit Branding/Labeling**: Mentions of "green," "sustainable," "social," or recognized ESG certifications.

2. **Implicit ESG Cues**: References to outcomes like community well-being, reducing inequality, environmental stewardship, or robust governance—even if not labeled "ESG."

3. **Scope & Depth**: Frequency, detail, and substance of ESG mentions throughout the main text. Are these fleeting references or a well-developed theme?

- **Range**: 1-10

- **1** = Virtually no ESG-related content (explicit or implicit).

- **10** = Significant emphasis, multiple references to ESG concepts (labeled or unlabeled), substantial discussion or branding.

- **Actual Reasoning** (~150 words)

- Explain why you assigned the chosen score.

- Cite both **explicit** and **implicit** signals of ESG in the main text, noting any repeated emphasis or special branding.

- Clarify how robust or superficial the ESG claims appear.

2.3 COMPOSITE SCORES

After you evaluate each dimension (E, S, G), produce:

- **composite_potential_score**: 1-10

- **composite_potential_reasoning** (~150 words): Summarize the overarching "Potential ESG" across E, S, and G.

- **composite_actual_score**: 1-10

- **composite_actual_reasoning** (~150 words): Summarize the

overarching "Actual ESG" across E, S, and G.

3. FOCUS ON MAIN CONTENT OVER APPENDICES

- You may reference appendices if relevant, but place **more emphasis on the main body** of the disclosure, as appendices may be truncated or less reliable.

4. FINAL OUTPUT FORMAT (JSON ONLY)

At the end of your analysis, output **only** a single JSON object with the **exact** structure and keys below, in this order:

```
{  
  "disclosure_validity": "string",  
  "environmental": {  
    "potential_score": "number or string",  
    "potential_reasoning": "string",  
    "actual_score": "number or string",  
    "actual_reasoning": "string"  
  },  
  "social": {  
    "potential_score": "number or string",  
    "potential_reasoning": "string",  
    "actual_score": "number or string",  
    "actual_reasoning": "string"  
  },  
  "governance": {  
    "potential_score": "number or string",
```

```
    "potential_reasoning": "string",
    "actual_score": "number or string",
    "actual_reasoning": "string"
  }},
  "composite_potential_score": "number or string",
  "composite_potential_reasoning": "string",
  "composite_actual_score": "number or string",
  "composite_actual_reasoning": "string"
}}
```

NOTES:

- If "disclosure_validity" = "This does not look like a primary market disclosure.", then **all other fields** should be "N/A".
- Do **not** include any text outside of this JSON object.
- Use ~150 words of reasoning text for each reasoning field (potential_reasoning and actual_reasoning per dimension, plus composite reasonings).
- Return the final result strictly in JSON format, with no additional commentary.

5. GFOA ESG GUIDELINES & GENERAL ESG PRINCIPLES

Environmental (E):

{gfoa_e_criterion}

Social (S):

{gfoa_s_criterion}

Governance (G):

{gfoa_g_criterion}

Use these guidelines, along with fundamental ESG principles, to

assess alignment and potential.

6. TEXT TO ANALYZE

{decoded_text} """,

},

]

2.7.7 GFOA ESG Standards Used in the Prompts

GFOA Environmental (E) Prompt

GFOA ENVIRONMENTAL (E) GUIDANCE COMPREHENSIVE SUMMARY

SECTION 1. OVERVIEW: ESG & THE ROLE OF E

-
- ESG (Environmental, Social, Governance) factors can significantly affect a governments credit profile. For the E component, this includes exposure to climate risks (floods, wildfires, hurricanes, droughts), environmental changes (sea-level rise, shifting agricultural patterns), and infrastructure vulnerabilities.
 - ESG factors reflect a communitys long-term sustainability. Investors and rating analysts increasingly assess ESG risks using external data, making it critical for municipal issuers to tell their own story of environmental challenges and actions.

SECTION 2. WHY ENVIRONMENTAL DISCLOSURE MATTERS

- Investors focusing on impact investments want clarity on the environmental impact of municipal bonds. Market demand, credit ratings, and bond pricing are influenced by how well issuers communicate environmental risks and mitigation strategies.
- Transparent disclosure allows governments to:
 - Demonstrate readiness and resiliency to investors.
 - Ensure that outside analysts don't rely on incomplete or out-of-context data.
 - Provide a catalyst for ongoing environmental initiatives (e.g., improved climate adaptation, stronger infrastructure planning).

