# Does Climate Change Concern Lead to Greenium?

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**Abstract**

To date the (non-)presence of green bond premium (i.e., greenium) has been debated. It is still unclear, however, how broadly and genuinely the notion of climate change is perceived by investors and urges them to mitigate its risk and uncertainty through green investments—a likely effective channel of greenium. To this end, I draw on the data from the US municipal bond market, which is largely populated by retail investors and segmented by states due to heterogeneous tax exemptions. I take a model-free matching approach and construct a matched bond data set to conduct a series of descriptive analyses. I find substantially higher demands for green munis in some states, which may point to the serious concern about human-induced climate change as well as to a call for environmental sustainability. Exploiting a quasi-experimental design based on natural disasters, the future agenda is to examine the degree to which an exogenous disaster-induced *change* in individual preferences for climate risk—as opposed to the *level*, which has been the focal point in extant research—leads to more demand for green bonds (relative to brown bonds).

**Keywords:** green bond, extreme weather, natural disaster, climate change, WTP–WTA disparity, red/blue state, air pollution, COVID-19

**JEL Classification:** D14, G12, Q51, Q54

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# 1 Introduction

The scale and frequency of natural catastrophic events are reportedly accelerating due to global warming and the attention to climate change is proportionally on the rise. Investors in the financial markets are no exception to this impact and the investment landscape is undoubtedly being reshaped. Indeed, climate change is a pressing phenomenon (i) which may drive a socially oriented investor to donate a portion of wealth for its mitigation, but (ii) which could be too elusive for an average investor given its intangibility represented by the global scale and polarized public opinion. In these circumstances, green bonds—green assets that are earmarked for environmentally-friendly projects[1]—can serve as an effective measure against the climate risk, enabling issuers and investors to inform strategies on its mitigation and adaptation (WEF, 2018).

Of particular interest is how this relatively new financial instrument is valued in the financial market. Using municipal or corporate bond data, some researchers suggest that there is no greenium (Larcker and Watts, 2019; Flammer, 2020).[2] Anecdotal evidence also supports this view, reporting that a vast majority of retail and institutional investors (in the municipal bonds market) are reluctant to sacrifice a financial return for an environmental benefit by virtue of the continually opaque relationship between environmental benefit and lower risk (S&P Global Ratings, 2019b; Chiang, 2018). Moreover, the slow growth of US companies to issue corporate green bonds is arguably the reflection that the greenium is marginal at best and insufficient to cover the additional cost born by extra paperwork (e.g., regular reporting) (S&P Global Ratings, 2019a). It is true that the eco-friendly status of municipal green bonds can attract attention from environmentally-conscious individuals, but their lower yields also keep these green bonds out of the hands of investors who cannot take advantage of tax exemption, in particular, many major green bond buyers such as foreign insurance companies and pension funds (Chiang, 2017). The US green bond market thus remains largely retail-driven through SRI funds and wealth management channels. Other scholars, nevertheless, do find some empirical evidence that green bonds trade at a premium (or at a discount) (Baker et al., 2018; Zerbib, 2019; Alessi, Ossola, and Panzica,

[1]Green project use-of-proceeds categories include "renewable energy, energy efficiency, pollution prevention and control, environmentally sustainable management of living natural resources and land use, terrestrial and aquatic biodiversity conservation, clean transportation, sustainable water and waste water management, climate change adaptation, eco-efficient and/or circular economy adapted products, production technologies and processes, green buildings which meet regional, national or internationally recognized standards or certifications" (MSRB, 2018a).

[2]Greenium is the premium that green assets trade to otherwise identical non-green securities (Larcker and Watts, 2019).

2019; Kapraun and Scheins, 2019). In addition, Chiang (2017) endorses the notion that high-net-worth individual investors are more likely to show disposition for non-peculiarity in comparison to institutional investors. In sum, the existence of greenium continues to be a legitimate controversy.

Despite this rich body of literature on greenium, however, surprisingly little attention has been given to the interplay between greenium and climate change concern. At the individual level, a wealth of studies does document the link between an amplified concern on climate change through natural disaster experiences and the corresponding behavioral responses which usually follow. As an example, Spence et al. (2011) contend that a likely reasoning of a person's unwillingness to resort to climate change mitigation measures is the simple lack of first-hand experience and the association with its potential consequences—put differently, individuals who have direct exposure to events that are likely linked with climate change are more concerned and inclined to undertake sustainable behaviours accordingly. For another example, Bergquist, Nilsson, and Schultz (2019) examine the impact of an extreme-weather-event experience, the hurricane Irma, on beliefs about climate change, and find that intentions to take actions that can help prepare for and mitigate the climate change were afterwards strengthened. To put this into perspective, individuals correct their bias against the climate risk through personal experiences.

Even more, cognitive bias on the climate risk is not only limited to individuals but is observed in institutional actors as well. Another related strand of studies spans the impact of natural disasters on individual's perception and behavior. For instance, a growing literature on the financial markets indicates that climate risks may not be correctly priced and an accurate estimate of climate change risk poses a challenge to investors (Krueger, Sautner, and Starks, 2020; Hong, Li, and Xu, 2019; Daniel, Litterman, and Wagner, 2016). Alok, Kumar, and Wermers (2020) document that due to salience bias professional money managers misestimate climatic disaster risk, which can enter their portfolio if a disaster affects portfolio firms, as they unreasonably underweight their portfolio holdings of firms located in the disaster area. These pieces of evidence are consistent with the fact that climate risks modelling and the financial sector cannot efficiently price it without obtaining high-quality data and tools (WEF, 2018).

Against this backdrop, this paper empirically investigates the unexplored channel of greenium by throwing additional light on the climate change concern on a local scale. That is, one of the key sources of greenium is likely expected to emerge from the environmental concerns about anthropogenic climate change, or the long-term shift in climate patterns as a result of human activities. In this regard, this paper develops conjectures inspired by as well as nested within a body of research addressing the link between the perception climate risk and the ensuing behavioural response. My first hypothesis (Hypothesis 1) postulates that the valuation of green bonds accommodates the intensity of climate change concern at the local level. Some literature underpinning this conjecture documents that the reactions to personal experience of natural disasters are moderated by the state of mind, especially the ex-ante climate belief (Kunreuther et al., 2014; Mildenberger et al., 2017). Furthermore, one of the particular features in this paper is the focus on the municipal bond investors in the US, who are essentially high-income households and thus are hardly financially constrained and hold on to the asset on a long term basis. I give particular attention to this aspect owing to the fact that (i) US municipal bonds are typically bought by taxable investors including via intermediaries (e.g., mutual funds) and (ii) investors can benefit from the state and municipal taxes exemption—corresponding to their residential area—in addition to federal tax exemption.

After examining the association between the intensity of local climate belief and the green bond pricing in levels, I elucidate the *change* in the preference for sustainability. More precisely, my second hypothesis (Hypothesis 2) conjectures that that investors who have been personally exposed to extreme weathers and natural disasters—which can be arguably attributed to the result of human activities and connects with the broader story of climate change—may respond by investing more in green assets. In particular, I exploit a variation in the preferences for climate risk, which can be exogenously induced by personal experiences of extreme weather and natural disaster events. These events may (temporarily) impact the pricing of green bonds—endorsed by a wealth of literature suggesting that the effect only lasts in a short-term of window—but could be washed out in the entire period, indicating that greenium may not be confirmed under *levels* approach. Put differently, the temporary shock to the sustainability preference induced by weather-related disaster events may be too elusive to be captured in a levels approach to identifying greenium, which has been the mainstream extant research. To my knowledge only a few in climate finance literature exploits this research design, which leverages the shock to the preference for sustainability (e.g., Brandon and Krueger, 2018; Duan and Li, 2019; Choi, Gao, and Jiang, 2020).

As regards data and methods, I adopt a matching method to examine the differential pricing between green and brown bonds in the US municipal bond market: I implement the matching procedure based on same issuer, same dated date, maturity within one year difference, same aggregate ratings, and same coupon rates. As a result, I find empirical evidence under Hypothesis 1 that strongly lends support to the idea that differential pricing between green bonds and brown bonds arises according to different local regions with different climate belief intensity: the local region is measured at the state level on this matter using the survey of local climate change belief from Yale Climate Opinion Map. This finding is indeed substantiated by the anecdotal account in Massachusetts claiming that the green investors were willing to pay the premium for the green label and the issuer had the luxury of resetting the issuance size upwards and thus lowering the offering yield. Furthermore, other states such as in New York, Washington D.C., and even Texas show greenium–esque characteristics akin to Massachusetts. However, California surprisingly shows that green bonds are priced and traded at a discount. Moreover, I extend this analysis by using a bivariate frequency distribution between bond yields and intensity of climate belief. In doing so, I consider two variables, Human and $CO_2$limits, which are measured both at the state and county levels. In either case, local areas with lower climate change belief appear to associate green bonds with higher yields: in particular, this feature is more notable for the callable bond universe.

Hence, I add to the body of literature concerning the controversial topic of whether greenium exists by pointing to the corroborated evidence on a local scale. With regards to the second hypothesis, I experiment with weather-related disasters (e.g., heat wave, wind storm) but only report the preliminary results. The drawback of the matching methods underpinning the analysis under Hypothesis 1, however, is that it is infeasible to control for a host of variables. Thus, a regression approach together with access to Mergent database is left as a lucrative avenue for future study. The key is to examine the degree to which an exogenous disaster-induced *change* in individual preferences for climate risk—as opposed to the *level*, which has been the focal point in extant research—leads to more demand for green bonds (relative to brown bonds).

As a robustness check of behavioral sensitivity, I additionally postulate that the COVID-19 pandemic might have induced local residents to perceive air quality as a pressing issue, thereby shifting their preference for environmental problems encompassing air quality and urging them to act by taking countermeasures. It is certainly true that this behavioral mechanism takes place entirely through a different channel devoid of climate change concern, but the idea here is to elucidate how behaviourally responsive locals can be in the presence of the perceived aggravation in the external environment. This test is left for future research as well.

The remainder of the paper is organized as follows. Section 2 develops hypotheses and

Section 3 outlines the data collection process. Section 4 exhibits the empirical results. Section 5 tests the robustness of the results by using a different shock, COVID-19, to sustainability preference. Section 6 concludes.

# 2 Hypotheses development

The exposure to natural catastrophes in the US—such as droughts, severe storms, heat waves, wildfires, and other climate change induced hazards—is increasingly surging (Melillo, Richmond, and Yohe, 2014). On the one hand, a sizeable amount of scientific studies assessing contextual factors documents that these natural disasters and extreme weather events are proportionally attributed to anthropogenic climate change (Figure 1). On the other hand, there are studies stressing that the overall environmental awareness in the US is still dormant. For example, Egan and Mullin (2017) report that Americans still attach a low level of salience to climate change. Another study from Leiserowitz (2006) claims that although Americans consider climate change as a moderate risk, they do not view it as a pressing issue that calls for immediate measures—socioeconomic issues such as the state of the economy, public financing, and healthcare and environmental issues that are pertinent to daily life such as the standard of sanitation rank as higher priority because of their high relevance to locality. In other words, global climate change is perceived as a distant issue and not as pressing as local issues by Americans.

Furthermore, the work of Mildenberger et al. (2017) can be classified as the middle ground of this debate. The authors argue that climate opinion polarization among the general US public cannot be reduced to a simple political dichotomy between Republicans and Democrats. They find substantial within-party geographic variation on the intensity of climate beliefs, which shows spatial divergence at state and local scales. In line with this observation, empirical research in social science does show how one perceives climate change risks and uncertainties through external reality as well as observers' internal states, needs, and the cognitive and emotional functions (Kunreuther et al., 2014). These pieces of evidence may be able to explain why greenium is not substantively confirmed at the spatial aggregate level in previous studies whereby region-specific characteristics cancel out each other. This line of reasoning leads to Hypothesis 1:

**Hypothesis 1**: The valuation of green bonds reflects the intensity of local belief in climate change

According to Bennett and Wang (2019), the demand for municipal bonds in the primary market falls following natural disaster events and they attribute this behavior to salience theory of choice—that is, investors unjustifiably demand less bonds despite the little concern of issuer's default owing to the financial aid from federal and state governments. Besides, Cole, Ness, and Ness (2018) find that natural disasters such as tornadoes and wildfires lower municipal bond spreads but find no evidence that hurricanes affect municipal bond spreads in a similar manner.

This paper does not directly support nor negate these claims but instead engages in the framework encompassing the opposing effects on green and brown municipal bonds that may arise after the personal experience of disaster events. In particular, I argue that the net effect of the disaster on green bonds is more ambiguous in comparison to brown bonds. Although it is a legitimate expectation that the demand for green bonds will similarly drop in the absence of non-pecuniary preference, this logic does not apply to a socially oriented investor, who is by definition equipped with non-pecuniary utility. More important, even a neutral investor may possess a vested interest in holding green assets inasmuch as this investor feels concerns about climate change induced disasters and comes to view the investment as an effective mitigation measure against human-induced climate risk. A probable scenario is that the neutral investor internalizes the state of his surrounding environment in the aftermath of a natural disaster and integrates its intrinsic value into the domain of his (pecuniary) utility.

This line of reasoning centers on what is termed as WTP–WTA disparity in prior literature. A wider disparity between WTA and WTP is observed to a greater degree in public goods such as environmental goods than in items that are ordinarily traded in the markets (Horowitz and McConnell, 2002; Haab and McConnell, 2002; Irwin, 1994). Boyce et al. (1992) argue that although the several explanations for this phenomenon in relation to environmental goods is available, the intrinsic "moral" values characteristic to these commodities are the driver; intrinsic values are captured by WTA measures but excluded from WTP measures. Brown and Gregory (1999) claim that both economic and psychological account for WTP–WTA disparity: economic reasons range from income effects, transaction costs to implied value, and the profit motive; psychological reasons encompass the endowment effect, legitimacy, ambiguity, and responsibility.

