Municipal-Treasury spreads and local stock returns*

Fotis Grigoris

November 2023

Abstract

This study shows that municipal bond yields are informative about the risk exposures and expected returns of local firms. An investment strategy that buys (sells) firms located in states where the municipal-Treasury spread is high (low) earns an average return of 0.36% per month. This return differential cannot be explained by limits-to-arbitrage, industry agglomeration, or a host of prominent asset-pricing characteristics. Rather, the municipal-Treasury spread predicts stock returns because it serves as an observable proxy of local fundamentals, such as labor productivity. Firms' risk exposures are higher and state-level fundamentals are weaker in states with higher municipal-Treasury spreads.

*Fotis Grigoris is at the Tippie College of Business, University of Iowa, Pappajohn Business Building, Iowa City, IA 52245 (e-mail: fgrigoris@uiowa.edu). I am grateful to my dissertation committee, Ric Colacito, Eric Ghysels (co-chair), Chris Lundblad (co-chair), and Gill Segal, for their continuous support, mentoring, and encouragement. This paper has also benefited from comments from Yasser Boualam, Stephen Brown, Oleg Chuprinin (discussant), Jennifer Conrad, Stefania D'Amico, Jesse Davis, Anthony Diercks, Dobrislav Dobrev, Andrey Ermolov (discussant), Andra Ghent, Andrei Gonçalves, Christian Heyerdahl-Larsen, Yunzhi Hu, John Hund, Kris Jacobs, Preetesh Kantak, Nina Karnaukh (discussant), Cami Kuhnen, Yan Liu, Dermot Murphy, Marcelo Ochoa, Adam Reed, Jacob Sagi, Donghwa Shin, Andreas Stathopoulos, Noah Stoffman, Charles Trzcinka, Wenyu Wang, and seminar participants at the 32nd Australian Finance and Banking Conference, 2020 Midwest Finance Association annual meeting, Cornerstone Research (New York City), the University of Alberta, the University of South Carolina, the Federal Reserve Board, Washington University in St. Louis, the University of Michigan, Purdue University, the University of Georgia, Indiana University, the University of North Carolina at Chapel Hill, and the Virtual Municipal Finance Workshop. Some of the results in this paper were previously circulated under the title of "The Term Structure of Municipal Bond Yields, Local Economic Conditions, and Local Stock Returns." All errors are my own. First Draft: November 10, 2018.

The $4 trillion U.S. municipal debt market provides a key source of funding for state and local governments and allows these entities to finance their current expenditures by selling debts backed by their expected future cash flows. Given the importance of this market for the provision of essential public services and retirement benefits, a growing body of literature focuses on pricing municipal debt (e.g., Ang, Bhansali, and Xing (2014) and Schwert (2017)) and microstructure issues related to the decentralized broker-dealer market through which municipal debts are traded (e.g., Cestau, Hollifield, Li, and Schürhoff (2019)). There is, however, scarce evidence of whether municipal bond yields convey useful information about future *local* (i.e., state-level) economic outcomes. This is in spite of the plethora of studies that examine whether Treasury yields and credit spreads predict *aggregate* economic outcomes, such as real economic activity and risk premia (e.g., Harvey (1988); Fama and French (1989); Estrella and Hardouvelis (1991); Gilchrist and Zakrajšek (2012)).

In this study I document that the level of a state's municipal-Treasury spread (denoted the "municipal spread" hereafter) is indeed informative about local economic outcomes, namely local equity returns. Specifically, I show that firms located in states where the municipal spread is high (i) earn stock returns that are 0.36% per month higher and (ii) have higher market betas than firms located in states where this spread is low. Moreover, this return differential cannot be explained by mispricing, limits-to-arbitrage, or industry agglomeration. I reconcile facts (i) and (ii) by showing that the municipal spread is higher in states where local economic fundamentals are weaker. As such, a state's municipal spread provides an observable signal of the state's otherwise difficult-to-elicit economic fundamentals that, in turn, affect the risk exposures and expected returns of local firms.

I focus on the information content of the municipal spread for three key reasons. First, since the cash flows underlying municipal bonds depend on *future* economic activity, municipal yields should embed investors' expectations of each bond issuer's economic prospects. Second, the municipal spread is immune to changes in Treasury yields and is *state-specific* by construction. Third, while the municipal spread depends on the tax benefits of owning municipal debt (Green, 1993; Ang, Bhansali, and Xing, 2012; Longstaff, 2011) and liquidity and default risks (Wang, Wu, and Zhang, 2008; Ang et al., 2014; Schwert, 2017; Chun, Namvar, Ye, and Yu, 2019), credit risk has been shown to be the largest driver of the tax-adjusted spread (Schwert, 2017).[1] This means that deteriorating local economic conditions can lead to higher municipal spreads and, in turn, signal bad times for local firms through less spending on both vital infrastructure (e.g., fewer roads and worse utilities can increase the cost of doing business in an area) and services (e.g., worse education and healthcare can harm worker productivity), among other channels. Thus, the tax-adjusted municipal spread is a natural predictor of the economic conditions that local firms are exposed to.

With this in mind, I measure the level of each state's tax-adjusted municipal spread as follows. I begin by constructing the monthly term structures of municipal bond yields for each of the 50 United States and Washington, D.C., using transaction-level data from the Municipal Securities Rulemaking Board (MSRB). These term structures provide a representative one- to 30-year municipal bond yield for each state and span January 1998 through December 2020. Next, I adjust each state's municipal yield curve for the tax exemptions associated with owning municipal debt and then subtract the maturity-matched Treasury yield. Finally, I obtain the average level of each state's municipal spread by estimating the Diebold and Li (2006) representation of the Nelson and Siegel (1987) term-structure model. The advantage of this final step is that the level of the municipal spread is based on the entire term structure of yields in each state and not just the yields for a small set of (potentially arbitrary) maturities (see Ang and Piazzesi (2003) and Ang, Piazzesi, and Wei (2006b)).

I then use this measure to document that higher tax-adjusted municipal spreads do indeed predict lower local asset prices. I establish this fact by constructing an investment strategy that buys (sells) firms located in states where the municipal spread is high (low). This trading strategy, which I refer to as the "HML-Muni" spread (i.e., the high-minus-low municipal spread) earns an average return of about 0.36% per month. The HML-Muni spread

[1] As part of my analysis, I decompose the municipal spread into its liquidity and credit components and show that my results are most consistent with the municipal spread reflecting local credit risk. I also show that the municipal spread is highly correlated with state CDS spreads among the small set of states and the short time series for which these CDS data are available.

is not explained by differences in industry composition across states, and a host of portfolio double sorts and Fama and MacBeth (1973) regressions also confirm that the HML-Muni spread is not driven by other characteristics that are known to predict returns, such as value or momentum. Collectively, these results highlight that current municipal yields in each state are informative about the future returns of local firms.

Why do firms in states with a high municipal spread earn higher returns? I show that the answer hinges on the fact that firms located in these states with a larger default risk premium embedded in their municipal bond yields are more exposed to aggregate risk. I establish this by first documenting that firms in states with higher municipal spreads not only have larger CAPM betas, but that the CAPM renders the alpha of the HML-Muni spread economically small and statistically insignificant. Second, I show that (i) the positive association between the municipal spread and risk exposures and (ii) the insignificant pricing error of the HML-Muni also arise if I use alternative measures of aggregate productivity, such as labor productivity from the Bureau of Labor Statistics (BLS). Thus, the data indicate that firms located in states with higher municipal spreads are indeed riskier.