SECTION 3. IDENTIFYING KEY ENVIRONMENTAL RISKS

- Governments should identify their primary environmental/climate risks, focusing first on those most likely to occur or that would have the greatest impact on creditworthiness. Examples:
 - Inland flooding, tornadoes, droughts, extreme winter storms.
 - Wildfires in high-risk areas.
 - Hurricanes, coastal flooding, and sea-level rise in coastal regions.
 - Water supply or quality issues (including drought-driven stress).
 - Infrastructure strain due to changing climate patterns (heat, storms, etc.).
- If possible, gather local expertise: public works or emergency management officials may already track or plan around climate risks. Also consult state or regional hazard mitigation plans, or consider third-party environmental risk assessments.

SECTION 4. QUANTIFYING & MITIGATING ENVIRONMENTAL RISKS

- **Quantification**: Provide estimates of potential economic or financial impacts (e.g., on tax base, pledged revenues, property values, infrastructure replacement costs) when feasible. Include disclaimers that such projections are inherently uncertain.
- **Mitigation Efforts & Resiliency**: Investors and analysts want insight into:
How the government is responding to identified risks (e.g., improved drainage for flood-prone areas, wildfire prevention programs).
Resiliency projects or sustainability policies (greenhouse gas reduction strategies, climate action plans).
Emergency management protocols and preparedness (e.g., evacuation routes, disaster relief funding, insurance programs).

SECTION 5. INCORPORATING E DISCLOSURE IN OFFERING DOCUMENTS

- **Materiality**: If environmental risks could materially affect a governments financial health or bond security, they should be disclosed in offering documents. Include:
Specific risk factors by geography (coastal vs. inland, urban vs. rural).
Known impacts on past or recent extreme weather events.
Policy actions taken to address environmental threats.
- **Forward-Looking Statements**: Provide the most accurate information possible with appropriate cautionary language. The SEC generally does not penalize issuers for good-faith forward-looking disclosures if they include disclaimers about uncertainties.
- **Peer & Regional Comparisons**: Smaller or resource-constrained governments can look to neighboring jurisdictions for examples of environmental disclosures, especially when risks are regionally shared (e.g., hurricane-prone coasts, wildfire corridors).

SECTION 6. EXAMPLES OF ENVIRONMENTAL FACTORS TO DISCUSS

- Frequent or severe natural disasters and their potential economic impact.
- Climate change effects on agriculture, tourism, or major local industries.
- Availability and diversity of energy sources (e.g., reliance on a single power generation method).
- Specific recent experiences: major flood/hurricane events, wildfire damage, or infrastructure stress due to rising temperatures.
- Quantitative data (if available): cost estimates for repair, estimated property value losses, or projected revenue impacts from climate shifts.

SECTION 7. VOLUNTARY & ONGOING ENVIRONMENTAL DISCLOSURE

- Governments may opt to share environmental risk information periodically, even outside of bond sales. This can improve transparency but should be delivered consistently to all market participants.
- Continual updates on climate adaptation projects, policy changes, or new risk assessments can strengthen investor confidence. Any newly significant events or emerging risks should be included in subsequent bond offerings.

SECTION 8. PRACTICAL STEPS FOR PREPARING E DISCLOSURE

1. ****Identify Subject-Matter Experts****: Designate one or more officials with climate/environment expertise to gather and interpret data.
2. ****Focus on Most Material Risks****: Start with the highest-likelihood, highest-impact issues. Less critical risks can be added later.

3. **Consult Existing Data**: Use state hazard mitigation plans, national/regional climate assessments, and peer disclosures to guide your approach.
4. **Quantify When Possible**: Investors appreciate numerical estimates or scenarios but ensure disclaimers clarify inherent uncertainties.
5. **Summarize Key Mitigation Efforts**: From emergency response strategies to infrastructure upgrades. Emphasize ongoing or planned resilience measures.
6. **Use Disclaimers Appropriately**: Forward-looking statements, links to external sites, and references to third-party analyses should include cautionary language on data reliability and future uncertainties.
7. **Review & Update**: Continuously refine environmental disclosures with each bond issuance to remain current (e.g., note recent storms, new policies, or updated forecasts).