In strong connection with the notion of WTP–WTA disparity, literature addressing the reaction of individuals (including individual investors) to climate risk realized through extreme weathers and natural disasters abound as exhibited in Table 1. In this regard, my conjecture genuinely hinges on the assumption that these natural-disaster experiences have sizeable impact on preference, attitude, and belief to the point that it encourages investors to (temporarily) change their behavior and mitigate climate change. Certainly, it empirically calls into question whether investors show desire for mitigation measures of climate change; as Stern (1992) points out, even in the presence of climate change risk people may not attempt to take efforts to mitigate it but rather adjust their personal values and adapt to what they are confronted with. To come to the point, the intensity of one's behaviours, and actions stimulated by the climate change concern boils down to the extent to which one genuinely comes to believe in climate change, internalize the value, and link the root cause to human activities. Given the underlying psychological aspects of how environmental concern may arise in the wake of natural disaster events, I postulate Hypothesis 2 as follows.

**Hypothesis 2**: Personal experience of natural disaster events reinforces the perception of human-induced climate change, thereby leading to higher valuation of green bonds in the post-disaster period

In the end, I provide supplementary information on the above-mentioned hypotheses. Specifically, I put forward Hypothesis 1 and 2 together with the premise that for tax-exemption motive, households correspondingly invest in the state they reside in through municipal bonds (e.g., Ang, Bhansali, and Xing, 2010; Cole, Liu, and Smith, 1994). This is because the municipal bond market is supported primarily by individual investors seeking to shield income from taxes, most of whom buy municipal bonds to hold them rather than to trade them—leading to the low market liquidity (Chiang, 2018).[3] From issuers' standpoint, this tax exemption allows them to benefit from lower financing cost (i.e., lower yields) but within the green muni bond market, this entails benefits as well as shortcomings (Chiang, 2018).

[3]In the US, investors can purchase bonds in the primary market or the secondary market and most ordinary investors, along with large institutions, buy bonds in the secondary market. Moreover, in the US municipal bond market, the lion's share is held by individual investors directly (40.8%) and indirectly via large cap mutual funds (24.6%) (Chiang, 2018)—the indirect ownership via mutual funds presumably occurs because of the low minimum investment thresholds (e.g., $2,500).

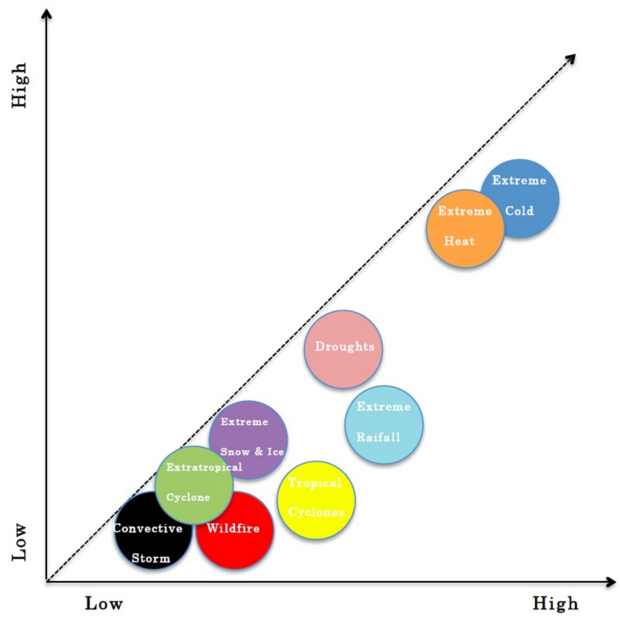
Table 1: Systematic literature review on the link between personal disaster experience and the ensuing behavioral patterns

In relation to Hypothesis 2, this table presents a systematic literature review on the link between personal disaster experience and the ensuing behavioral responses.

| Authors | Country | Hazard | Design | Summary of findings |
|---|---|---|---|---|
| Baldauf, Garlappi, and Yannelis (2019) | US | Sea level rise | Theory, Regression | Climate change beliefs affected by sea level rise, in turn, influence real estate market prices |
| Duan and Li (2019) | US | Temperature increase | Regression | Abnormally high local temperature has a substantial negative effect on approval rate of mortgage lending at the county level in the US |
| Goldsmith-Pinkham et al. (2020) | US | Sea level rise | Regression | Local beliefs, incorporating regional exposure to sea level rise, have a bearing on municipal bond pricing as purchasers are mostly local retail investors because of the tax advantages of in-state ownership |
| Hazlett and Mildenberger (2019) | US | Wildfire | Regression | Experiences with wildfires enhance willingness-to-act only in groups that are more concerned and believe in human-caused climate change. Climate threats can enhance willingness-to-act, but predominately where the public already holds pro-climate beliefs |
| Konisky, Hughes, and Kaylor (2015) | US | Extreme weather | Regression | Positive association between personal extreme weather were revealed experience and expressions of concern on climate change |
| Lang and Ryder (2016) | US | Wind storm | Regression | Climate change related online searches surge after months following a wind storm event, suggesting that the people are displaying concern on climate change due to first hand experience |
| Li, Johnson, and Zaval (2011) | US, AU | Temperature increase | Survey, Regression | People were more likely to make pro-environmental donations after interpreting local temperature increases as evidence for global warming |
| Rudman, McLean, and Bunzl (2013) | US | Wind strom | Survey, Descriptive statistics | New Jersey residents were found to be more likely to support a green politician after experiencing Hurricane Sandy and Hurricane Irene than before each hurricane occurred, suggesting that exposure to extreme weather enhances pro-environmentalism |
| Spence et al. (2011) | UK | Flooding | Survey | A link between climate change perceptions and the willingness to reduce personal energy use was found stronger in the group who had personally experienced recent flooding |

Figure 1: The attribution of specific events to anthropogenic climate change

The horizontal axis evaluates the perceived strength of the link between climate change and the event type. The vertical axis assesses the same link based on scientific methods (National Academies of Sciences, Engineering and Medicine, 2016)




# 3 Data and sample description

My initial sample under Hypothesis 1 builds on a matching procedure based on the structure of issued date, maturity, coupon rate, and credit ratings. The advantage of matching similar two securities is that to a large extent it can control for the confounding factors that affect the bond yields. I take this model-free matching approach and describe the matching procedure in what follows.

First, I prepare two CUSIP lists of green bonds from Bloomberg sorted on callable property after filtering out attributes such as federally taxable and being subject to AMT: I use the Green Instrument Indicator to identify green bonds. Municipal bond issuance before June 2013 are dropped because they are unlikely to have been originally marketed as Green bonds—essentially excluding CREB and QECB green bonds (Baker et al., 2018; LW). Second, using these CUSIP lists I pull dated date,[4] maturity, and coupon rates from MSRB database. Third, I use the first 6 digits of CUSIP (i.e., issuer identifier), dated date, maturity (one year difference is allowed), and coupon rates of these green bonds to pull potential brown bond matches from MSRB database for each green bond—obviously I have to ex-

[4]Unlike LW, I do not use issuance date because MSRB only offers dated date: I do not have access to Mergent. Still, issuance date and dated date most of the time exactly match.

clude the green-labelled bonds from these potential matches. Fourth, I web scrape Fidelity website to pull credit ratings, issuance amount, issuance state, and information of callability for green bonds as well as these potentially matched brown bonds. Given that data entry errors are prevalent in Bloomberg, I opt to identify an embedded call option based on both Bloomberg and fidelity data—if there is a disagreement between these two data sources, I drop the observations.[5] In the last step, I sift the matched brown bonds based on the following attributes: same issuer, same dated date, maturity within one year difference, same aggregate ratings, and same coupon rates, whereby the ratings are converted to a scale of 1 to 22 following LW: 1 is the highest rate, 22 is the lowest or unrated, and the aggregate rating is the average of S&P and Moody's ratings. In the end, the period of the final sample ranges from September 2014 to June 2020. The observations associated with the sample construction procedure are tabulated in Table 2. In the end, I obtain 360 non-callable green bonds and 395 callable green bonds.

An additional note is needed on the process of same coupon rate matching. In this study, coupon rates are exactly matched, while LW allow in their baseline case different coupon rates conditional on non-callable bond universe. In other words, they match coupon rates only when there is a callable feature attached to the bonds. Although it is imperative to match coupon rates for the callable bond universe—given that a bond embedded with a call option may exert a non-negligible influence on the pricing of bonds—I essentially take a conservative approach and also strictly match coupon rates for non-callable bond universe since anecdotal accounts and prior studies indicate that coupon rates and issuance size can affect pricing (LW).

Moreover, in constructing a subsample limited to the primary market (or the secondary market), I use List Offering Price/Takedown indicator consistent with LW, showing that "the transaction price was reported as a primary market sale transaction executed on the first day of trading of a new issue." Moreover, around 0.9% of bond transactions show zero or negative yields. Although a non-positive yield is theoretically achievable, I eventually drop all of the transactions with non-positive yields. This is because they are inconsistent with the dollar price, which is expected to be substantially high—this was not confirmed, however, indicating that these observations are likely to be data entry errors.

Panels A and B of Table 3 show that the mean yield differential between green and brown

[5] LW employ Mergent data to identify embedded call option of municipal bonds. The authors use both Bloomberg and Mergent to decide on the green labels of municipal bonds.

Table 2: Sample construction

The table below summarizes the construction of the matched bond sample based on the issuer, dated date, same aggregate credit ratings, and coupon rate. A margin of error of one year is allowed for maturity. The sample is limited to municipal bonds issued after June 2013. The first (second) column shows the number of green (brown) bonds in the sample.

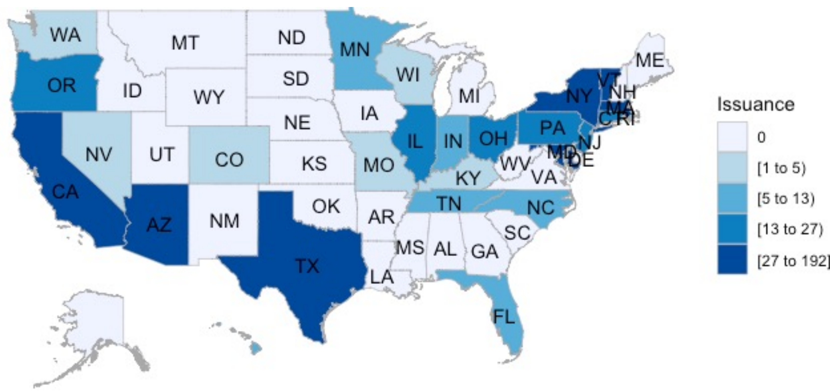
| | Green bonds | Matched brown bonds |
|---|---|---|
| Full green bond sample (Bloomberg) | 8420 | – |
| Non-callable universe | 3435 | – |
| Callable universe | 4985 | – |
| MSRB matched | 1045 | 1253 |
| Non-callable universe | 577 | 731 |
| Callable universe | 468 | 522 |
| Same issuer/rating/coupon rate/dated date | 755 | 807 |
| Non-callable universe | 360 | 397 |
| Callable universe | 395 | 410 |

bonds in my sample is −1.1 bps. However, if the whole sample is divided into non-callable and callable bond universes as shown in Table 4, the mean yield differential between green and brown bonds in non-callable (callable) universe becomes −5.6 (4.4) bps. In this respect, in addition to the difference in sample period, a difference between the descriptive statistics of yields can emerge principally from the difference in the data source. Specifically, while LW uses initial offering yield from Mergent, I use transaction data in the primary and secondary markets from MSRB. For comparison, I replicate the sample of LW by restricting my sample up to July 2018 and eliminating the distinction between non-callable and callable bond universes. According to the statistics provided by LW as well as Panels C and D of Table 3, the descriptive statistics of the green bond sample of LW (my sample) are 2.24% (2.84%) for mean yield, 2.23% (2.93%) for median yield, 5.36 (5.91) for mean issuance amount ($MM), 3.90% (4.24%) for mean coupon rates, and 2.62 (6.82) for mean aggregate ratings. My sample consists more of lower ratings bonds and this is driven by unrated bonds: the median of the aggregate ratings is 3.50 and thus much higher (Panel C of Table 3). Overall, this tendency leads to systematically higher yields in my sample.

In order to proxy for environmental concern on a local scale, I use the survey of local climate change belief from Yale Climate Opinion Map constructed by Howe, Mildenberger, Marlon et al. (2015)—in attempt to quantify how personal experiences with environmental

Figure 2: Cumulative municipal issuance of green bonds by state

This figure illustrates the cumulative number of municipal issuance counted at the state level over the period 2014–2020. The data only includes the green bonds that are matched with brown bonds.




phenomena are associated with climate change perceptions, beliefs, attitudes, behaviors, and policy support, the authors collectively refer to these constructs as public opinion about climate change, or climate opinions.[6] These data are measured both at the state and county levels and include a rich set of climate opinion related variables. As clarified in the database website, the inability to disentangle the effect of model improvement in mapping local climate belief from the genuine shift in actual belief over 2014, 2016, 2018, 2019, and 2020 data makes it challenging to fully draw on the panel structure of these data. Therefore, I use the survey data in 2018 in this study. In particular, I use as baseline cases the Human variable (the percentage estimate of "who think that global warming is caused mostly by human activities") and the $CO_2$limits variable (the percentage estimate of "who somewhat/strongly support setting strict limits on existing coal-fire power plants"). I also examine three more variables, Happening ("who think that global warming is happening"), Worried ("who are somewhat/very worried about global warming"), and HarmUS ("who think global warming will harm people in the US a moderate amount/a great deal") but only report these results briefly. Pearson correlation coefficients among these variables are substantially high—over 90% at the state level and over 77% at the county level .