To better understand this risk, I explore the idea that (i) a state's municipal spread acts as a visible indicator of the local economic conditions that affect all local firms and (ii) firms in economically weaker states suffer more during aggregate downturns. I demonstrate this in two ways. First, I show that the municipal spread is larger in states with weaker macro-level (i.e., output-per-worker) and micro-level (i.e., sales-per-employee) measures of productivity. Second, I show that the HML-Muni spread is highly concentrated among the most local firms in each state, which I proxy for using either each firm's geographic dispersion (García and Norli, 2012) or labor-to-capital ratio. The key assumption here is that firms with geographically concentrated operations that rely more on labor are more heavily influenced by local economic conditions. Collectively, this evidence helps to explain why firms in states with higher municipal spreads are risky: when aggregate shocks hit the national economy, firms located in these less productive states perform particularly poorly.[2]

[2]The negative relation between municipal spreads and state-level productivity could reflect that high

Finally, I rule out several alternative explanations for the HML-Muni spread and conduct numerous robustness checks. For instance, I show that the spread is not driven by mispricing and limits-to-arbitrage (e.g., Korniotis and Kumar (2013)) or an underreaction to cash flow news (e.g., Smajlbegovic (2018)). The spread is also insensitive to methodological variation in the portfolio formation procedure (e.g., different portfolio breakpoints) and alternative measures of the level of the municipal spread (e.g., methods that do not require estimating a term-structure model). Decomposing the municipal spread into its credit and liquidity risk components also shows that the HML-Muni spread is driven by the credit risk component, consistent with the interpretation for the spread provided above. These facts, among others, indicate that the HML-Muni spread is a prominent feature of the data.

Taken together, my results highlight that the municipal debt market not only provides vital source of funding for state and local governments, but also provides valuable and timely information about risks and returns of local firms. This is in spite of the fact that municipal bonds are traded in an opaque market in which concerns regarding liquidity are rampant.

Related literature. My analysis of the information content of municipal bond yields draws on the growing literature that examines the information impounded in these yields. One strand of this literature shows that municipal yields change in response to specific events, such as the funding statuses of public pensions (Novy-Marx and Rauh, 2012), political risk (Babina, Jotikasthira, Lundblad, and Ramadorai, 2020; Gao, Murphy, and Qi, 2019), newspaper closures (Gao, Lee, and Murphy, 2020), opioid usage (Cornaggia, Hund, Nguyen, and Ye, 2021), climate risk (Painter, 2020; Goldsmith-Pinkham, Gustafson, Lewis, and Schwert, 2021), and bank financing (Dagostino, 2022). Another strand of this literature decomposes these yields into parts related to the tax benefits of owning municipal debt, liquidity risk, and default risk (Wang et al., 2008; Ang et al., 2014; Schwert, 2017). Notably, Schwert (2017) shows that over 70% of the tax-adjusted spread between general obligation (GO) municipal and Treasury yields reflects credit risk, despite the infrequency of municipal defaults.

cost of capital states tend to invest less in infrastructure, such as roads, and services, such as healthcare, which hampers productivity. Similarly, the negative relation between productivity and returns can be microfounded by assuming that inputs-to-production are costly to adjust (e.g., İmrohoroğlu and Tüzel, 2014).

In contrast to these studies that explore why municipal bond yields vary, I show that this variation in yields is itself informative about the risk and expected returns of local firms. I establish this fact by first constructing the average monthly spread between tax-adjusted municipal bond yields and Treasury bond yields for each of the 50 United States and Washington, D.C. I then show that a high-minus-low portfolio that buys (sells) firms located in states where the municipal spread is high (low) – referred to as the HML-Muni spread – earns an average return of 0.36% per month. Through the lens of Schwert (2017), and as confirmed by a yield decomposition, this indicates that the local credit risk captured by the municipal spread predicts the expected returns of local firms.

This study also contributes to the literature on return predictability across the United States. Although past studies show that stock returns are influenced by the location of a firm's headquarters and operations (e.g., Pirinsky and Wang (2006); Hong, Kubik, and Stein (2008); García and Norli (2012)), there is no consensus as to why this is the case. For instance, Korniotis and Kumar (2013) and Da, Warachka, and Yun (2018) suggest that the equity market is partially segmented along state lines, such that home-biased investors impact local asset prices. While Korniotis and Kumar (2013) propose that local investors induce local assets to become mispriced, Da et al. (2018) indicate that countercyclical fiscal policies reduce the consumption risks of local investors, and hence the cost of equity for local firms. However, neither explanation accounts for the HML-Muni spread, which is not driven by either easy-to-misprice firms or states with countercyclical fiscal policies.[3]

Unlike these studies that explain geographic variation in stock returns via the interaction between limits-to-arbitrage and different *prices* of risk across states, my results indicate that states are also heterogeneous with respect to their *quantity* of risk. This is broadly in line with Tuzel and Zhang (2017), who show that risk exposures vary across more granular metropolitan statistical areas (MSAs). While aligned with the HML-Muni spread, cross-

[3]Geographic differences in returns may also arise if investors underreact to geographic variation in cash flow news (Smajlbegovic, 2018; Parsons, Sabbatucci, and Titman, 2020). In contrast to this possibility, I find no evidence that the HML-Muni spread is explained by an underreaction to cash flows. For example, earnings surprises are indistinguishable between firms in states with high and low municipal spreads.

sectional differences in the Tuzel and Zhang (2017) measure of "local beta" do not, however, explain the HML-Muni spread. Controlling for MSA-level betas through either Fama and MacBeth (1973) regressions or portfolio double sorts still produces an economically large and significant HML-Muni spread. This suggests that the level of each state's municipal spread conveys some additional and value-relevant information about the risk exposures of local firms that is not completely captured by the more granular MSA-level beta.

Finally, my study also relates to the literature that uses asset prices to predict real and financial outcomes (e.g., Keim and Stambaugh (1986); Fama and French (1989); Ang et al. (2006b)). Notably, prior studies show that commercial paper (Bernanke, 1990; Friedman, Kuttner, and Bernanke, 2008), corporate bond (e.g., Gilchrist and Zakrajšek (2012)), loan spreads (Saunders, Spina, Steffen, and Streitz, 2021), and junk bond yields (Gertler and Lown, 1999) predict *aggregate* economic activity. Moreover, Grigoris (2022) shows that municipal spreads predict *local* economic activity, such as a state's gross state product (GSP). In a similar vein, I show that *local* credit spreads, which I proxy for using the municipal spread, predict the expected returns of *local* firms. This is distinct from Han, Subrahmanyam, and Zhou (2017), who show that *firm-level* CDS yields predict *firm-level* returns.

1 Data

My sample period ranges from January 1998 through December 2020. Data on municipal bond and Treasury bond yields, stock return, and accounting characteristics are obtained from the sources outlined below.

Municipal bond yields. I construct the monthly term structures of state-level municipal bond yields using transaction-level data from the MSRB. I use this MSRB data, along with issuer- and bond-level characteristics from the Mergent Municipal Bond Database, to build each term structure by following the procedure detailed in Section OA.2 of the Online Appendix. In short, I use the Nelson and Siegel (1987) model to extract the underlying municipal yield curve associated with the monthly transactions observed in each state and the

District of Columbia. I retain yields related to maturities ranging from one to 30 years, as very short-term bonds carry negligible risk, while there is a steep decline in trading volume for bonds with very long maturities (see Figure OA.1 in the Online Appendix).