SECTION 9. LINK TO CREDIT CONSIDERATIONS

- Environmental (E) risks can influence ratings if they meaningfully threaten a governments revenue, economy, or infrastructure. Proactive planning and candid disclosures may improve a credit rating outlook or mitigate negative impacts.
- Rating agencies already include governance considerations in their scoring, so detailing how local governance bodies handle environmental challenges can further demonstrate readiness and transparency.

SECTION 10. FINAL THOUGHTS

- Communicating environmental awareness and preparedness is in the governments best interest, potentially resulting in stronger investor demand (green or impact investors) and more favorable pricing.

- Even if no significant environmental risk exists, issuers may benefit from explicitly stating that position in their disclosures to preempt investor questions.
- Ultimately, robust E disclosure is about demonstrating that the government acknowledges its environmental challenges and is proactively managing them, which can foster investor trust and market stability.

GFOA Social (S) Prompt

GFOA SOCIAL (S) GUIDANCE COMPREHENSIVE SUMMARY

SECTION 1. OVERVIEW: THE S IN ESG

- GFOAs recommended practices for ESG include separate considerations for E (Environmental), S (Social), and G (Governance). This summary focuses on Social factors.
- Unlike environmental risks, there is less consensus on exactly which social factors are most material to credit analysis. Consequently, issuers may need to decide for themselves which social factors meaningfully affect their governments long-term ability or willingness to repay debt.
- By proactively disclosing relevant S issues, governments can communicate important information to investors and rating agencies regarding the overall vitality and social well-being of the community.

SECTION 2. EXAMPLES OF SOCIAL FACTORS

Although definitions vary, GFOA notes that some common examples of S factors might include:

Availability and affordability of housing (especially for vulnerable populations)

Demographic shifts and population trends

Income levels, wealth, and income disparities

Changes in employment/unemployment, workforce skills, and job opportunities

Affordability of government services and tax rates (or potential erosion of the tax base)

Labor relations, union negotiations, pensions, and OPEB obligations

Access and quality of health services (public health considerations)

Quality of public education, vocational training, and educational attainment

Internet access and digital infrastructure

SECTION 3. IDENTIFYING & REFRAMING EXISTING S DATA

- Many governments already disclose S-like data without explicitly labeling it as social. For example, official statements often include population changes, per capita income, poverty rates, or local employment figures.
- To strengthen ESG disclosures, issuers can highlight whether these trends pose significant operational or financial challenges, or if they have meaningful implications for debt repayment. Governments should consider:
 1. Whether recent demographic trends (e.g., out-migration) could impact tax revenues over time.
 2. If income disparities or population shifts threaten future economic stability or service demand.
 3. Whether a lack of affordable housing or reduced labor force participation could weaken the tax base or hamper economic growth.

SECTION 4. TEMPORARY VS. LONG-TERM SOCIAL FACTORS

- S factors can be temporary or persistent. A short-lived event causing civil unrest might not materially affect credit quality if it doesn't alter long-term financial or operational stability.
- By contrast, a long-term rise in unemployment or a persistent decrease in population can erode a government's economic base over time. Similarly, chronic underinvestment in public education or healthcare might undermine the workforce and, ultimately, tax revenues.
- Governments should focus on social factors that could have a ****lasting impact**** on their ability to meet debt obligations, considering whether specific demographic or socioeconomic conditions are likely to persist.

SECTION 5. NEXUS TO CREDIT QUALITY

- Determining which S factors may materially affect a government's credit is often challenging. Many social issues are indirect and play out over longer time horizons.
- Nonetheless, if a social factor has the potential to reduce revenue, raise expenditures, or alter the fundamental economic strength of a community, it may be relevant to bond repayment and warrant disclosure.
- When an issuer identifies a factor that could have a ****material adverse impact**** on financial stability, it should explain:
 1. How this factor could influence the ability to repay debt.
 2. Whether there are any ongoing programs or strategies aimed at mitigating negative effects (e.g., workforce development initiatives, affordable housing projects).
 3. Quantitative or qualitative data reflecting the factor's scope (e.g., local unemployment trends, tax base erosion, shifting population levels).

SECTION 6. INCORPORATING S FACTORS INTO DISCLOSURES

- **Primary & Voluntary Disclosure**:

If an identified S factor is considered material (i.e., it has a clear nexus to credit quality and the repayment of bonds), it should be addressed in the official statement or continuing disclosures.