[6]They validate high-resolution opinion estimates using a multilevel regression and poststratification (MRP) model whereby the model accurately predicts climate change beliefs, risk perceptions and policy preferences at the state, congressional district, metropolitan and county levels, using a concise set of demographic and geographic predictors.

Table 3: Summary statistics: full sample and LW replication

Panels A and B summarize the matched green and brown bonds, respectively, where callable and non-callable universes are combined. Panels C and D quasi-replicate the sample of LW by restricting the sample period up to July 2018 and the primary market data. The symbol † indicates that the data exclusively come from primary market source.

| **Panel A: GB (combined)** | Mean | SD | $p^{1\%}$ | $p^{25\%}$ | $p^{50\%}$ | $p^{75\%}$ | $p^{99\%}$ | Obs. |
|---|---|---|---|---|---|---|---|---|
| Yield to maturity (%) | 2.48 | 0.77 | 0.80 | 1.94 | 2.47 | 3.03 | 4.06 | 51203 |
| Dollar price (% Par) | 113.37 | 8.40 | 98.15 | 106.04 | 115.41 | 119.52 | 128.85 | 51203 |
| Yield to maturity (%)† | 2.80 | 0.88 | 0.89 | 2.1 | 2.9 | 3.6 | 4.30 | 5722 |
| Dollar price (% Par)† | 108.38 | 10.64 | 98.10 | 100.0 | 100.0 | 119.4 | 129.21 | 5722 |
| Issue amount ($MM) | 4.93 | 9.14 | 0.09 | 0.62 | 2.08 | 4.79 | 44.5 | 755 |
| Coupon rate (%) | 4.24 | 1.02 | 1.78 | 3.45 | 5.00 | 5.00 | 5.0 | 755 |
| Aggregate rating | 6.69 | 5.31 | 1.00 | 2.00 | 3.50 | 12.50 | 22.0 | 755 |

| **Panel B: BB (combined)** | Mean | SD | $p^{1\%}$ | $p^{25\%}$ | $p^{50\%}$ | $p^{75\%}$ | $p^{99\%}$ | Obs. |
|---|---|---|---|---|---|---|---|---|
| Yield to maturity (%) | 2.41 | 0.74 | 0.82 | 1.89 | 2.40 | 2.93 | 4.07 | 55441 |
| Dollar price (% Par) | 113.87 | 7.79 | 98.01 | 108.74 | 115.45 | 119.22 | 128.74 | 55441 |
| Yield to maturity (%)† | 2.70 | 0.89 | 0.93 | 2.0 | 2.72 | 3.44 | 4.17 | 4227 |
| Dollar price (% Par)† | 109.42 | 10.85 | 97.95 | 100.0 | 100.00 | 119.97 | 130.61 | 4227 |
| Issue amount ($MM) | 5.67 | 11.10 | 0.05 | 0.82 | 2.37 | 5.6 | 52.35 | 807 |
| Coupon rate (%) | 4.29 | 1.01 | 1.75 | 3.70 | 5.00 | 5.0 | 5.00 | 807 |
| Aggregate rating | 6.47 | 5.28 | 1.00 | 2.00 | 3.50 | 12.5 | 22.00 | 807 |

| **Panel C: GB (LW replic.)** | Mean | SD | $p^{1\%}$ | $p^{25\%}$ | $p^{50\%}$ | $p^{75\%}$ | $p^{99\%}$ | Obs. |
|---|---|---|---|---|---|---|---|---|
| Yield to maturity (%)† | 2.84 | 0.82 | 1.24 | 2.15 | 2.93 | 3.55 | 4.30 | 4344 |
| Dollar price (% Par)† | 108.46 | 10.70 | 97.99 | 99.75 | 100.00 | 119.59 | 128.78 | 4344 |
| Issue amount ($MM) | 5.91 | 10.61 | 0.11 | 0.52 | 2.43 | 5.46 | 49.69 | 511 |
| Coupon rate (%) | 4.19 | 1.05 | 1.75 | 3.15 | 5.00 | 5.00 | 5.00 | 511 |
| Aggregate rating | 6.82 | 5.15 | 1.00 | 2.50 | 3.50 | 12.50 | 12.50 | 511 |

| **Panel D: BB (LW replic.)** | Mean | SD | $p^{1\%}$ | $p^{25\%}$ | $p^{50\%}$ | $p^{75\%}$ | $p^{99\%}$ | Obs. |
|---|---|---|---|---|---|---|---|---|
| Yield to maturity (%)† | 2.83 | 0.83 | 1.21 | 2.15 | 2.86 | 3.59 | 4.17 | 3284 |
| Dollar price (% Par)† | 108.62 | 10.61 | 97.95 | 99.84 | 100.00 | 119.26 | 129.24 | 3284 |
| Issue amount ($MM) | 6.59 | 12.73 | 0.06 | 0.94 | 2.8 | 5.87 | 63.77 | 555 |
| Coupon rate (%) | 4.26 | 1.05 | 1.75 | 3.50 | 5.0 | 5.00 | 5.00 | 555 |
| Aggregate rating | 6.45 | 5.05 | 1.00 | 2.50 | 3.5 | 12.50 | 12.50 | 555 |

Table 4: Summary statistics of matched bonds across non-callable and callable universes

This table summarizes the descriptive statistics of the matched bonds whereby Panels A and B represent non-callable universe and Panels C and D represent callable universe. Yield and dollar price are the transactions data from both the primary and secondary market. Aggregate rating is the average of S&P and Moody's ratings whereby 1 is the highest rate and 22 is the lowest or unrated.

| **Panel A: GB (non-call)** | Mean | SD | $p^{1\%}$ | $p^{25\%}$ | $p^{50\%}$ | $p^{75\%}$ | $p^{99\%}$ | Obs. |
|---|---|---|---|---|---|---|---|---|
| Yield to maturity (%) | 1.86 | 0.55 | 0.54 | 1.48 | 1.90 | 2.26 | 3.04 | 14808 |
| Dollar price (% Par) | 115.70 | 7.56 | 99.50 | 111.35 | 116.96 | 121.07 | 130.07 | 14808 |
| Issue amount ($MM) | 2.79 | 4.48 | 0.02 | 0.37 | 1.08 | 2.9 | 21.27 | 360 |
| Coupon rate (%) | 4.17 | 1.18 | 1.63 | 2.90 | 5.00 | 5.0 | 5.00 | 360 |
| Aggregate rating | 6.98 | 5.76 | 1.00 | 2.00 | 3.50 | 12.5 | 22.00 | 360 |

| **Panel B: BB (non-call)** | Mean | SD | $p^{1\%}$ | $p^{25\%}$ | $p^{50\%}$ | $p^{75\%}$ | $p^{99\%}$ | Obs. |
|---|---|---|---|---|---|---|---|---|
| Yield to maturity (%) | 1.92 | 0.56 | 0.6 | 1.52 | 1.95 | 2.30 | 3.22 | 19910 |
| Dollar price (% Par) | 115.46 | 6.90 | 99.5 | 111.84 | 116.28 | 119.99 | 129.44 | 19910 |
| Issue amount ($MM) | 4.47 | 8.76 | 0.00 | 0.44 | 1.6 | 3.83 | 44.77 | 397 |
| Coupon rate (%) | 4.21 | 1.16 | 1.65 | 3.00 | 5.0 | 5.00 | 5.00 | 397 |
| Aggregate rating | 6.70 | 5.77 | 1.00 | 2.00 | 3.5 | 12.50 | 22.00 | 397 |

| **Panel C: GB (callable)** | Mean | SD | $p^{1\%}$ | $p^{25\%}$ | $p^{50\%}$ | $p^{75\%}$ | $p^{99\%}$ | Obs. |
|---|---|---|---|---|---|---|---|---|
| Yield to maturity (%) | 2.73 | 0.71 | 1.02 | 2.28 | 2.76 | 3.2 | 4.10 | 36395 |
| Dollar price (% Par) | 112.41 | 8.54 | 97.99 | 104.10 | 114.56 | 118.8 | 128.57 | 36395 |
| Issue amount ($MM) | 6.88 | 11.56 | 0.09 | 1.06 | 3.02 | 6.9 | 50.97 | 395 |
| Coupon rate (%) | 4.30 | 0.85 | 2.12 | 3.70 | 5.00 | 5.0 | 5.00 | 395 |
| Aggregate rating | 6.43 | 4.86 | 1.00 | 2.50 | 3.50 | 12.5 | 12.53 | 395 |

| **Panel D: BB (callable)** | Mean | SD | $p^{1\%}$ | $p^{25\%}$ | $p^{50\%}$ | $p^{75\%}$ | $p^{99\%}$ | Obs. |
|---|---|---|---|---|---|---|---|---|
| Yield to maturity (%) | 2.68 | 0.69 | 1.04 | 2.24 | 2.71 | 3.14 | 4.10 | 35531 |
| Dollar price (% Par) | 112.97 | 8.11 | 97.88 | 105.83 | 114.93 | 118.76 | 128.15 | 35531 |
| Issue amount ($MM) | 6.84 | 12.88 | 0.08 | 1.68 | 3.25 | 6.36 | 72.84 | 410 |
| Coupon rate (%) | 4.37 | 0.84 | 2.13 | 3.88 | 5.00 | 5.00 | 5.00 | 410 |
| Aggregate rating | 6.24 | 4.76 | 1.00 | 2.50 | 3.50 | 12.50 | 12.50 | 410 |

# 4 Descriptive analysis based on matched bonds

## 4.1 Univariate analysis in levels

In this subsection and the next, I examine the potential yield differentials between green and brown bonds. Armed with the bond sample constructed through matching procedure, I employ levels approach here as opposed to the approach exploiting the natural experiment setting emerging from disaster events. Following LW, I investigate the differentials between green and brown bonds with the framework of Gaussian kernel density and Silverman rule for bandwidth selection. Unlike LW, however, I separate the callable and non-callable bond universes for three reasons. First, the callable bond universe shows much higher yields and is more frequently traded as well than the non-callable bond universe, resulting in the discrepancy in the number of observations at the MSRB transaction level. Second, the differential pricing of green and brown bonds tends to show inconsistent results across non-callable and callable universes—for instance, sometimes there is a green bond premium (discount) in the (sub)sample of non-callable bond universe, while there is a green bond discount (premium) in the (sub)sample of callable bond universe. Blending these two (sub)samples will likely subdue each other's characteristics and blur important aspects. Third, as the yield distribution of each universe exhibits a unimodal distribution, a mixture of both universes likely follows a bimodal distribution. While the mean (median) is the most effective in capturing the central tendency of a symmetrical (asymmetrical) unimodal distribution, this is not the case for a bimodal distribution and therefore mode is a more suitable measure. Hence, I refrain from combining these two universes.

Table 5 shows the results of bond yield differentials and issuance amount across particular states. The choice of states relies on the intensity of green bond issuance as illustrated in Figure 2. In testing the median difference of green and brown bond distributions, I use Mann-Whitney-Wilcoxon (MWW) test. Although Wilcoxon (matched-pairs) signed-rank test is also used to assess whether medians across matched samples differ, the observations have to be exactly matched—note that my sample is based on observations at the transaction level and this condition does not realistically hold. Another potential choice is the Mood median test but this test has its shares of trouble as well regarding power and efficiency issues. A critical feature on Mann–Whitney–Wilcoxon (MWW) test is that it is an equality evaluation of two distributions and thus does not specifically address the medians of the distributions. The null hypothesis is stated such that two samples are drawn from an identical distribution with an identical scale parameter—on the other side of the coin, the alternative hypothesis is postulated such that one distribution is stochastically larger than the other.

Technically, there are additional conditions (e.g., location shift) to interpret MWW test as a median test but these topics are beyond the scope of the paper.

Overall, the empirical results exhibited in Table 5 point to a mixed view. This claim is even more substantiated after visualizing the yield differentials as a whole as well as for each state (Figures 3–9). In particular, taking a closer look at individual states, Massachusetts surfaces as a noteworthy subject because of its unambiguous evidence in support of the greenium. The mean (median) yield differential between green and brown bonds in Massachusetts is $-0.4$ ($-2.0$) bps for the non-callable universe and is $-22.9$ ($-17.5$) bps for the callable universe—significantly suggestive of green bond premium especially for the callable universe. What makes this fact ever more encouraging for environmentalists is that this is indeed the case even though the issuance amount of green bonds substantively outnumbers that of brown bonds. In reference to Hypothesis 1, this firm evidence of greenium conforms to the fact that Yale Climate Opinion Map clearly ranks Massachusetts as one of the top states with strong climate belief. Moreover, Green City Bonds Coalition (2015) documents anecdotal evidence that green bonds were indeed priced at premium in Massachusetts.[7] It writes as follows:

> [T]he green bond sale was 3x oversubscribed and the AA+ rated green bonds sold at lower yields than the muni market's AAA yield curve.... [W]hen we first

[7] The following is an in-depth quote from Green City Bonds Coalition (2015):

> Much can be learned from the Massachusetts offering because the Commonwealth was offering green and non-green bonds at the same time, with the same rating. In some ways, Massachusetts had an even easier time marketing the green bonds than the non-green bonds because they were able to tell potential investors a more persuasive story about the impact of the bonds and the projects the proceeds were going to fund. The green bond sale was 3x oversubscribed and the AA+ rated green bonds sold at lower yields than the muni market's AAA yield curve! Massachusetts was also able to expand its investor base, as residents and local retail investors who hadn't considered buying municipal bonds before were attracted by the green story: the Commonwealth received $260 million in orders from retail investors, an unprecedented amount for them. These new investors reported that they appreciated knowing the specific projects their investments were funding, as well as the fact that, as residents, they would experience the benefits of the projects first-hand into the future.