Table OA.1 in the Online Appendix provides the summary statistics of these term structures both within and across states. For instance, the average one (20) year municipal bond yield is 1.77% (3.97%) per annum. Notably, the levels (first differences) of the yield curves I construct have an average correlation of 0.97 (0.64) with those from Bloomberg, which are available for only a subset of 19 states.[4] Figure OA.2 in the Online Appendix then displays the average term structure of municipal bond across all states underlying the sample.

Treasury data. Treasury yield data from Liu and Wu (2021) are used to measure the monthly term structure of the nominal risk-free rate.[5]

Stock return and accounting data. Monthly stock return data are from the Center for Research in Security Prices (CRSP), and accounting data are from the CRSP/Compustat Merged file. Asset-pricing factors related to the Fama and French (1993, 2015) and Carhart (1997) models are from the data library of Kenneth French, and the q-factors of Hou, Xue, and Zhang (2015) are from the Global-q data library.

1.1 The municipal-Treasury spread

I obtain the monthly term structures of municipal bond yields for each of the 50 United States and Washington, D.C., by following the procedure detailed in Section OA.2 of the Online Appendix. This procedure uses the *cross section* of yields in each state i to measure the state's term structure of municipal bond yields at the end of each month t. As such, the term structure of yields for each state i is observable at the end of each month t. With these term structures in hand, I express the zero-coupon yield of a m-month municipal bond

[4]As explained in Section OA.2 of the Online Appendix, Bloomberg produces yield curves for only a subset of 19 states because they apply significantly stricter filters to the MSRB data. These stricter filters are employed, in large part, to better capture the *cross-section* of yield at a very high (i.e., intra-day) frequency. In contrast, I can apply significantly fewer filters to the MSRB transaction data since I am primarily interested in measuring the term structure of yields at a lower (i.e., monthly) frequency.

[5]These data are available at `https://sites.google.com/view/jingcynthiawu/yield-data`.

issued by state i at the end of month t as

$$y_{i,t}(m) = (1 - \tau_{i,t}) \left[Y_t(m) + \phi_{i,t}(m) \right]. \tag{1}$$

Equation (1) shows that municipal bond yields depend on three determinants: the underlying maturity-matched Treasury yield, $Y_t(m)$; a wedge that captures the difference in yields between taxable Treasury bonds and tax-advantaged municipal bonds, $(1-\tau_{i,t})$; and a state-specific component of municipal bond yields, $\phi_{i,t}(m)$.

The state-specific component of yields in equation (1) is my empirical object of interest as this aspect of yields is the most likely to reflect local economic conditions. Schwert (2017), for instance, focuses on GO bonds and shows that over 70% of the variation in $\phi_{i,t}(m)$ captures issuer-level default risk. While Ang et al. (2014) suggest $\phi_{i,t}(m)$ is driven by liquidity risk, both Wang et al. (2008) and Novy-Marx and Rauh (2012) also find that $\phi_{i,t}(m)$ contains a large credit risk component. Thus, drawing on the growing literature that employs credit spreads to forecast firm- and macro-level outcomes (e.g., Gilchrist and Zakrajšek (2012); Han et al. (2017)), I consider whether state-level credit risk is associated with the expected returns of local firms. Section 4.2 decomposes $\phi_{i,t}(m)$ into default and liquidity risk components and confirms that my results are indeed most consistent with the notion that $\phi_{i,t}(m)$ predominantly reflects local credit risk.

Tax adjustment. Since municipal bond holders are often exempt from paying both federal income taxes on interest from municipal debt and state incomes taxes on interest from debts issued by their state of residence, there is a wedge between the yields of tax-exempt municipal and taxable Treasury bonds. I account for this difference in tax treatment by following the tax-adjusted procedure employed by Schwert (2017). That is, I scale municipal yields by $\frac{1}{(1-\tau_{i,t})}$, where $1 - \tau_{i,t} = (1 - \tau_t^{Fed})(1 - \tau_{i,t}^{State})$, and τ^{Fed} and $\tau_{i,t}^{State}$ are the top statutory federal and state income tax rates for state i at time t, respectively.[6]

Applying this tax adjustment and then subtracting the maturity-matched Treasury yield

[6] The tax rates are from the NBER's TAXSIM program (`https://users.nber.org/~taxsim/`). Table 9 shows that my key results are essentially unchanged if I do not apply this tax adjustment.

allows me to express the tax-adjusted municipal-Treasury spread as $\tilde{y}_{i,t}(m)$, where

$$\tilde{y}_{i,t}(m) \equiv [y_{i,t}(m) \;/\; (1 - \tau_{i,t})] - Y_t(m) = \phi_{i,t}(m). \tag{2}$$

As discussed above, the tax-adjusted municipal-Treasury spread (denoted the "municipal spread" hereafter) is my object of interest since $\tilde{y}_{i,t}(m)$ captures the state-specific component of municipal yields and serves as a natural measure of local economic conditions.

1.2 Measuring the level of the municipal-Treasury spread

With a measure of each state's municipal spread in hand, I consider whether the *level* of the municipal spread in month t predicts the future average returns of local firms. My focus on yields as a predictor of expected returns is partly motivated by studies showing that aggregate economic outcomes and expected returns may be predicted by (i) Treasury yields (e.g., Harvey (1988); Fama and French (1989); Estrella and Hardouvelis (1991); Ang et al. (2006b)) and (ii) credit spreads (e.g., Bernanke (1990); Gilchrist and Zakrajšek (2012)). Moreover, I also draw on studies that document that firm-level credit spreads convey information about firm-level returns (e.g., Han et al. (2017)).

I examine the information content of the *level* of each state's municipal spread by harnessing an empirical approach that is motivated by the large literature on term structure modeling. Specifically, my main measure of the level of the municipal spread is based on the Nelson and Siegel (1987) term-structure model. This approach captures variation in yields across the entire term structure of municipal spreads rather than focusing only on a small set of yields associated with (potentially arbitrary) maturities (Ang and Piazzesi, 2003; Ang et al., 2006b; Diebold, Rudebusch, and Aruoba, 2006). As an alternative and model-free approach, I also define the level of the municipal spread as $\tilde{y}_{i,t}(240)$, or state i's 20-year municipal spread. While this alternative is easy to construct, the drawback is that this approach exploits information in only one point on the entire term structure.

I measure the level of each state's municipal spread by distilling that state's term structure of municipal spreads into a low-dimensional set of yield factors that drive variation in yield spreads across all maturities (Litterman and Scheinkman, 1991). Namely, I use the Diebold and Li (2006) representation of the Nelson and Siegel (1987) model to express the m-month municipal spread as a maturity-dependent linear combination of three time-varying and state-specific yield factors. While this model was developed to describe Treasury yields, the same model has also been applied in other contexts. For example, Broner, Lorenzoni, and Schmukler (2013) apply the model to yield spreads in emerging markets and Yu and Salyards (2009) use the model to study corporate bond yields. As such, this model provides a theoretically and empirically motivated method to distill each state's term structure of municipal spreads into a low-dimensional set of state-level yield factors via

$$\tilde{y}_{i,t}(m) = L_{i,t} + S_{i,t}\left(\frac{1-e^{-\lambda m}}{\lambda m}\right) + C_{i,t}\left(\frac{1-e^{-\lambda m}}{\lambda m} - e^{-\lambda m}\right) + v_{i,t}(m). \tag{3}$$

Here, $\tilde{y}_{i,t}(m)$ is the municipal spread for a bond outstanding in state i in month t that has m months-to-maturity (recall equation (2)) and $\{L_{i,t}, S_{i,t}, C_{i,t}\}$ is the set of state-level yield factors to be estimated. These factors often denoted the level, slope, and curvature of the yield curve (see Diebold et al. (2006)). The term multiplying each factor is a maturity-dependent loading, λ is a shape parameter that governs the loadings of $S_{i,t}$ and $C_{i,t}$, and $v_{i,t}(m)$ is the bond's pricing error. As equation (3) is estimated using the *cross section* of municipal yield spreads in each state at the end of each month t, the resulting yield factors are observable at the end of each month. Consequently, the investment strategy in Section 2 that is based on these yield factors is tradable.