Governments can also choose to publish voluntary updates on social factors through investor relations websites or periodic reports, but these should be consistent, accurate, and made available to the market as a whole.

- **Context & Mitigation**:

Investors and analysts value context: describe why the social factor is significant, any current or projected impacts, and any policies or programs in place to respond.

For instance, if rising income inequality threatens consumer spending or tax collection, outline relevant economic development projects or revenue diversification strategies.

SECTION 7. EVALUATING MATERIALITY & DURATION

- While some social factors might attract public or media attention, they may not necessarily be material to long-term finances. Governments should distinguish between short-term disruptions and structural challenges that could impair revenues or service delivery.
- Where data or trends suggest a sustained, long-range effect (e.g., a declining population that reduces the tax base), it's more likely that this factor is relevant for disclosure.
- When possible, quantify the potential impacts and provide historical or trend data showing how social dynamics have evolved, remembering to include

disclaimers if making forward-looking statements.

SECTION 8. BEST PRACTICES FOR S DISCLOSURE

1. ****Assess Existing Documentation****: Many demographic and economic statistics are already present in official statements. Reframing them under an S lens can show how they relate to creditworthiness.
2. ****Identify Key Trends****: Determine whether trends in housing, income levels, education, or health are merely short-term fluctuations or indicative of deeper, systemic changes.
3. ****Establish Credit Link****: Make the connection between significant social factors and the issuers ability to repay debt this is crucial for investors and rating agencies evaluations.
4. ****Explain Mitigation Efforts****: If a government implements policies or programs (e.g., job training, community health initiatives) to address social risks, highlight these to demonstrate proactive management.
5. ****Coordinate with Counsel & Advisors****: As with any disclosure, consult bond counsel, disclosure counsel, and municipal advisors to ensure legal and regulatory compliance.
6. ****Regular Review & Updates****: Keep S factors current as conditions evolve or new data becomes available. Incorporate significant developments or new policies into subsequent bond offerings and voluntary disclosures.

SECTION 9. FINAL THOUGHTS

- Social factors, like environmental or governance issues, have always played a role in community well-being. The current ESG focus gives issuers an opportunity to spotlight and communicate ongoing social challenges and

solutions.

- By openly addressing relevant social trends, governments may strengthen investor confidence, reduce uncertainty, and underscore their commitment to the long-term health of the community.
- Ultimately, clear S disclosure is about demonstrating awareness of significant social risks, articulating the measures in place to address them, and linking these factors to the governments financial and operational outlook.

GFOA Governance (G) Prompt

GFOA GOVERNANCE (G) GUIDANCE COMPREHENSIVE SUMMARY

SECTION 1. OVERVIEW: G IN THE ESG FRAMEWORK

- GFOA has developed best practices for each element of ESG Environmental (E), Social (S), and Governance (G). This section highlights the G factor.
- Governance has traditionally been integral to rating agency reviews and investor assessments, as it encompasses leadership structures, policies, decision-making processes, financial management, and transparency.
- While E and S factors often require new or additional disclosure, many G factors are already routinely covered in bond offering documents. The ESG focus provides an opportunity to confirm that the governance information you already disclose is complete, consistent, and clearly articulated.

SECTION 2. WHY GOVERNANCE MATTERS FOR CREDIT QUALITY

- Governance is the operational backbone of a public entity. It includes legal authority to issue debt, oversight frameworks, budgeting and financial

management policies, and overall organizational capacity.

- Well-articulated governance structures and robust policies can enhance credit quality by ensuring stability through economic cycles and unforeseen events (e.g., natural disasters, public health crises).
- Rating agencies and investors pay close attention to governance because it reflects how effectively a government can respond to challenges, manage finances, and maintain transparency.

SECTION 3. COMMON GOVERNANCE FACTORS IN OFFERING DOCUMENTS

Governance factors often appear in official statements without explicit G labeling.