Another insightful quote from Green City Bonds Coalition (2015) is the following:

> In fact, when we first came to market with an initial $300 million offer, we got a little over $1.1 billion of orders! So in response, we upped the size to $350 million and lowered the spread by 15 basis points.... Some of this pricing benefit can be attributed to the green credentials of the bond, in the sense that $100 million of orders were from SRI investors that would not have bought one of our non-green bonds, but of course, it is difficult to quantify how much of the pricing benefit can be attributed solely to the green label. But, it was clear that we benefited financially from having a green label.

> came to market with an initial \$300 million offer, we got a little over \$1.1 billion of orders! So in response, we upped the size to \$350 million and lowered the spread by 15 basis points.

My empirical results indeed endorse this anecdotal account and are clearly illustrated in Figure 6. Furthermore, although the anecdote is unique to the period of 2014–2015, I continue to find strong patterns of greenium in this region, especially in the callable bond universe, even after restricting the sample to (i) the period after 2014–2015, (ii) secondary market, or (iii) the intersection of both conditions. In reference to the other states, it stands to reason that similar patterns can be found in Washington D.C. area.

In California, however, green bonds are surprisingly priced and traded at a discount as shown in Figure 5. The mean (median) yield differential between green and brown bonds is 4.2 (11.9) bps for the non-callable bond universe and 3.5 (1.1) bps for the callable bond universe. These characteristics starkly contrast with those of Massachusetts and Washington D.C. Besides, the differences in issuance amount make it more puzzling to interpret this discrepancy because the issuance amount of green bonds is smaller than that of brown bonds. Nevertheless, one potential reason of this discount could be that a good deal of municipal bonds targeting financing environmentally-friendly projects do not use a green label and thus investors do not have a strong preference for the green bond labels in California. As a matter of fact, the outstanding amount of these unlabeled climate-friendly bonds significantly exceed labeled green bonds (Chiang, 2017; MSRB, 2018a).

Furthermore, even the patterns shown by states that are traditionally considered to be conservative are mixed. For instance, in Texas the mean (median) yield differential is -13.7 (-15.0) bps and green bonds are significantly priced and traded at a premium in the non-callable universe: there is no significant yield differential in the callable universe. In Arizona, by contrast, the mean (median) yield differential is 18.1 (17.8) bps and green bonds are significantly priced and traded at a discount in the callable universe: there is no significant yield differential in the non-callable universe.

Nonetheless, an immediate concern arises that it is not the local climate opinion that drives up the green bond valuation but other confounding factors are at play. In one case, to examine the possibility of issuance amount serving as a confounder, the statistics are in parallel shown in Table 5 as well as in Figures 3–9. Another possibility is the difference in institutional ownership between green and brown bonds that affects the bond valuation. Chiang (2017) reports that "U.S. institutional investors unanimously say they are not currently willing to sacrifice yield for green bonds" and that "brokerage firms and underwriters stressed that institutional clients are unwilling to pay up for green bonds." Chiang (2017) continues that unlike high-net-worth individuals, a vast majority of institutional investors will not readily pay a premium. Hence, this concern requires further investigation and will be left for future.

Table 5: Bond yield differentials and issuance amount: comparison across green bond intensive states

Panels A, B, and C below summarize the bond yield differentials and issuance amounts with respect to states with a prominent history of green bond issuance. Note that (i) Washington D.C. is additionally included for interest despite the moderate number of issuance and (ii) the last rows in Panels A and B and the row in Panel C represent all the states in the US. The last column shows the cumulative issuance amount (in millions). Yields are from MSRB transaction database and include both the primary and the secondary market data. The mean and median yield differences are examined based on Welch-Test and Mann–Whitney–Wilcoxon (MWW) test, respectively.

**Panel A: Non-callable universe**

| | # unique bonds | | Yield (mean) | | | | Yield (median) | | | | Issuance ($MM) | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | GB | BB | GB | BB | Difference | *p*-value (Welch) | GB | BB | Difference | *p*-value (MWW) | GB | BB |
| Arizona | 26 | 24 | 1.936 | 1.936 | 0.0 | 0.989 | 1.97 | 2.0 | -0.03 | 0.328 | 102.68 | 86.055 |
| California | 56 | 60 | 1.739 | 1.696 | 0.042 | 0.008 | 1.78 | 1.661 | 0.119 | 0.0 | 249.72 | 374.205 |
| Massachusetts | 26 | 26 | 1.855 | 1.859 | -0.004 | 0.715 | 1.89 | 1.91 | -0.02 | 0.239 | 187.09 | 451.025 |
| New York | 107 | 108 | 2.025 | 2.136 | -0.111 | 0.0 | 2.109 | 2.198 | -0.089 | 0.0 | 198.835 | 78.465 |
| Texas | 9 | 8 | 1.891 | 2.028 | -0.137 | 0.036 | 1.93 | 2.08 | -0.15 | 0.006 | 7.87 | 5.08 |
| Washington D.C. | – | – | – | – | – | – | – | – | – | – | – | – |
| All states | 360 | 397 | 1.861 | 1.917 | -0.056 | 0.0 | 1.9 | 1.95 | -0.05 | 0.0 | 1003.445 | 1773.105 |

**Panel B: Callable universe**

| | # unique bonds | | Yield (mean) | | | | Yield (median) | | | | Issuance ($MM) | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | GB | BB | GB | BB | Difference | *p*-value (Welch) | GB | BB | Difference | *p*-value (MWW) | GB | BB |
| Arizona | 37 | 33 | 2.647 | 2.466 | 0.181 | 0.0 | 2.7 | 2.522 | 0.178 | 0.0 | 275.83 | 177.03 |
| California | 113 | 139 | 2.502 | 2.467 | 0.035 | 0.0 | 2.54 | 2.529 | 0.011 | 0.0 | 973.765 | 1293.24 |
| Massachusetts | 27 | 30 | 2.469 | 2.698 | -0.229 | 0.0 | 2.585 | 2.76 | -0.175 | 0.0 | 683.185 | 198.87 |
| New York | 85 | 86 | 3.441 | 3.429 | 0.012 | 0.314 | 3.558 | 3.638 | -0.08 | 0.0 | 387.31 | 298.5 |
| Texas | 25 | 22 | 3.108 | 3.151 | -0.043 | 0.207 | 3.2 | 3.177 | 0.023 | 0.107 | 33.675 | 23.27 |
| Washington D.C. | 5 | 5 | 2.541 | 2.621 | -0.081 | 0.011 | 2.581 | 2.692 | -0.111 | 0.005 | 86.055 | 126.275 |
| All states | 395 | 410 | 2.725 | 2.681 | 0.044 | 0.0 | 2.757 | 2.71 | 0.047 | 0.0 | 2718.5 | 2803.465 |

**Panel C: Combined universe**

| | # unique bonds | | Yield (mean) | | | | Yield (median) | | | | Issuance ($MM) | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | GB | BB | GB | BB | Difference | *p*-value (Welch) | GB | BB | Difference | *p*-value (MWW) | GB | BB |
| All states | 755 | 807 | 2.475 | 2.406 | 0.069 | 0.0 | 2.47 | 2.4 | 0.07 | 0.0 | 3721.945 | 4576.57 |

Figure 3: Differential pricing across non-callable and callable bond universes (full sample)

The sample spans the entire period Sep 2014–June 2020. The first (second) row demonstrates the differential structure of yield (original issuance amounts) distributions between the non-callable and callable universes. Yields are recorded at the transactional level (MSRB) and both the primary and secondary market data are included. The mean (median) yield differential between green and brown bonds is $-5.6$ ($-5.0$) bps for the non-callable bond universe and is 4.4 (4.7) bps for the callable bond universe—significantly suggestive of green bond premium especially for callable bonds.

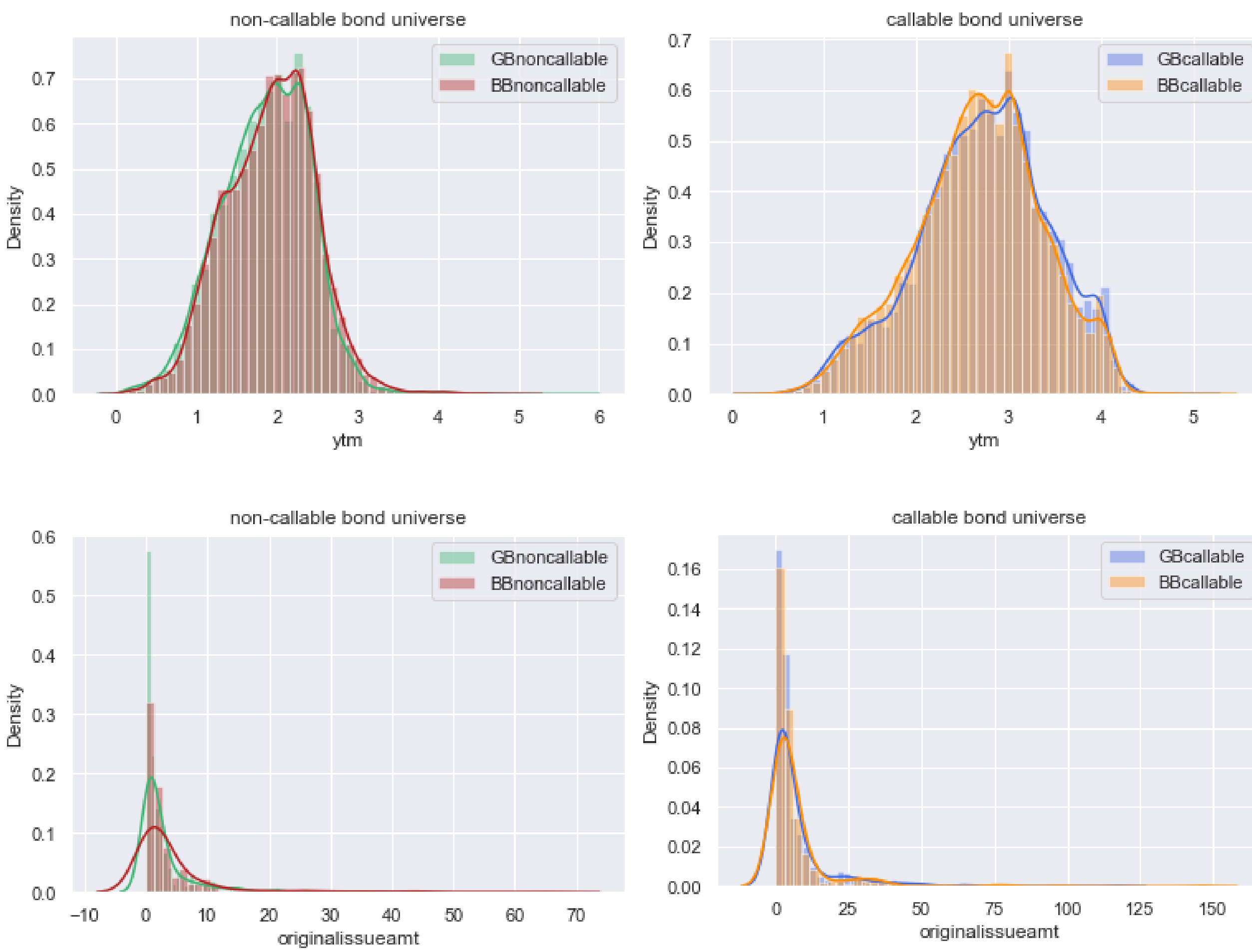


Figure 4: Differential pricing across non-callable and callable bond universes (Arizona)

Conditioning on Arizona state, the subsample spans the entire period Sep 2014–June 2020. The first (second) row demonstrates the differential structure of yield (original issuance amounts) distributions between the non-callable and callable universes. Yields are recorded at the transactional level (MSRB) and both the primary and secondary market data are included. The mean (median) yield differential between green and brown bonds is 0.0 (−0.3) bps for the non-callable bond universe and is 18.1 (17.8) bps for the callable bond universe—significantly suggestive of green bond premium especially for callable bonds.