I obtain the yield factors in equation (3) by fixing $\lambda = 0.0240$ and estimating a cross-sectional OLS regression for each state i at the end of each month t. This choice of λ implies that the loading on $C_{i,t}$ is maximized for bonds with around seven- to eight-year maturities, roughly corresponding to the average maturity of municipal bonds in the MSRB transaction-level data (see Table OA.1 in the Online Appendix).[7] While λ may, in principle,

[7]Figure OA.3 in the Online Appendix shows the model's factor loadings with $\lambda = 0.0240$.

vary across states and over time, estimating $\lambda_{i,t}$ alongside the yield factors requires non-linear methods, such as non-linear least squares. I do not consider this generalization in my baseline analysis, for two reasons. First, Diebold et al. (2006) note that fixing λ achieves numerical stability without sacrificing model fit. Second, I ensure that my results are not driven by any particular choice of λ by simply measuring the level of the municipal spread as $\tilde{y}_{i,t}(240)$, thereby avoiding the need to estimate equation (3) altogether.

1.3 Summary statistics of the municipal yield factors

Figure 1 shows the dynamics of the level of the municipal spread obtained from equation (3). Here, the figure reports the GSP-weighted average value of $L_{i,t}$ and the cross-sectional dispersion of $L_{i,t}$ across states. The key takeaway is that $L_{i,t}$ shows a significant amount of time-series and cross-sectional variation, spiking during the 2008 to 2009 crisis and the onset of the COVID-19 pandemic in March 2020. As expected, the level of the municipal spread is countercyclical and has a correlation of -0.17 (-0.10) with the growth rate of industrial production (excess market returns). This once again supports the notion that the level of the municipal spread is related to state-level credit risk.[8] Moreover, the large dispersion in yield spreads across states indicates that the cross-sectional asset-pricing tests implemented in Section 2.1 are sufficiently powerful to examine the relation between local economic prospects, as reflected by the level of the municipal spread, and the expected returns of local firms.

Summary statistics in Panel A of Table 1 show that $L_{i,t}$ has a mean of 3.60% and a time-series volatility (cross-sectional dispersion) of 0.90% (0.71%). While the level of the municipal spread is somewhat volatile, the average spread is positive throughout the sample period, reaching a minimum (maximum) of 1.82% (8.01%). This factor is also somewhat persistent, with a one-month (12-month) autocorrelation coefficient of 0.89 (0.07). The table also reports the same summary statistics for the $S_{i,t}$ and $C_{i,t}$ factors from equation (3).

[8] Beyond the evidence in Table 9 that shows that variation in the level of the municipal-Treasury spread is driven by the credit- rather than the liquidity-risk component of yields, Section OA.12 of the Online Appendix also shows that changes in the level of a state's municipal-Treasury spread are positively and significantly correlated with changes in the state's CDS yields in 21 out of 23 states with available data.

While the yield factors in equation (3) are often referred to as the level ($L_{i,t}$), slope ($S_{i,t}$), and curvature ($C_{i,t}$) of the Treasury yield curve, it is not clear how changes in these factors affect the term structures of municipal spreads. Thus, I ascribe an economic interpretation to each factor by examining its correlation with key municipal yield spreads. These correlations are computed by finding the GSP-weighted average time-series correlation between the state-level yields and yield factors across states. These GSP-weighted correlations are then reported in Panel B of Table 1.

The results show that $L_{i,t}$ is indeed closely related to the level of the municipal spread, as the average correlation between $L_{i,t}$ and $\tilde{y}_{i,t}(240)$ across the states is 0.88. Thus, I refer to $L_{i,t}$ as the "level" factor. Since increases in $S_{i,t}$ ($C_{i,t}$) are associated with decreases in the $\tilde{y}_{i,t}(240) - \tilde{y}_{i,t}(12)$ ($\tilde{y}_{i,t}(360) - \tilde{y}_{i,t}(120)$) yield spread, I refer to $S_{i,t}$ and $C_{i,t}$ as the "short-term slope" and "long-term slope" factors, respectively. This is because increases in $S_{i,t}$ ($C_{i,t}$) flatten the short-term (long-term) slope of the term structure of municipal spreads.[9] Finally, Panel B of Table 1 reports the time-series correlations between the three sets of yield factors. The GSP-weighted $L_{i,t}$ ($S_{i,t}$) factor is moderately correlated with the GSP-weighted $S_{i,t}$ ($C_{i,t}$) factor, while the $L_{i,t}$ and $C_{i,t}$ factors are weakly negatively correlated.[10]

2 Municipal yield spreads and local stock returns

2.1 Portfolio returns

Local stock returns. I implement all asset-pricing tests by defining a set of local (i.e., state-level) stock returns. Specifically, each state's returns are constructed using all firms headquartered in a given state (or Washington, D.C.) according to their Compustat

[9]While it is common to define the curvature of the yield curve as $2 \times \tilde{y}_{i,t}(120) - \tilde{y}_{i,t}(12) - \tilde{y}_{i,t}(360)$ this empirical proxy of curvature has a lower correlation with $C_{i,t}$ than $\tilde{y}_{i,t}(360) - \tilde{y}_{i,t}(120)$.

[10]The non-zero terms in the off-diagonal elements of this correlation matrix highlight a key difference between the latent yield factors extracted via the Diebold and Li (2006) framework and those extracted via Principal Component Analysis (PCA). While PCA allows factor loadings to vary, such that the extracted yield factors are mutually orthogonal, the yield factors extracted via the Diebold and Li (2006) model are conditional on a fixed set of factor loadings and are not required to be mutually orthogonal by construction.

headquarter (HQ) locations, supplemented with HQ location data from 10-K/Q filings.[11] I use a firm's HQ location as a proxy for the firm's location in accordance with the literature that examines the geography of stock returns and firm-level investment (e.g., Coval and Moskowitz (1999, 2001); Pirinsky and Wang (2006); Dougal, Parsons, and Titman (2015)). Moreover, Tuzel and Zhang (2017) document that roughly two thirds of the firms in their sample base the majority of employees in the firm's HQ location. Together with Chaney, Sraer, and Thesmar (2012), who show that production facilities tend to cluster in the state of a firm's HQ, this suggests that HQ location is a suitable baseline proxy for a firm's location.

While I use Compustat's HQ location as my main proxy for a firm's location, Section 3.2 ensures that my results are robust to this definition. There, I construct state-level portfolios using an approach motivated by García and Norli (2012). That is, I group firms into portfolios based on the geographic scope of each firm's operations as elicited from the firm's 10-K filings and I only retain the most local firms in each state-level portfolio.