Examples include:

1. **Organizational Structure**
 - Elected vs. appointed boards, legal formation (home rule, state statute, or constitution), and any unique provisions regarding governance roles or powers.
2. **Legal Authority to Issue Debt**
 - Statutory or constitutional limits, voter approval requirements, procedural steps to authorize bond issuance.
3. **Policy Transparency**
 - Existence and enforcement of written budget, debt, and financial management policies.
 - How these policies underpin prudent fiscal practices and strengthen bond security.
4. **Management & Oversight Framework**
 - Internal controls, board/commission oversight, strategic planning processes, and how decisions are documented or published.
5. **Financial Reporting**

- Reliability of accounting systems, timeliness of audits, ongoing budget monitoring, and frequency of financial updates to governing bodies or the public.

6. ****Risk Culture & Mitigation****

- Cybersecurity strategies, internal risk assessment protocols, adherence to state/federal mandates, or emergency fund practices.

7. ****Pension & OPEB Management****

- Funding status of pension obligations, annual required contributions, and any budgetary prioritization of these liabilities.

8. ****Long-Term Infrastructure & Budgeting****

- Deferred maintenance strategies, infrastructure investment planning, revenue forecasting, and capacity for multi-year budgeting.

SECTION 4. HIGHLIGHTING GOVERNANCE FACTORS IN THE ESG CONTEXT

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- Although issuers already disclose much of this information, the ESG framework encourages a more deliberate presentation of how governance promotes accountability and resilience.
 - Governments can demonstrate how good governance underpins credit strength by clearly explaining:
 1. Decision-making processes and their legal basis.
 2. Strategies for maintaining fiscal integrity over the bonds term.
 3. Methods for monitoring, reporting, and adapting policies to new challenges (e. g., unexpected events such as COVID-19 funding administration).

SECTION 5. IDENTIFYING & DISCUSSING RELEVANT G FACTORS

- Begin by reviewing your existing disclosures to see which governance practices (organizational structure, financial policies, transparency measures) are already mentioned.
- Emphasize how these governance elements contribute to stable operations and debt repayment.
 - For instance, strong internal controls may reduce the risk of fraud or financial mismanagement.
 - Thoughtful budget policies, multi-year forecasting, and capital planning signal prudent resource stewardship.
- If certain governance elements are new or recently enhanced (e.g., updated procurement policies or new audit procedures), highlight them to show how your entity adapts over time.

SECTION 6. CONNECTING G TO CREDIT QUALITY & DEBT REPAYMENT

- Clarify how robust governance can positively influence a governments ability to service its debt:
 - Transparent budget practices can improve investor confidence and help manage volatility.
 - Defined policies on reserves or rainy-day funds ensure liquidity during economic downturns.
 - Pension/OPEB funding approaches reveal a governments commitment to long-term obligations.
- Conversely, a lack of governance clarity or unstable leadership structures may raise questions about financial risk.

SECTION 7. EVOLUTION OF GOVERNANCE FACTORS

- Governance demands evolve alongside new legal requirements, funding opportunities , and public expectations. For example, the COVID-19 pandemic required swift implementation of grant tracking and policy decisions, highlighting the importance of nimble yet accountable governance.
- By periodically reviewing governance disclosures, issuers can ensure they remain current with any changes in law, technology, or political structures.

SECTION 8. DISCLOSURE CONSIDERATIONS

- Governance factors can be featured in multiple areas of the primary offering documents and continuing disclosures:
 1. **Legal & Organizational Overview**: Summarize governance structures, authority, and accountability.
 2. **Financial Policies & Management**: Discuss budget frameworks, financial controls, and reporting timelines.
 3. **Long-Term Liabilities & Risk Management**: Show how governance frameworks address pension liabilities, OPEB, cybersecurity, and infrastructure investment gaps.
- As with E and S factors, GFOA recommends consulting bond counsel, disclosure counsel, and municipal advisors to ensure that any ESG-related governance disclosures are accurate, relevant, and aligned with market expectations.
- Voluntary disclosure through investor relations websites or periodic updates can further highlight a governments commitment to transparency and strong governance.

SECTION 9. FINAL THOUGHTS

- Governance is foundational for public-sector entities, shaping all aspects of operations, finances, and policy decisions. The ESG perspective simply underscores the value of clearly articulating good governance practices.
- Issuers should ensure that governance disclosures within their offering documents are comprehensive and up-to-date, reflecting the active role of leadership, sound fiscal policies, and commitment to transparency.
- When effectively described, robust governance can bolster investor confidence, potentially improving bond pricing and market access by demonstrating the governments capacity to manage resources responsibly over the long term.

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