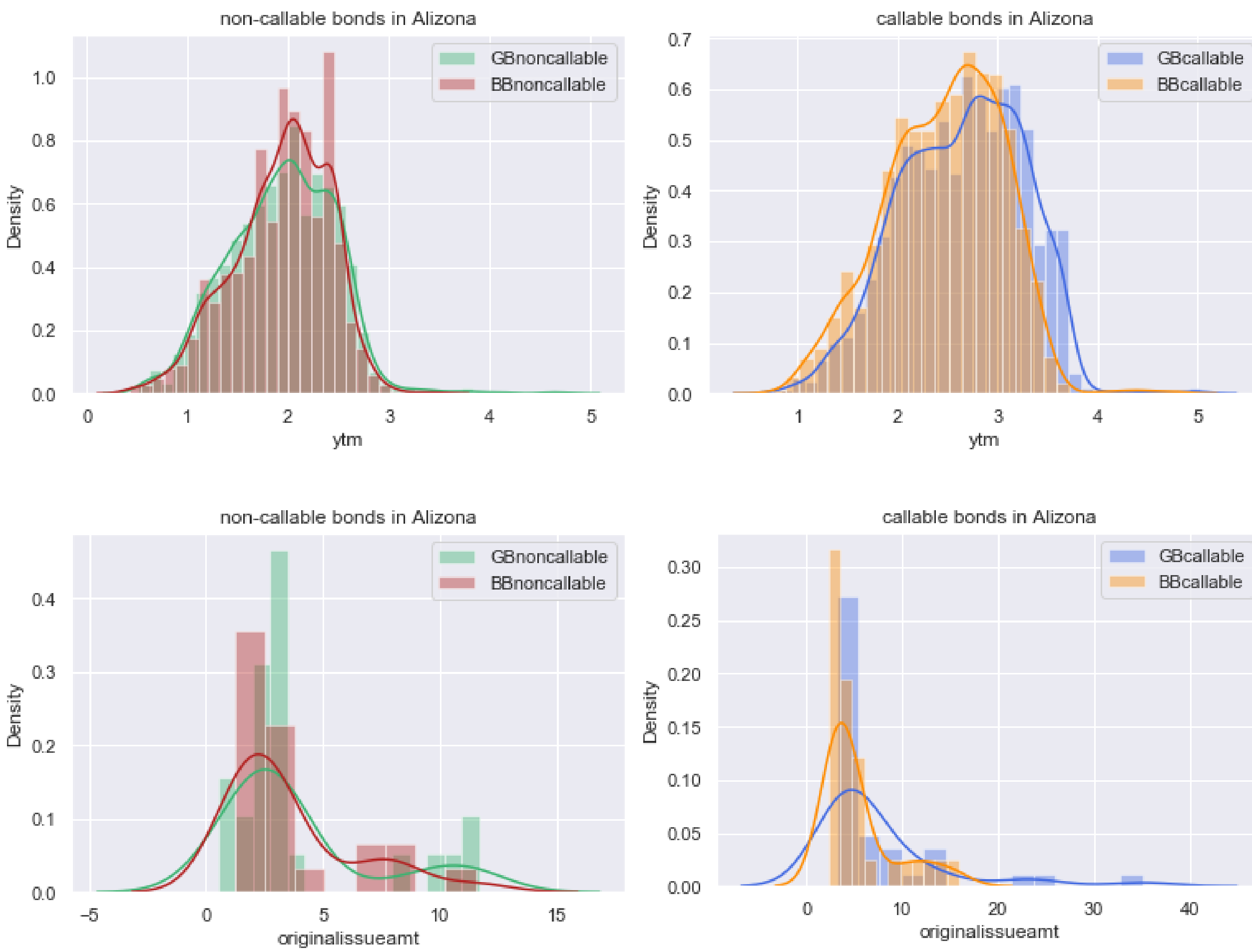


Figure 5: Differential pricing across non-callable and callable bond universes (California)

Conditioning on California state, the subsample spans the entire period Sep 2014–June 2020. The first (second) row demonstrates the differential structure of yield (original issuance amounts) distributions between the non-callable and callable universes. Yields are recorded at the transactional level (MSRB) and both the primary and secondary market data are included. The mean (median) yield differential between green and brown bonds is 4.2 (11.9) bps for the non-callable bond universe and is 3.5 (1.1) bps for the callable bond universe—significantly suggestive of green bond premium especially for callable bonds.

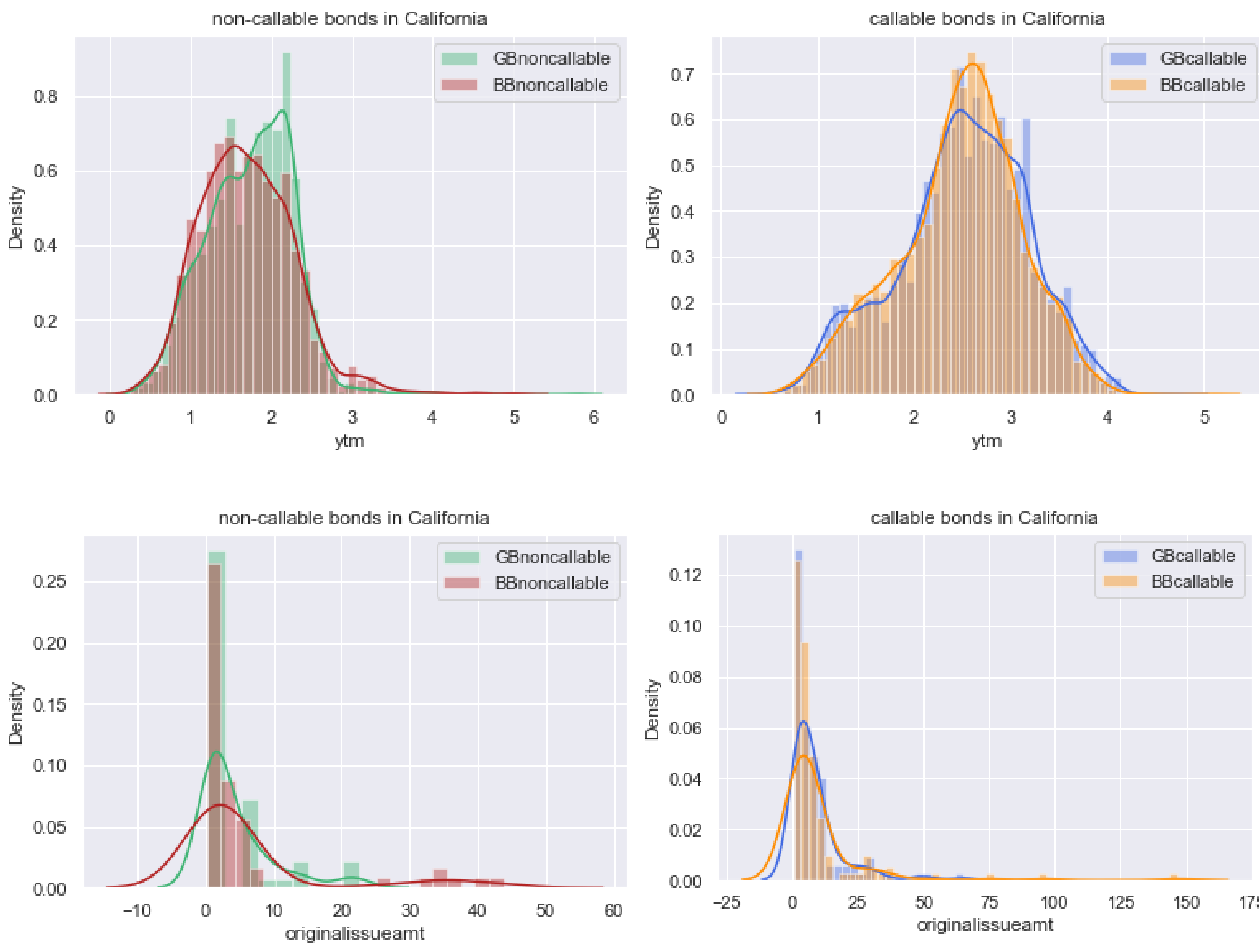


Figure 6: Differential pricing across non-callable and callable bond universes (Massachusetts)

Conditioning on Massachusetts state, the subsample spans the entire period Sep 2014–June 2020. The first (second) row demonstrates the differential structure of yield (original issuance amounts) distributions between the non-callable and callable universes. Yields are recorded at the transactional level (MSRB) and both the primary and secondary market data are included. The mean (median) yield differential between green and brown bonds is $-0.4$ ($-2.0$) bps for the non-callable bond universe and is $-22.9$ ($-17.5$) bps for the callable bond universe—significantly suggestive of green bond premium especially for callable bonds.

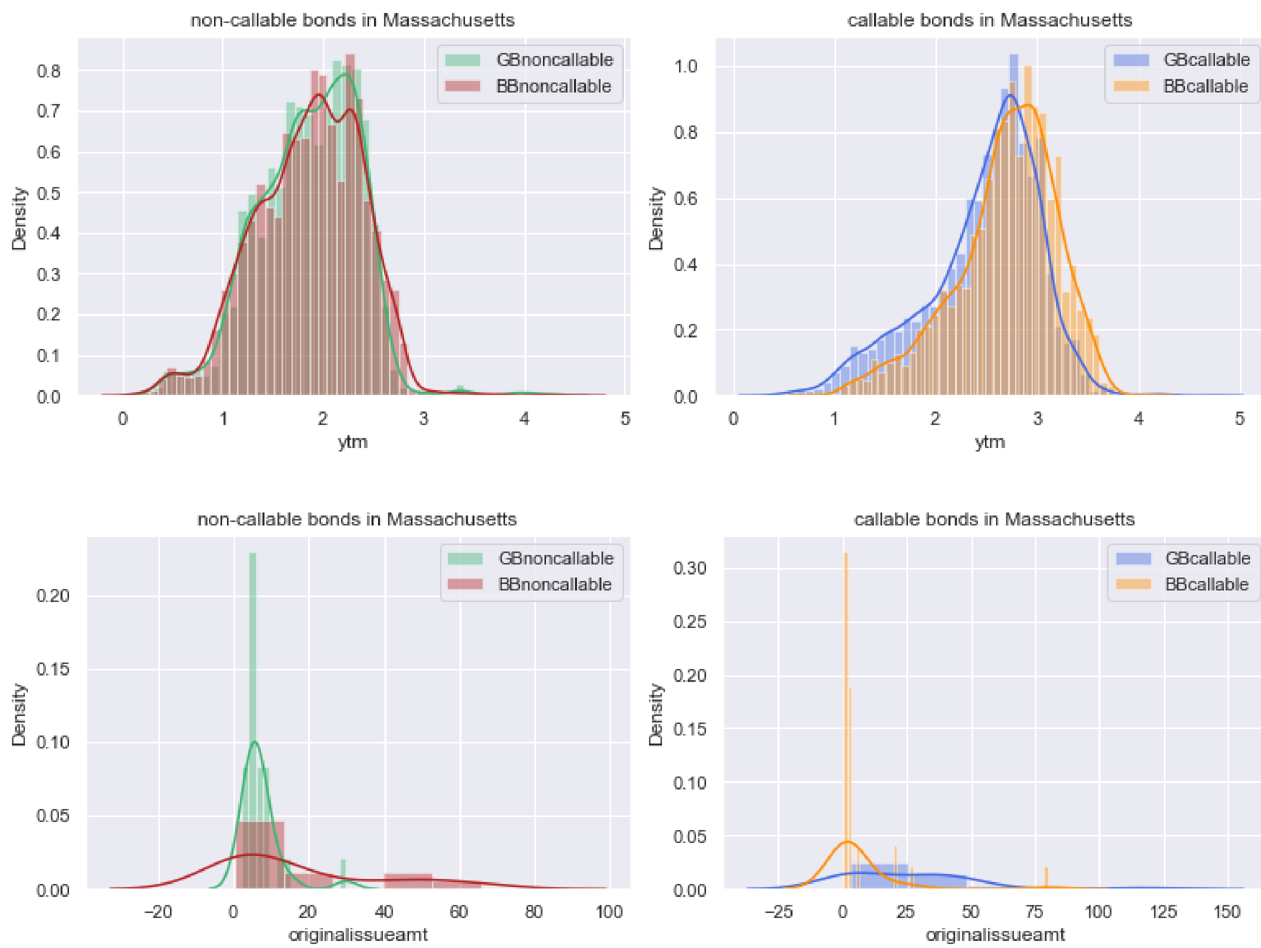


Figure 7: Differential pricing across non-callable and callable bond universes (New York)

Conditioning on New York state, the subsample spans the entire period Sep 2014–June 2020. The first (second) row demonstrates the differential structure of yield (original issuance amounts) distributions between the non-callable and callable universes. Yields are recorded at the transactional level (MSRB) and both the primary and secondary market data are included. The mean (median) yield differential between green and brown bonds is $-11.1$ ($-8.9$) bps for the non-callable bond universe and 1.2 ($-8.0$) bps for the callable bond universe.

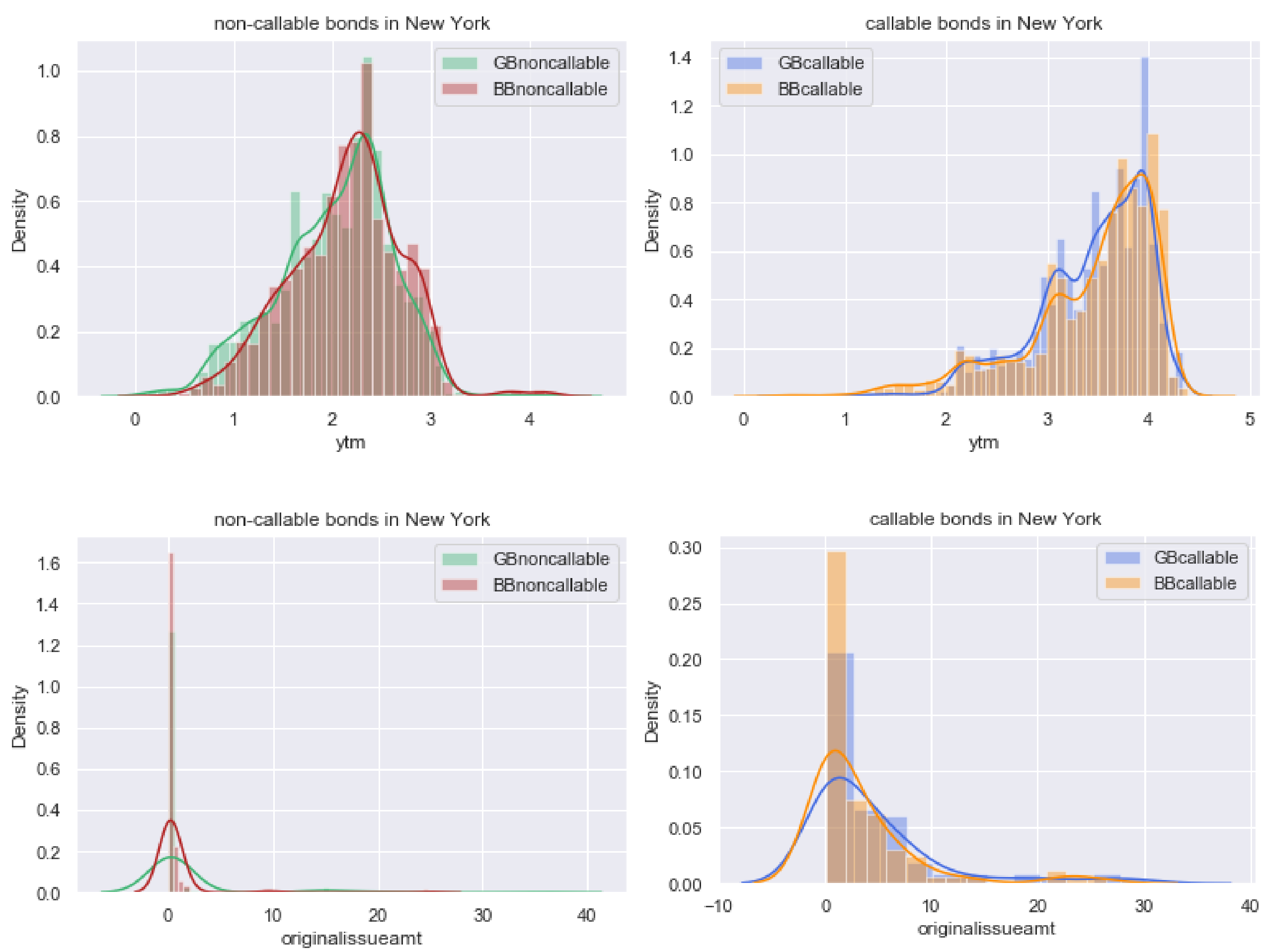


Figure 8: Differential pricing across non-callable and callable bond universes (Texas)

Conditioning on Texas state, the subsample spans the entire period Sep 2014–June 2020. The first (second) row demonstrates the differential structure of yield (original issuance amounts) distributions between the non-callable and callable universes. Yields are recorded at the transactional level (MSRB) and both the primary and secondary market data are included. The mean (median) yield differential between green and brown bonds is $-13.7$ ($-15.0$) bps for the non-callable bond universe and is $-4.3$ (2.3) bps for the callable bond universe.