After identifying each firm's HQ location, I retain the firms in each state that are common stocks (CRSP SHRCD code 10 or 11) listed on the NYSE/AMEX/NASDAQ exchanges, excluding financial firms and utilities. I then compute the value-weighted mean return across all stocks in each state's portfolio. To reduce measurement error, I exclude states with fewer than ten firms satisfying the aforementioned data filters at any time in the sample period.[12] This results in a panel of stock returns for the 31 states that remain in the sample.

Portfolio formation. I examine the relation between the *current* level of a state's municipal spread and *future* stock returns by sorting the cross-section of states into portfolios based on the level of each state's municipal spread. Specifically, I obtain the level of the municipal spread in state i at the end of each month t (i.e., $L_{i,t}$) by estimating equation (3). I then sort states into portfolios based the average values of $L_{i,t}$ over the preceding three

[11] Supplementing the location from Compustat with location data from each firm's 10-K/Q filings overcomes the fact that Compustat only reports the most recent HQ location for each firm.

[12] This requirement removes the following 20 states and districts from the sample: Alaska (AK), Alabama (AL), Washington, D.C. (DC), Delaware (DE), Hawaii (HI), Idaho (ID), Kansas (KS), Louisiana (LA), Maine (ME), Mississippi (MS), Montana (MT), North Dakota (ND), New Hampshire (NH), New Mexico (NM), Rhode Island (RI), South Carolina (SC), South Dakota (SD), Vermont (VT), West Virginia (WV), and Wyoming (WY). Table OA.1 in the Online Appendix shows that average number of firms in each state.

months. Each portfolio is held for one month before rebalancing all portfolios at the end of month $t + 1$. This monthly rebalancing captures conditional variation in the level of each state's term structure of municipal spreads.

Three portfolios are formed at the end of each month from January 1998 through November 2020. The low (high) portfolio includes the five states with the lowest (highest) level of the municipal spread in the prior month, while the medium portfolio contains the remaining states.[13] Since each state-level portfolio comprises many underlying firms (often hundreds), this choice of portfolio breakpoints produces three well-diversified portfolios.[14]

Portfolio returns. Table 2 reports the monthly returns of portfolios formed on the level of each state's municipal spread. The results show that there is an economically and statistically significant difference between the returns of the high and low municipal spread-sorted portfolios. Notably, the portfolio that buys (sells) firms located in states where the level of the municipal spread is high (low) earns an average value-weighted return of 1.10% (0.74%) per month. Thus, the high-minus-low return spread, which I refer to as the "HML-Muni" spread, is 0.36% per month and statistically significant at the 5% level.[15] As the monthly volatility of the HML-Muni spread is 2.71%, the Sharpe ratio of the spread is 0.46 per annum, roughly matching the market's Sharpe ratio of 0.43 over the same time period.

The table also shows that, by constitution, the average level of the municipal spread monotonically increases from 2.98% to 4.31%. Furthermore, as there are typically 413 (492)

[13]Section 4.2 shows that these results are robust to numerous aspects of the baseline portfolio formation procedure, such as changing the number of states in each portfolio, using different portfolio rebalancing frequencies, measuring the level of the municipal spread in different ways, and excluding specific states.

[14]Table OA.4 in the Online Appendix reports the transition matrix associated with this portfolio formation procedure. The table shows that a state sorted into either the low or the high portfolio has an approximately 80% chance of remaining in the same portfolio in the next month. A state currently in the middle portfolio has about a 5% chance of transitioning into one of the extreme portfolios in the following month. Additionally, Figure OA.4 in the Online Appendix displays the frequency of portfolio membership by state and shows that all states are sorted into multiple portfolios over the sample period, while Figure OA.5 displays the proportion of transitions over time and shows that transitions are dispersed throughout the sample. Finally, Table OA.11 shows that no spread emerges when sorting states on the unconditional level of the municipal spread. Combined, these results indicate that the portfolio formation procedure is picking up conditional variation in the level of the municipal spread rather fixed differences in average yields across states.

[15]Figure OA.6 in the Online Appendix translates this average monthly return into the cumulative return of investing in the HML-Muni spread over the sample period.

firms underlying the high (low) portfolio, the composition of each portfolio in terms of the number of underlying firms is similar to that which would arise from sorts conducted at the firm rather than the state level. Finally, three key robustness checks are also reported.

First, to ensure that the value-weighted returns of each portfolio are not driven by a small number of large firms in each state (e.g., the Target Corporation in Minnesota or the Ford Motor Company in Michigan), I construct the HML-Muni spread by equal-weighting the firms in each state-level portfolio. The results show the equal-weighted spread remains sizable at 0.26% per month and statistically significant at the 5% level.

Second, to account for differences in industry composition across states (e.g., oil and gas extraction dominates the Texas portfolio, while chemical manufacturing is prevalent in the North Carolina portfolio), I construct the HML-Muni spread using industry-adjusted portfolio returns. These returns are calculated by subtracting the monthly value-weighted return of the appropriate Fama-French 10 industry group from each firm's raw monthly return. The table shows that the industry-adjusted HML-Muni spread is 0.27% per month, a quantity that is statistically significant at the 10% level.

Third, to verify the HML-Muni spread is not driven by differences in firm size, value, and momentum across geographically disparate states (e.g., the possibility that technology firms in California are value oriented, while manufacturing firms in Michigan are growth oriented), I also construct a characteristic-adjusted return spread. This adjustment is implemented by subtracting the appropriate Daniel, Grinblatt, Titman, and Wermers (1997) benchmark return from each firm's raw monthly return.[16] The characteristic-adjusted HML-Muni spread remains economically sizable at 0.33% per month and significant at the 5% level.

Overall, Table 2 shows that variation in the level of each state's municipal spread predicts geographic differences in stock returns: returns are significantly higher in states where the level of the municipal yield curve is higher, regardless of how portfolio returns are measured.

[16] This is not the only way I verify this fact: Section 2.2 reports portfolio characteristics, Section 2.3 conducts Fama and MacBeth (1973) regressions that control for prominent characteristics, and Table OA.5 in the Online Appendix reports portfolio double sorts that further confirm that the HML-Muni spread persists after controlling for the return spreads associated with the small number of confounding characteristics.

The next sections show that (i) the HML-Muni spread is not a manifestation of known asset-pricing characteristics and (ii) discuss why the HML-Muni spread arises. In short, there is a risk-based explanation for the spread, as firms located in states with high municipal spreads are more exposed to systematic risk and consequently earn higher average returns.

2.2 Portfolio characteristics

Table 2 reports this paper's key stylized fact and shows that the current level of a state's municipal spread is informative about future local stock returns. The purpose of the following sections is twofold. First, I report the characteristics of each spread-sorted portfolio to ensure that the HML-Muni spread is not driven by any firm-level characteristics that are known to predict returns. Second, after establishing that the HML-Muni spread is not driven by these characteristics, I propose a risk-based explanation for why the level of the municipal spread predicts cross-sectional differences in returns.

To make sure that the HML-Muni spread does not simply reflect differences in characteristics, such as profitability and investment, across states, Table 3 reports the portfolios' characteristics. These characteristics are industry-adjusted to account for the effects of industry agglomeration and are computed in three steps: (1) I assign each firm to a Fama-French 10 industry group and subtract the relevant industry's cross-sectional mean characteristic from each firm's characteristic; (2) I compute the value-weighted average of each characteristic across all firms in a given state; and (3) I compute the equal-weighted average of these state-level characteristics across all states assigned to each portfolio. Table 3 then reports both the time-series averages of these portfolio-level characteristics and the differences in these characteristics between the high and low spread-sorted portfolios.