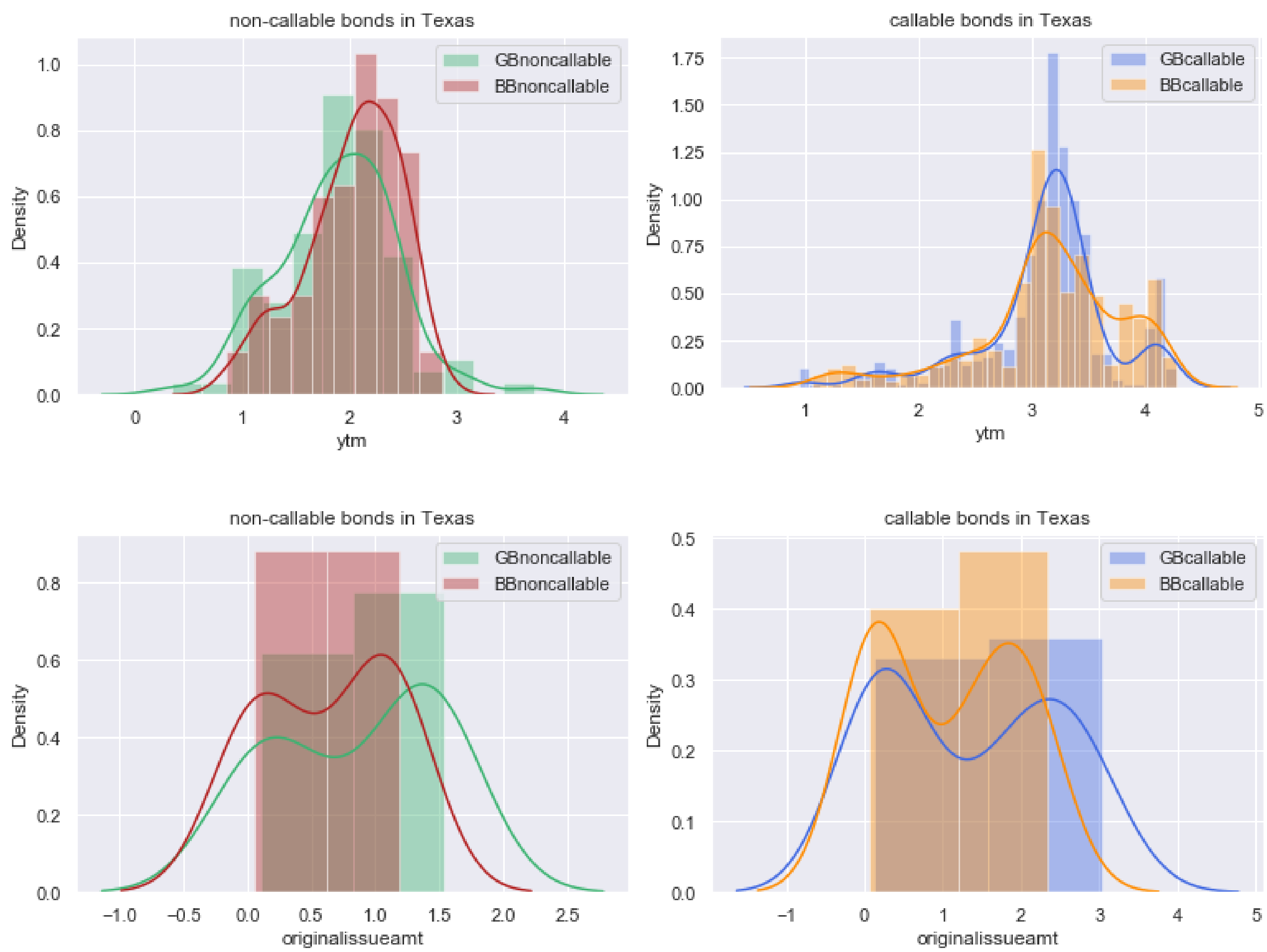
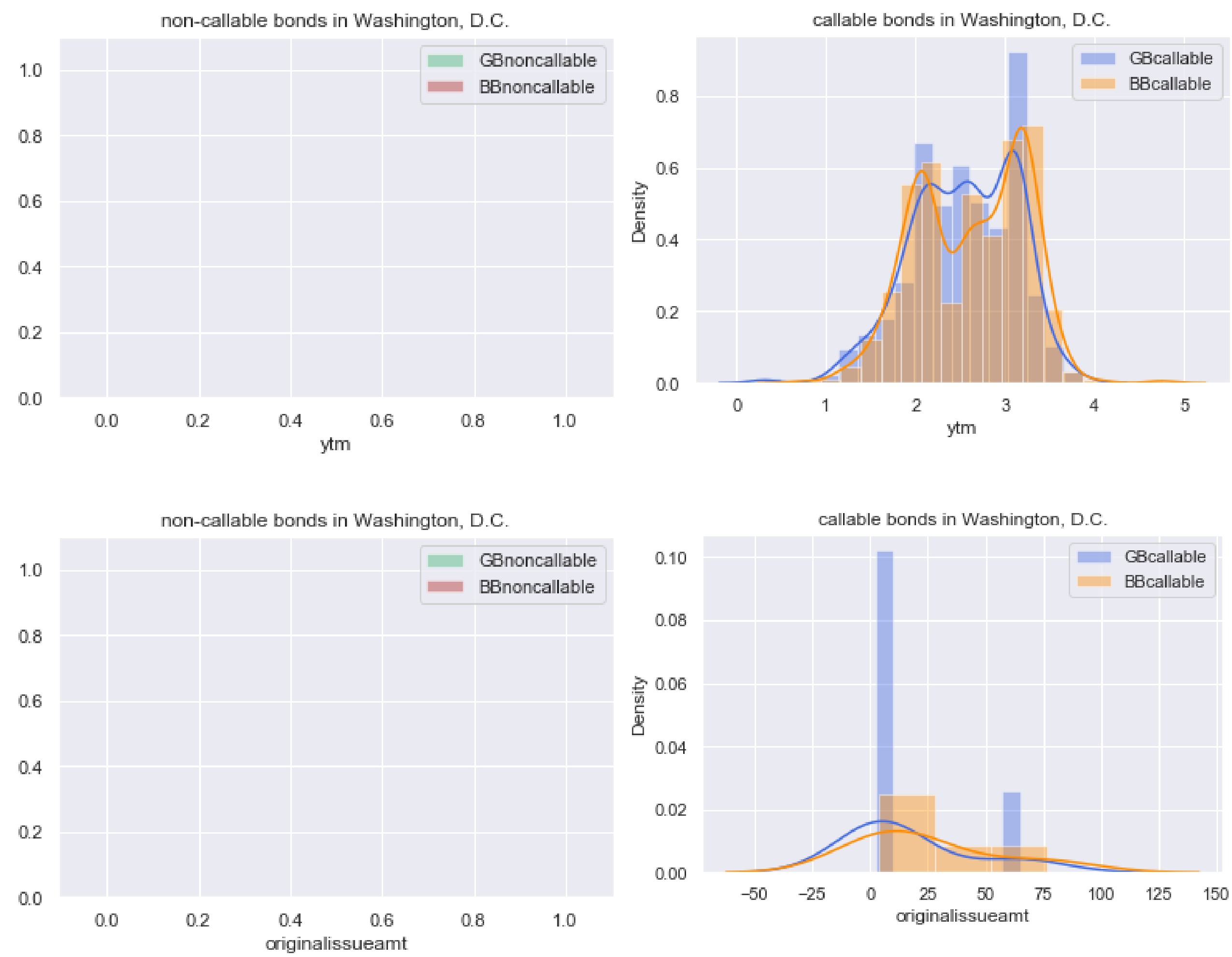


Figure 9: Differential pricing across non-callable and callable bond universes (Washington D.C.)

Conditioning on the District of Columbia, the subsample spans the entire period Sep 2014–June 2020. The first (second) row demonstrates the differential structure of yield (original issuance amounts) distributions between the non-callable and callable universes. Yields are recorded at the transactional level (MSRB) and both the primary and secondary market data are included. The mean (median) yield differential between green and brown bonds is −8.1 (−11.1) bps for the callable bond universe. No data for non-callable bonds. Five green callable bonds are matched with five brown callable bonds.



## 4.2 Bivariate analysis in levels

Hazlett and Mildenberger (2019) document that actions in response to a direct wildfire experience are moderated by climate opinion. Here I extend the analysis in the previous subsection by additionally conditioning on the geographic areas based on the intensity of local climate belief. In doing so, I present the results with Human and $CO_2$limits variables, which are measured both at the state and county levels. In this respect, across-state as well as within-state variation of climate beliefs paints a colorful picture.[8] To put this into perspective, the state-level values are not necessarily a good representation of its entirety given that there is a significant amount of within-state variation.

With this contextual information in mind, I plot the relationship between bond yield and local belief in climate change. Using local climate belief measured both at the state and county level, Figure 10 and 11 illustrate bivariate frequency distributions with contour lines, where $x$-axis represents yield and $y$-axis represents climate belief intensity: each figure targets Human and $CO_2$limits variables, respectively, to measure local climate belief. Moreover, as to the callable bond universe on the right-hand side of Figures 10 and 11, areas with lower climate change belief (lower $y$ values) are apparently more likely to associate green bonds with higher yields (higher $x$ values). Regarding the non-callable bond universe on the left-hand side, the patterns do not contradict those of callable bond universe but the magnitudes in differences between green and brown bonds appear to be minimal.

Figure 12 and Figure 13 further illustrate differential pricing across high and low climate belief areas: again, Figure 12 (Figure 13) targets Human ($CO_2$limits) variable. Overall, I find perplexing results, particularly arising from the low climate belief areas in the non-callable universe. On the one hand, high climate belief areas do not show substantial differences in pricing between green and brown bonds. On the other hand, low climate belief areas show lower valuation of green bonds in both figures with respect to the callable bond universe—consistent with Hypothesis 1—while *higher* valuation of green bonds are shown with respect to the non-callable universe. Insofar as the results are driven by noise rather than signal—note that the width of the bars is wider, indicating observations are fewer relative to other figures—a meaningful interpretation is challenging and thus judgement should be postponed.

[8] For instance, Happening measured at the state level ranges from the lowest at 58.6 in West Virginia to the highest at 82.2 in District of Columbia (Washington D.C.). This variable takes the value of 74.8 in Massachusetts at the state level and within-state variation is relatively small, ranging from 70.5 to 81.3. In contrast, it equals to 76.2 in California at the state level and within-state variation is larger, ranging from 62.9 to 84.2. Even more prominent, it is recorded at 69.5 in Texas at the state level and within-state variation is extremely large, ranging from 50.7 to 80.7.

Figure 10: Bivariate frequency distributions with contour lines: Human

The sample spans the entire period Sep 2014–June 2020. The left (right) column illustrates noncallable (callable) bonds. In the first (second) row, local climate belief represented by Human variable is measured at the state (county) level. The observations include both the primary market and secondary market data.