Table 3 shows that there are no statistically significant differences among the spread-sorted portfolios in terms of leverage, total asset growth (Cooper, Gulen, and Schill, 2008), physical investment, organization capital (Eisfeldt and Papanikolaou, 2013), return momentum (Jegadeesh and Titman, 1993), short-term reversals (Jegadeesh, 1990), and idiosyncratic productivity (İmrohoroğlu and Tüzel, 2014). Thus, the HML-Muni spread cannot be explained by these common predictors of stock returns. Likewise, while there are significant differences in size, book-to-market ratios, profitability rates, and idiosyncratic return volatility between the low and high spread-sorted portfolios, these characteristics cannot explain the return spread either. This is because the return spreads associated with these characteristics run counter to the sign of the HML-Muni spread (e.g., large firms and growth firms tend to earn low, not high, average returns).

There are, however, two statistically significant differences in characteristics between the low and high spread-sorted portfolios that are aligned with the HML-Muni spread. Specifically, firms located in states where the level of the municipal spread is higher have significantly lower hiring rates (Belo, Lin, and Bazdresch, 2014) and higher local betas, or β (MSA) (Tuzel and Zhang, 2017). Thus, Section 2.3 conducts Fama and MacBeth (1973) regressions and portfolio double sorts that show that these two characteristics do not reconcile the high returns of firms located in states where the level of the municipal spread is high.

2.3 Fama-MacBeth and portfolio double-sort analyses

I perform Fama and MacBeth (1973) regressions to show that the level of the municipal spread is useful for predicting excess returns beyond the effects of the hiring rate, local beta, and a host of other characteristics known to predict returns. These regressions are implemented in two steps. First, in each month t, I estimate the following cross-sectional regression in which the dependent variable is state i's excess return in month $t+1$, and the independent variable is a vector of characteristics, $\boldsymbol{X}_{i,t}$, measured as of month t:

$$R_{i,t+1} = \beta_{0,t} + \boldsymbol{\beta}_t' \boldsymbol{X}_{i,t} + \varepsilon_{i,t+1}. \tag{4}$$

The vector $\boldsymbol{X}_{i,t}$ includes the level of the municipal spread ($L_{i,t}$ from equation (3)); the natural logarithms of the average size and book-to-market ratio of firms in state i; the average investment rate; hiring rate; profitability; organizational capital; firm-level productivity; local beta; and idiosyncratic volatility of firms in a given state. Each variable is divided by its unconditional standard deviation to aid comparisons between specifications. Second, after running these cross-sectional regressions, I then compute the time-series average of the estimated slope coefficient to assess the relation between a given characteristic and future stock returns, while holding other characteristics fixed. The results are reported in Table 4.

Column (1) of Table 4 shows that, without any controls, there is a positive and statistically significant association between the current level of a state's municipal spread and future returns. A one standard-deviation increase in a state's municipal spread in month t predicts a 0.31% higher return in month $t+1$. Columns (2) to (10) then present bivariate regressions showing that this positive and statistically significant relation persists regardless of which extra characteristic is included in equation (4). The fact that these common characteristics are statistically insignificant is not altogether unexpected, as many of the relations between these characteristics and expected returns are strongest at the firm level. Collectively, this evidence highlights that the municipal spread is a distinct predictor of local stock returns.

Portfolio double sorts. Table OA.5 in the Online Appendix supports the conclusion of this regression analysis by conducting portfolio double sorts. The table shows that controlling for the average value of each state's hiring rate or local beta (i.e., the characteristics in Table 3 that are aligned with the HML-Muni spread), and then sorting states based on the municipal spread, still results in an economically sizable and significant HML-Muni spread.

3 Municipal spreads and returns: a risk-based relation

This section documents a risk-based explanation for the HML-Muni spread. I show that the HML-Muni spread arises because states with higher municipal spreads tend to have weaker local economic fundamentals, such as lower labor productivity. Consequently, firms in these less productive states are risky because their returns covary more with aggregate economic conditions, especially during bad times. As such, these firms must provide investors with higher average returns.

To establish these facts, Section 3.1 begins by demonstrating that states with higher municipal-Treasury spreads do indeed covary more with aggregate economic conditions. There, I measure geographic differences in the risk exposures of local firms using the CAPM and two proxies of labor productivity. This section also shows that a single-factor asset-pricing model can explain the high returns of the HML-Muni spread. Section 3.2 explores this relation by showing that (i) the HML-Muni spread is indeed concentrated among the most localized firms and (ii) the municipal-Treasury spread is a reliable predictor of local (labor) productivity. Overall, the level of a state's municipal spread serves as an observable proxy for the *unobservable* health of a state's economy that affects the risks of all local firms.

3.1 Risk exposures and pricing errors

Having shown that (i) the municipal spread is informative about cross-sectional differences in average stock returns, and (ii) the HML-Muni spread is not driven by geographic variation in characteristics, such as hiring rates, I examine whether the relation between municipal spreads and local stock returns is explained by exposure to macroeconomic risk. Specifically, I examine whether geographic variation in exposure to aggregate productivity explains the HML-Muni spread. This is motivated by studies including Zhang (2005), Belo and Lin (2012), and İmrohoroğlu and Tüzel (2014) that show that exposure to aggregate productivity can explain several prominent return spreads, such as the value premium.

I estimate the following regression to examine the unconditional risk exposure of each municipal spread-sorted portfolio using different proxies for aggregate productivity

$$R^e_{p,t} = \alpha_p + \beta_p \text{AggProd}_t + \varepsilon_{p,t}. \tag{5}$$

Here, $R^e_{p,t}$ is the value-weighted excess return of portfolio p at time t, AggProd_t is a measure of aggregate productivity, and β_p captures the exposure of portfolio p to this measure. I implement this analysis using three different proxies for aggregate productivity: (i) excess market returns, (ii) labor productivity from the BLS, and (iii) a tradable proxy for labor productivity that is constructed by following the approach of Adrian, Etula, and Muir (2014).[17] Since labor productivity data are available only quarterly, equation (5) is estimated using quarterly returns. Consequently, α_p can be interpreted as a pricing error (e.g., the CAPM alpha) when using the two tradable proxies for aggregate productivity.

Table 5 shows each portfolio's exposure to aggregate productivity. Column (1) begins by reporting the average excess return of each portfolio and mimics the baseline results in Table 2, albeit on a quarterly basis. Columns (2) and (3) then show each portfolio's CAPM alpha and beta, respectively. The beta is not only monotonically increasing with the average level of the municipal spread, but the difference in betas between the low and high portfolio is 0.13 and statistically significant at the 5% level. This economically large difference in CAPM betas renders the CAPM alpha of the HML-Muni spread statistically insignificant and provides the first indication that there is a risk-based explanation for the spread.

Next, I consider the economic basis and robustness of this result. Tuzel and Zhang (2017) demonstrate that local firms' risk exposures vary based on their specific local factor markets, such as the markets for labor and real estate. As the difference in hiring rates between the low and high spread-sorted portfolios is one of the most prominent distinctions in Table 3, I consider whether firms have different exposures to labor productivity depending on their location. To this end, Columns (4) and (5) substitute labor productivity from the BLS for excess market returns in equation (5) and confirm that firms in states with higher municipal-Treasury spreads are indeed more exposed to fluctuations in (labor) productivity.