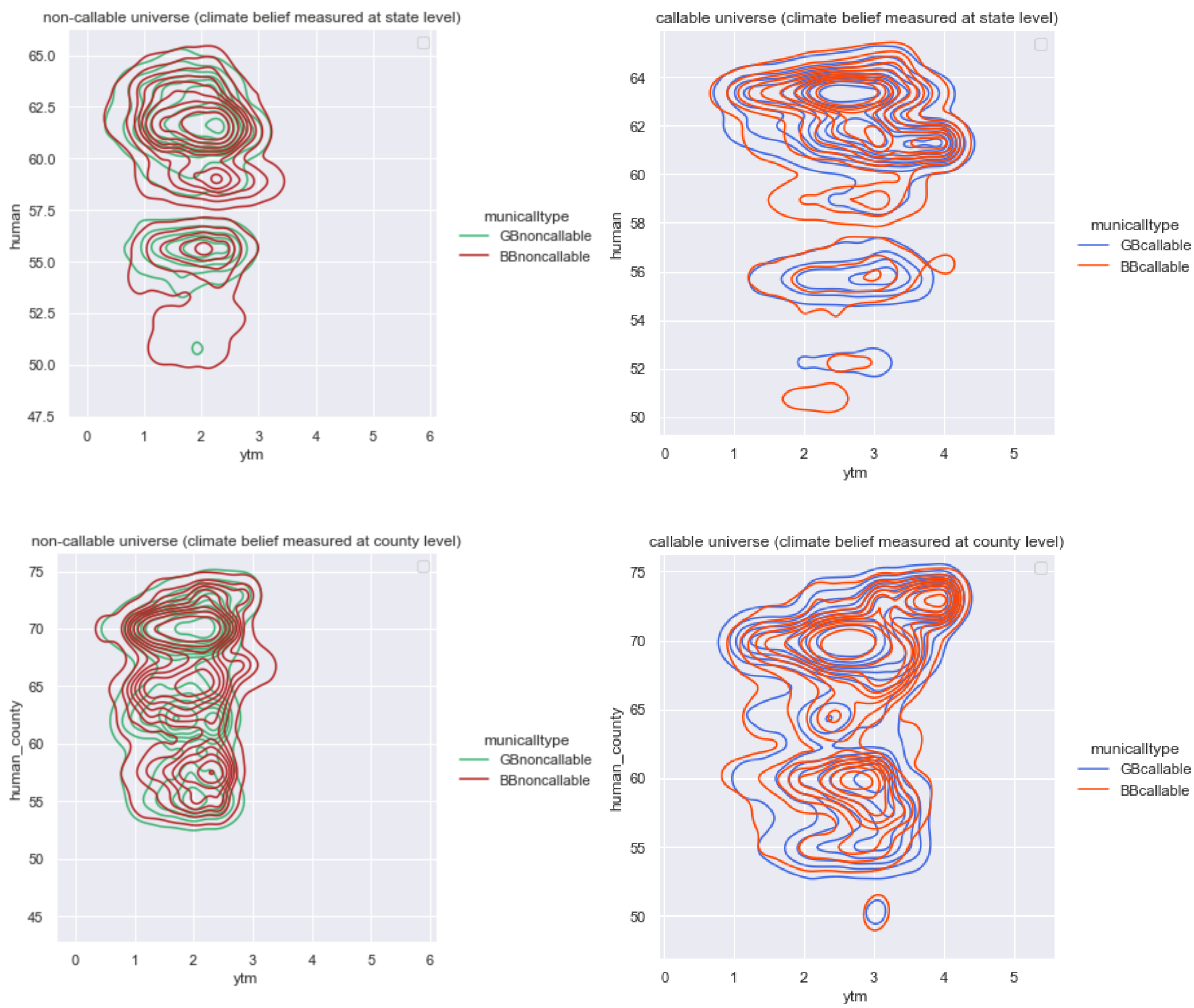


Figure 11: Bivariate frequency distributions with contour lines: $CO_2$limits

The sample spans the entire period Sep 2014–June 2020. The left (right) column illustrates noncallable (callable) bonds. In the first (second) row, local climate belief represented by $CO_2$limits variable is measured at the state (county) level. The observations include both the primary market and secondary market data.

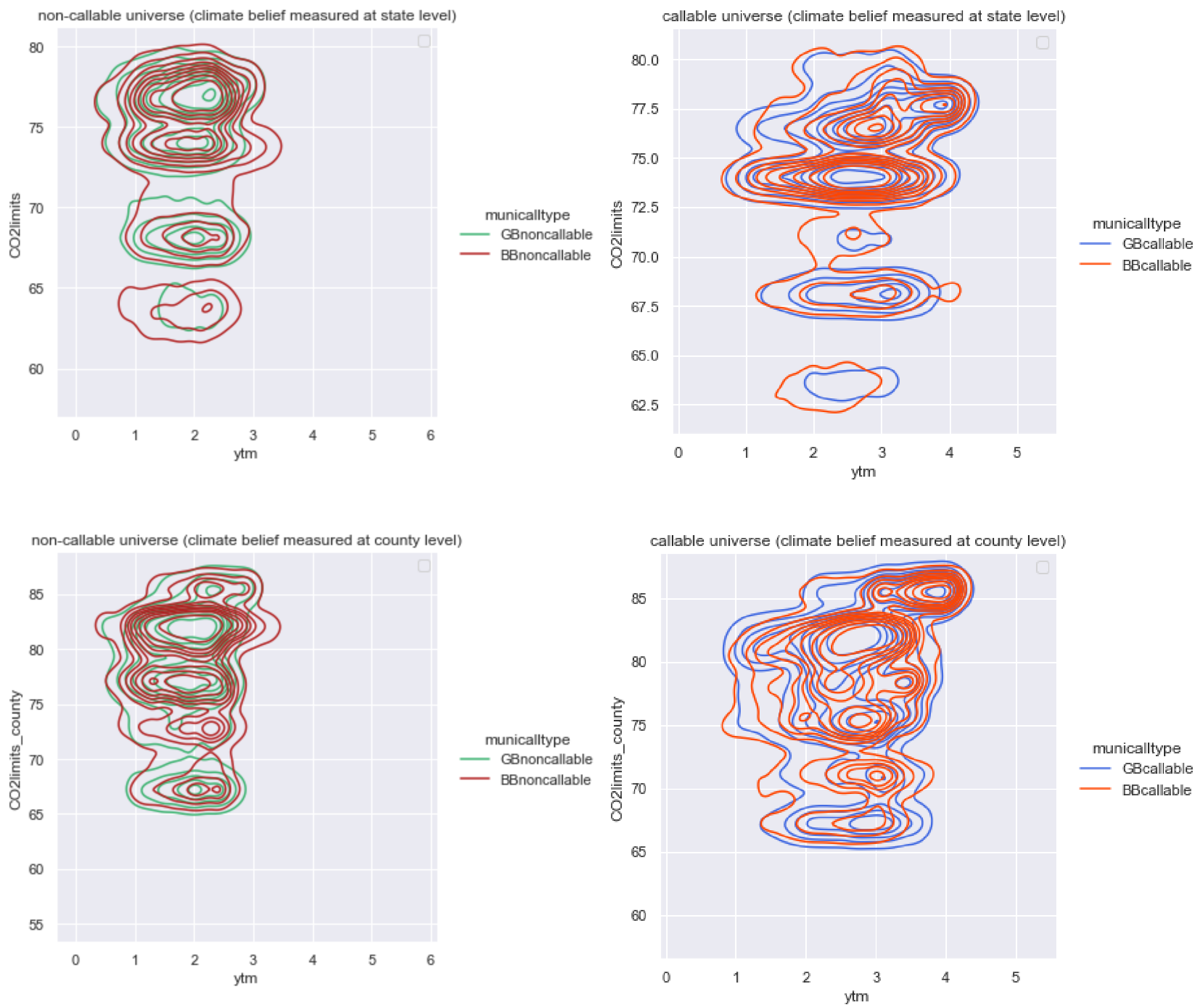


Figure 12: Differential pricing across high and low climate belief areas: Human

The sample spans the entire period Sep 2014–June 2020 and the local climate belief represented by Human is measured at the state level. The median value of Human variable is use to categorize high/low climate-belief areas. The left (right) column illustrates non-callable (callable) bond universe. The first (second) row illustrates the observations in high (low) climate belief areas.

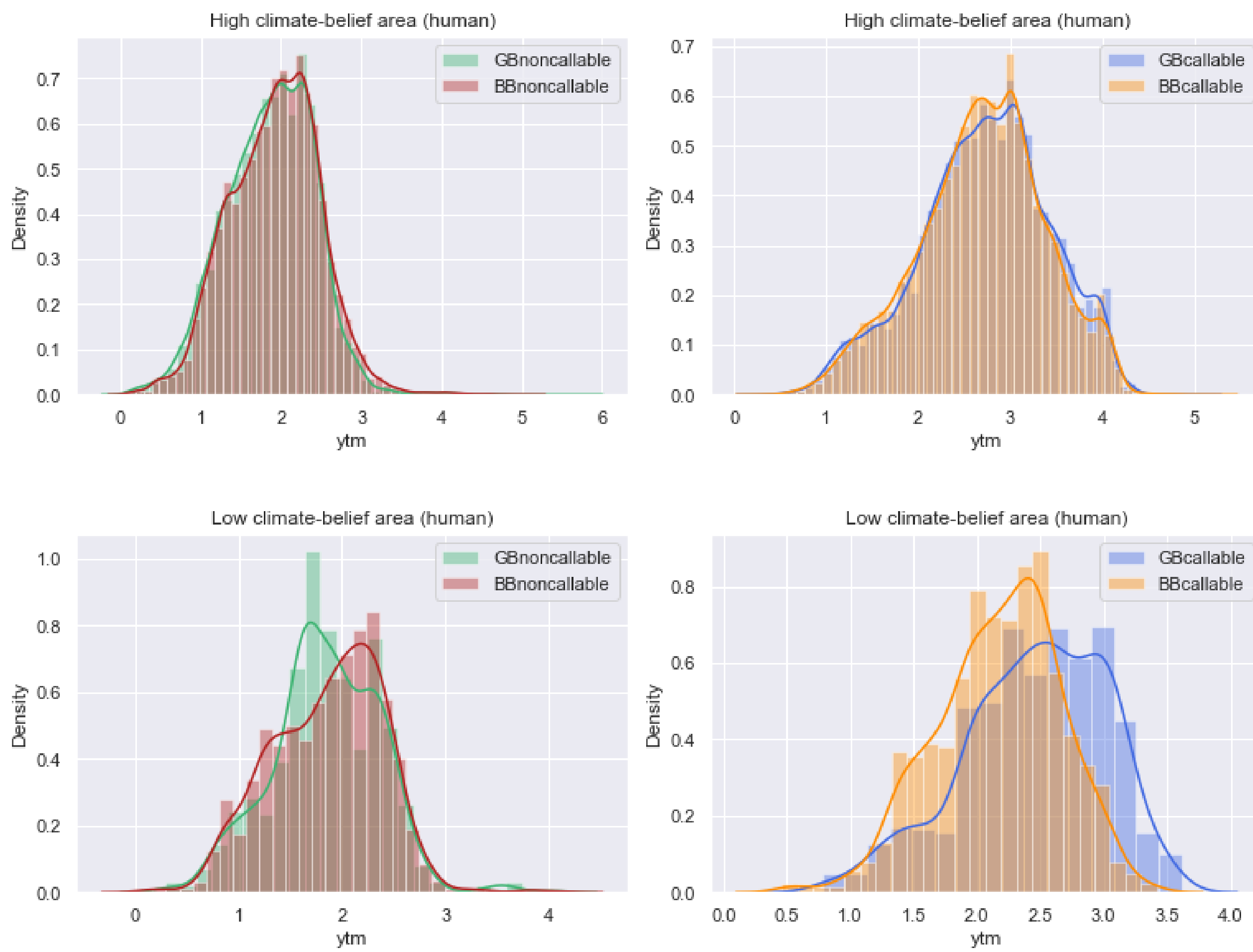


Figure 13: Differential pricing across high and low climate belief areas: $CO_2$limits

The sample spans the entire period Sep 2014–June 2020 and the local climate belief represented by $CO_2$limits is measured at the state level. The median value of $CO_2$limits variable is use to categorize high/low climate-belief areas. The left (right) column illustrates non-callable (callable) bond universe. The first (second) row illustrates the observations in high (low) climate belief areas.