Finally, since labor productivity from the BLS is not a tradable factor, the pricing error in Column (4) is uninterpretable. As such, Columns (6) and (7) employ a tradable version of the labor productivity factor and repeat the previous regressions. Once again, the results indicate that firms in states with higher municipal-Treasury spreads are more exposed to fluctuations in aggregate productivity. The pricing error in Column (6) is also half of the

[17] Specifically, I project labor productivity from the BLS on the quarterly returns of six size and B/M-sorted portfolios, the momentum factor from Carhart (1997), the excess market return, and the risk-free rate. Each basis asset is drawn from Kenneth French's data library and the fitted value of this projection is positively correlated with the non-traded measure of labor productivity from the BLS.

magnitude of the HML-Muni spread and statistically insignificant. This evidence further supports the notion that geographic differences in exposures to aggregate risk explain the HML-Muni spread. Overall, Table 5 supports a risk-based explanation for the spread.

Time-varying exposures. Section OA.3 in the Online Appendix demonstrates that a high municipal spread also predicts (i) the conditional market betas of the state-level portfolios, (ii) the conditional market betas of local firms, and (iii) the future excess returns of local firms. These results are obtained by estimating panel regressions that control for both firm characteristics and combinations of state, time, and industry fixed effects.

Together with Section OA.3 of the Online Appendix, this section demonstrates that firms in states with higher municipal spreads earn higher excess returns because they are more exposed to aggregate risk. Section 3.2 explores this relation in more detail and shows that (i) the HML-Muni spread is concentrated among the most localized firms in each state, and (ii) the level of the municipal spread negatively predicts local productivity. These facts highlight that a state's municipal spread serves as an observable, high-frequency, proxy for the latent productivity of the local economy that impacts the risk exposures of local firms.

3.2 Heterogeneity in firm localization and labor productivity

3.2.1 Differences in firm localization and labor intensity

Firm localization. The portfolio sorts in Section 2.1 use state-level portfolios that are constructed by assigning each firm to a state based on the location of the firm's HQ in Compustat, supplemented with HQ location data from the firm's 10-K/Q filings. While this approach produces state-level returns that are easy to construct, the location of a firm's HQ is only a rough proxy for the firm's exposure to a local economy. Therefore, if (i) the level of the municipal spread predicts local business conditions, and (ii) the returns of local firms are sensitive to the local business cycle, then the HML-Muni spread should be larger among firms whose operations are concentrated in the same state as the firm's HQ.

I examine this conjecture by following García and Norli (2012) to produce a more granular measure of local stock returns. That is, I construct state-level portfolios by crawling the Electronic Data Gathering, Analysis, and Retrieval (EDGAR) system of the U.S. Securities and Exchange Commission, and then counting the number of states each firm mentions in its 10-Ks. I then consider a firm headquartered in a particular state as more exposed to local economic conditions if the firm mentions fewer names of other states in its 10-K.

As a concrete example of the intuition underlying this test, consider two Minnesota-based firms: Electro-Sensors, Inc. (NASDAQ: ELSE), a manufacturer that lists fewer than five states in its 10-Ks, and the Target Corporation (NYSE: TGT), a retailer that often mentions all 50 states in its 10-Ks. To the extent that the level of Minnesota's municipal spread predicts business conditions in the state, the municipal spread in Minnesota is more likely to predict the returns of ELSE, whose investors and cash flows are likely concentrated in Minnesota, than the returns of TGT, whose investors and cash flows are likely dispersed across the country. I test this conjecture as follows.

I use the state-name counts from EDGAR to construct more granular measures of local stock returns in each month of the sample period by computing the average return of all firms headquartered in each state that mention fewer then five states in their 10-Ks in the previous year. A complementary set of returns is also produced using the firms that mention five or more states in their 10-Ks. I then repeat the portfolio sorts described in Section 2.1 using each set of returns. Since the former (latter) set of returns is constructed with firms whose operations are more (less) concentrated in each state, the HML-Muni spread is likely to be larger (smaller) in magnitude among more (less) localized firms.

The results of this test are reported in Panel A of Table 6 and show that the HML-Muni spread is 0.81% per month and statistically significant at the 10% level among the most local firms in each state.[18] In contrast, the spread is economically small (-0.09% per month) and statistically insignificant (t-statistic of -0.18) among less-local firms. In fact, a test on the null hypothesis that the spread among more-local firms exceeds the spread among

[18] The large spread but relatively small t-statistic reflects the fact that only a small number of locally headquartered firms satisfy this state-name count criterion in smaller states. This increases the volatility of the HML-Muni spread and reduces the t-statistic.

less-local firms is rejected at the 10% level. Together, these results support the conjecture that the returns of firms whose operations are more localized in each state are more sensitive to the local business cycle. That is, the level of the municipal spread is better at predicting cross-sectional differences in the returns of more localized firms.

Labor intensity. I complement the previous analysis by further considering whether firms that are more exposed to the local economy are more sensitive to changes in the level of a state's municipal spread. Specifically, I split the sample of firms into two groups based on the extent to which firms employ labor for production. The intuition behind this test is that firms that use a larger proportion of labor — a more localized factor of production — are more exposed to local economic conditions than firms that use more capital.

To examine this, I define a proxy of labor intensity based on the ratio of each firm's number of employees (Compustat Annual item EMP) to physical capital (Compustat Annual item PPENT). I consider firms with an above (below) median value of labor intensity in the fiscal year prior to each portfolio sort date as more (less) local. I then examine the HML-Muni spread among state-level portfolios that are constructed using only the firms in each state with either high or low levels of labor intensity. The results are reported in Panel B of Table 6 and show that, in line with Panel A, the HML-Muni spread is economically sizable (0.23% per month) and statistically significant (t-statistic of 1.94) among firms that rely on the (local) labor market most intensively. In contrast, the placebo test involving capital-intensive firms results in a statistically and economically insignificant spread of 0.08% per month. Although the difference in spreads is not statistically significant, the results are qualitatively in line with the proposed mechanism.

3.2.2 State-level labor productivity

Table 5 proposes an explanation for the HML-Muni spread: firms in states with higher municipal-Treasury spreads are more exposed to aggregate productivity risk and consequently earn higher average returns. In line with this logic, and consistent with the idea that local factor markets shape firms' risk exposures (Tuzel and Zhang, 2017), Table 6 shows that the

HML-Muni spread is indeed larger among firms that are more exposed to local economic conditions. The question that remains, which is addressed below, is why a higher municipal spread is associated with weaker local economic fundamentals and riskier local firms.

Given a high municipal-Treasury spread indicates a high cost of capital for the underlying state, it is natural to expect this to translate into less local investment. This high cost of borrowing could curtail investments in both physical infrastructure, such as roads and utilities, and essential services, such as education and healthcare, ultimately reducing the productivity of local firms and workers. Indeed, estimates provided by both Joulfaian and Matheson (2009) and Fisher and Wassmer (2014) suggest that each 1% increase in municipal borrowing costs reduces local government borrowing by about $25 per capita.