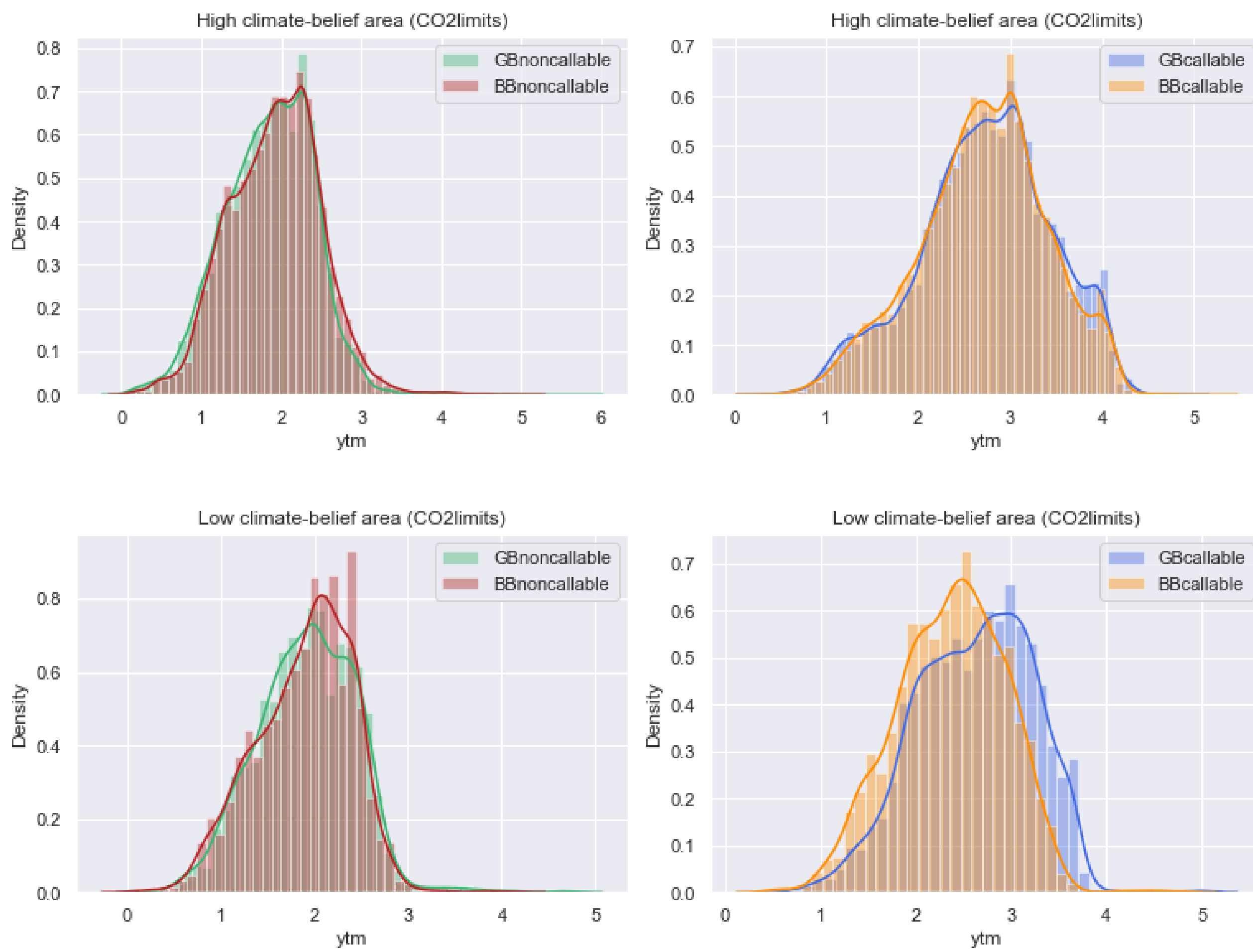
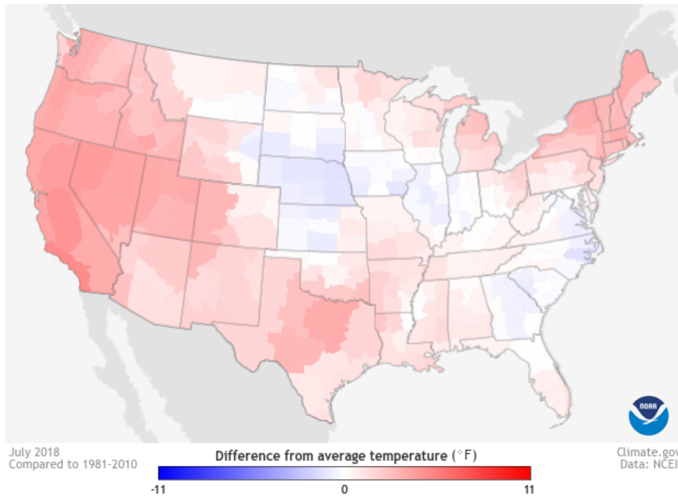


Figure 14: Heat wave in July 2018

The figure below sourced from NOAA demonstrates the deviation of the average monthly temperature in July 2018 from the benchmark computed over the period 1981–2010.



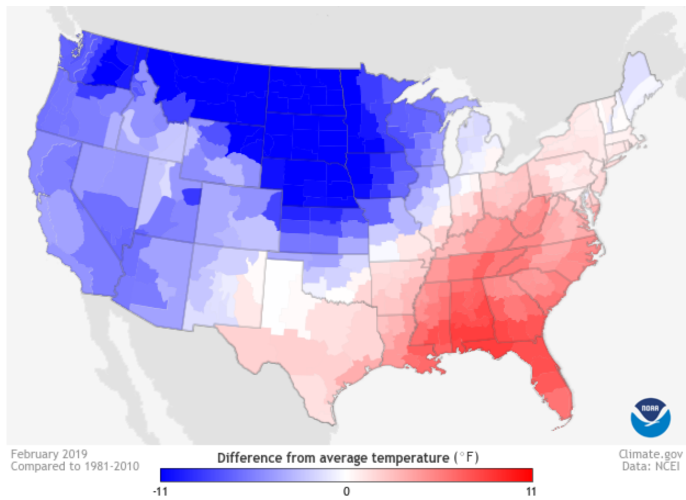

## 4.3 Yield differential analysis following extreme weather events

A variety of natural catastrophes can wreak havoc on US residents ranging from tropical cyclones, droughts, wildfire to floods. These events are intrinsically different from one another with respect to their risk and uncertainty, expected financial damage, and perceptional consequences (Howe et al., 2019). In relation to Hypothesis 2, I attempt to conduct in this subsection a few case studies on the extreme weather events—heat wave in 2018 as well as cold wave in 2014, 2015, and 2019—because they are geographically wide-ranging and generate substantial variation in data. Prior research suggests that relative abnormalities in temperature direct the attention of local people to climate change (e.g., Sisco, Bosetti, and Weber, 2017). Besides, another reason that justifies the focus on this hazard type is that other disasters such as flooding may not generate sufficient data variation due to its relatively narrow geographical range relative to extreme weathers—this is especially problematic when using the matched approach intrinsically accompanied by a smaller sample size and poses a serious challenge for statistical inference. It is thus vital that I focus on the reported short-term effect (e.g., Howe et al., 2019; Lang and Ryder, 2016; Choi, Gao, and Jiang, 2020; Egan and Mullin, 2012; Konisky, Hughes, and Kaylor, 2015),[9] and consider a few-month window

[9] Consistent with previous research, Konisky, Hughes, and Kaylor (2015) suggest that ideology, partisanship, and other attributes are more essential in accounting for personal climate opinions than personal disaster experiences. They report that the marginal effect of a single event is small and short lived—if an extreme event was experienced more than three months ago, the effect on the individual's view largely disappears; notwithstanding, they add that a substantial increase in the frequency or severity of extreme weather-related episodes has a nontrivial effect on individuals' climate change concerns.

Figure 15: Cold wave in February 2019

The figure below sourced from NOAA demonstrates the deviation of the average monthly temperature in February 2019 from the benchmark computed over the period 1981–2010.




following the extreme weather events. However, it was revealed in the previous analyses that even after controlling for a set of variables, the remaining difference between green and brown bonds emerging from confounders (e.g., issuance amount, institutional ownership) poses a great challenge in drawing an unambiguous conclusion on the existence of greenium. Therefore, a thorough examination of the few month window following extreme weather events is difficult to implement without using parametric approach—which allows for the control of multiple variables at the expense of a priori fixing the structure of parameters. Employing a regression approach, after gaining access to Mergent database together with county-level hazard data from SHELDUS, would be a fruitful avenue for future research.[10]

[10]Nevertheless, here I briefly cover preliminary results using descriptive analysis as motivating facts for future research. The effects of cold wave in 2019 and the heat wave in 2018 are nuanced, suggesting that it is hard to draw an informed conclusion from these data points. This is consistent with the findings from Howe et al. (2019) who report that although research are to some extent convinced of the positive link running from the short-term variation in temperature to climate opinions, the magnitude of this effect is not significant. Furthermore, even if climate change perception deepens, it remains ambiguous and debatable whether one makes further efforts to take mitigating measure actions or simply concede and adapt to it. Indeed some studies report the latter case (Wachinger et al., 2013; Brügger, A., Dessai, S., Devine-Wright et al., 2015).

## 5 Robustness checks: air quality and COVID-19

It is unquestionable that greenhouse gases are the leading cause of global warming. However, it is not justifiable to let this fact overshadow the gravity of air pollution problems. As a matter of fact, a spectrum of sources documents that climate change and air pollution are intertwined with one another and thus the reduction efforts should be united under one framework (e.g., Ramanathan and Feng, 2009). With respect to how local residents dynamically react to the change in air quality, a closer look at prior studies can effectively inform the direction of sustainability policies. Bord, O'Connor, and Fisher (2000) and Whitmarsh (2008) suggest that personal experience of illness induced by air pollution alters the perceptions of and behavioural responses to climate-related risks, thereby embedding enhanced pro-environmental values. Similarly, after conducting a survey Tvinnereim, Liu, and Jamelske (2017) report that Chinese respondents, capable of conceptually distinguishing between climate change and air pollution, were aware of the similar causes and detrimental impacts of the both phenomena. On a related note, Chang, Huang, and Wang (2018) interestingly find that more health insurance contracts are sold to Chinese locals when the air is polluted, but they are more likely to be canceled if air quality improves shortly afterward.

By distilling the similar behavioral patterns emerging from these documents, I further hypothesize that the COVID-19 pandemic may induce local people to perceive air quality as a non-negligible issue, thereby shifting their sustainability preference and urging them to take countermeasures such as investing in eco-friendly projects. There is no denying that this postulated behavioral mechanism takes place entirely through a different channel devoid of climate change concern, yet my focal debate here is to highlight how behaviourally responsive and resilient locals can be in the presence of the change in the external environment. Indeed, there are a good amount of sources that likely underpins this conjecture. For instance, mass media kept reporting the link between lockdown measures and the reduced GHG emissions and air pollution levels at the initial stage of the pandemic. Proportionally, corroborative evidence has been accumulating that supports the link between lower air quality and higher mortality rate due to COVID-19 (Wu et al., 2020; Pozzer et al., 2020).

In measuring the increased perception of COVID-19, one way is to follow Alfaro et al. (2020) and use the daily number using Google Trends on a local scale. Figure 16 shows that the search volume on the combination of "coronavirus" and "air pollution" begins to surge in late February and continues to grow until late April, after which the volume shows a downward trend. Figure 17 additionally demonstrates the search volume by regions. A

Figure 16: Searching volume trends on "coronavirus" and "air pollution"

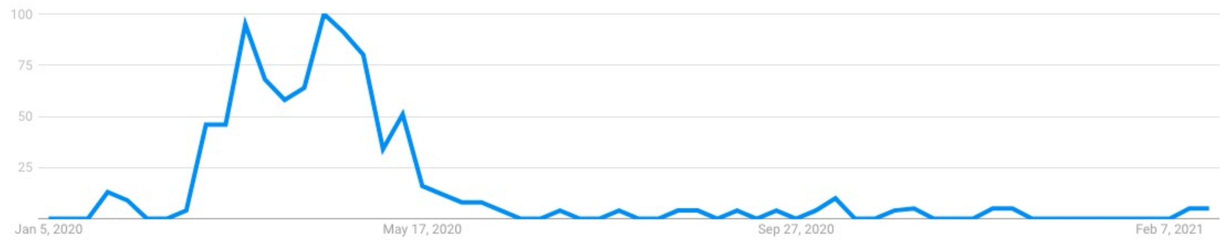
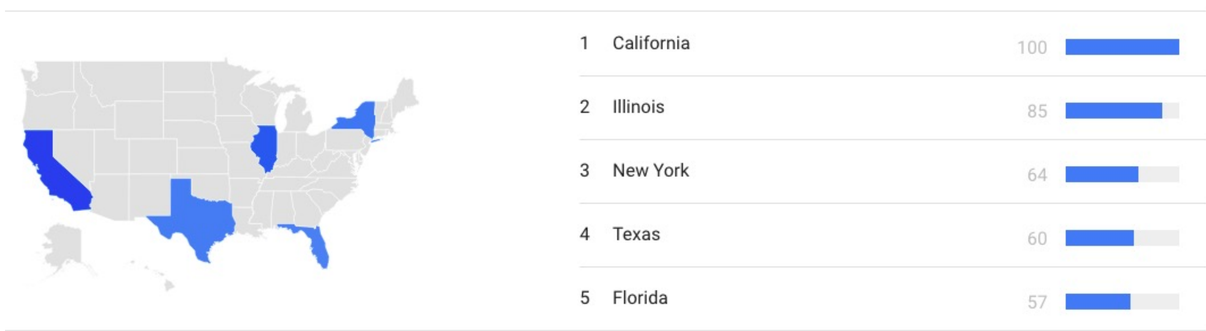



Figure 17: Searching volume trends on "coronavirus" and "air pollution" by subregion




thinkable approach to capturing the effect of COVID-19 on differential bond pricing is to divide the matched bond sample into two subsamples based on pre-COVID and post-COVID periods. Yet, this application is naïve in the sense that it neglects the confounding factors such as issuance amount and the structure of institutional investor, a central issue that was already uncovered in the levels analysis. Additionally, macroeconomic variables such as interest rates, inflation, yield curve, and economic growth are another set of factors that may influence bond yields. Hence, the ideal setup to study the exogenous shock of COVID-19 requires regression analysis, which is capable of controlling for a wide range of variables. However, this setup additionally requires access to Mergent database and thus should be left for future research.

# 6 Conclusion

Local information plays an imperative role in informing policy makers to decide on how to tackle climate change risks through mitigation and adaptation (Howe, Mildenberger, Marlon et al., 2015). In this study, using a model-free matching approach under the first hypothesis, I find strong evidence at the state level that green bonds are priced and traded at a premium (e.g., Massachusetts, Texas, Washington D.C.), at a discount (e.g., California), or mixed depending on the bond callability (e.g., New York). These patterns starkly contrast with the conclusion of LW in which they disprove the existence of greenium. This discrepancy arises presumably because their analysis is implemented in the absence of systematic regional characteristics, thereby balancing out each other's region-specific attributes at the aggregate level. In the presence of confounders, however, it remains to be explored whether the local environmental concern is truly the driver of the observed phenomena suggestive of greenium.

The second hypothesis in this paper postulates that greenium may temporarily arise from the environmental concerns about anthropogenic climate changes amplified by personal disaster experiences. Once again, the descriptive analysis set forth in this paper served as a stepping stone for the next step of regression analysis that can control for a number of confounding factors such as issuance amount and institutional ownership. Thus, a complementary investigation of natural disaster events alongside county level data from SHELDUS database—as opposed to state level data primarily used in this study—is left as an lucrative avenue for future research. This is ever more so as Konisky, Hughes, and Kaylor (2015) stress that geospatial analysis at a granular level is helpful in uncovering the relationship between a personal experience in climatic extreme events and informed climate opinions.

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