I empirically verify this link between local borrowing costs and local economic fundamental by showing that the level of a state's municipal spread is negatively correlated with various measures of labor productivity. I focus on labor productivity because, as highlighted in Section 3.1, labor is a more localized factor of production than capital. With this in mind, I document the direct link between the level of a state's municipal spread and labor productivity by estimating the following panel regression:

$$LP_{i,t} = \gamma_i + \delta_t + \rho L_{i,t} + \varepsilon_{i,t}. \tag{6}$$

Here, $LP_{i,t}$ is one of two proxies for labor productivity in state i at time t, and $L_{i,t}$ denotes the level of the state's municipal spread, obtained via equation (3). I measure productivity using either (i) the quarterly growth rate of gross state product (GSP) divided by total non-farm employment or (ii) the value-weighted average ratio of the natural logarithm of firm-level sales-to employees across all firms in each given state. All variables are scaled by their unconditional standard deviations so that the slope coefficient ρ is the correlation between the level of the municipal spread and labor productivity. Finally, γ_i (δ_t) denotes state (time) fixed effects. Table 7 reports the results of this analysis.

The results show a negative and robust connection between a state's municipal spread and labor productivity. This negative interaction arises regardless of whether labor productivity is measured at the macro level (Panel A) or the micro level (Panel B). This negative relation also arises when time fixed effects are included in the regressions, showing that the correlation is not driven by a small number of unrepresentative times during the sample period (e.g., the financial crisis). The negative correlation also arises when including state fixed effects in the regressions, highlighting that the results are not driven by a small set of states.

Finally, if inputs to production, such as physical capital, (Zhang, 2005), inventory (Belo and Lin, 2012; Jones and Tuzel, 2013), and labor (Belo et al., 2014) are costly to adjust, then firms in states with high municipal-Treasury spreads and low productivity will be riskier, as demonstrated by Table 5. This is because firms in less productive states with higher municipal-Treasury spreads will perform particularly poorly in bad states of the world, and will need to provide investors with higher average returns as compensation for bearing this risk. This intuition echoes İmrohoroğlu and Tüzel (2014), who quantitatively demonstrate how firms with lower idiosyncratic productivity are riskier. Moreover, this intuition is consistent with the results in Table OA.7 of the Online Appendix that shows that the magnitude of the HML-Muni spread is four times larger in recessions than expansions. While the difference in spreads between recessions and expansions is statistically insignificant, this most likely reflects the relatively few economic downturns during the 1998 to 2020 sample period.

Collectively, the results in this section highlight a risk-based explanation for why firms located in states with high municipal spreads earner high average returns: a high municipal spread serves as an observable (and high-frequency) proxy for a component of productivity that negatively affects all firms in each state, especially localized firms. Thus, a high municipal spread signals a lower productivity state and increased risk (betas) for local firms.

4 Alternative explanations and empirical robustness

Section 3 documents that there is a risk-based explanation for the HML-Muni spread. However, as this is not the first study to document geographic variation in stock returns, I examine several alternative mispricing-based explanations for why the HML-Muni spread may arise. Section 4.1 shows that none of these alternative explanations can reconcile the observed facts. Moreover, Section 4.2 shows that the HML-Muni spread is robust along several dimensions of the portfolio formation procedure described in Section 2.

4.1 Ruling out alternative explanations

Limits-to-arbitrage. Panel A of Table 8 reports the HML-Muni spread after removing difficult-to-trade firms from the sample. This ensures that the return spread is not driven by firms that face considerable limits to arbitrage. Specifically, the table reports the spread among stocks with larger market capitalizations (i.e., removing micro-cap firms), higher stock prices (i.e., removing firms with share prices of less than $5), higher trading volumes, and lower idiosyncratic return volatilities. To ensure that state-level differences in industry composition do not drive the HML-Muni spread, each column in Panel A reports industry-adjusted returns. In each case, the HML-Muni spread remains economically large and statistically significant. Thus, limits to arbitrage cannot explain the returns of the HML-Muni spread, further reinforcing the risk-based narrative proposed in Section 3.

Geographic variation in discount rates. Following Korniotis and Kumar (2013), studies such as Da et al. (2018) suggest that geographic variation in the *price* of risk can explain why returns covary with local business cycles. These studies posit that (i) local investors concentrate their wealth in local firms and (ii) risk sharing is limited across states. Thus, if local economic conditions worsen (improve), then local investors become more (less) risk averse and sell (buy) the equity of local firms. Thus, firms in states undergoing a relative recession (expansion) have low (high) current stock prices and earn high (low) future returns.

On the one hand, Korniotis and Kumar (2013) document that non-local investors are slow to exploit any differences in discount rates across states. This means that the least visible firms are likely to suffer the highest degree of mispricing and drive geographical variation in stock returns. On the other hand, Da et al. (2018) propose that differences in state-level fiscal policies influence the discount rates of local investors. Specifically, these authors show that firms located in states that implement countercyclical fiscal policies earn lower expected returns. This is because countercyclical policies reduce the consumption risks of local investors in states undergoing a relative recession.

I test whether these two mechanisms explain the HML-Muni spread. First, I construct the spread among firms that are highly visible to investors. Here, I measure firm-level visibility in three ways: the proxy of Hong et al. (2008), analysts following, and institutional ownership. If geographic variation in stock returns is induced by the mispricing of less visible firms, then the HML-Muni spread should be economically small among visible firms. The results in Panel B of Table 8 show that mispricing is unlikely to drive the HML-Muni spread, which remains economically large and significant among visible firms.

I also construct the HML-Muni spread among states that (i) implement different fiscal policies and (ii) have different tax privileges for holding locally issued municipal debt (a proxy for locally concentrated wealth from Babina et al. (2020)). An economically small spread among states with countercyclical fiscal policies or low tax privilege would suggest that the return spread may be driven by geographical variation in discount rates. However, in contrast to this narrative, Table OA.8 of the Online Appendix shows that the HML-Muni is statistically indistinguishable between states with procyclical and countercyclical fiscal policies and high and low tax privileges.

Underreaction to cash flow news. Geographic variation in stock returns may arise if investors (under)react differentially to news about future cash flows across states (Smajlbegovic, 2018; Parsons et al., 2020). Namely, if (i) firms in states with weak economic conditions (i.e., a high municipal spread) cut costs and increase cash flows but (ii) investors do not anticipate these changes, then the future profits of these firms will be higher than expected. Thus, the high returns of firms located in states with a high municipal spread may arise due to the *future* earnings surprises.

I examine this possibility by computing the *future* cash flow characteristics of the spread-sorted portfolios. Specifically, Table OA.9 in the Online Appendix reports the mean industry-adjusted characteristics of each portfolio 12 months after each portfolio formation date. The results show that firms located in states with a high municipal spread do not have significantly better future cash flows. In fact, the profitability of firms in high-spread states is often significantly *lower* than that of firms in low-spread states. Moreover, none of the measures of standardized unexpected earnings (SUE) from Livnat and Mendenhall (2006) are different across states. Thus, unlike the firm-level evidence in Smajlbegovic (2018), the market does not appear to systematically misjudge the future earnings of firms in states where economic conditions are expected to deteriorate. In fact, the results support the notion that firms in states with higher municipal spreads are less productive (recall Section 3.2).

4.2 Empirical robustness

Portfolio breakpoints. The baseline portfolio sorts in Section 2.1 assign five states to each of the low and the high spread-sorted portfolios. Here, I form portfolios by either (i) sorting either six or seven states into each of these portfolios or (ii) constructing rank-weighted portfolios in the spirit of Moskowitz, Ooi, and Pedersen (2012). This serves two purposes. First, if local stock returns are sensitive to local economic conditions, as reflected by the level of municipal spread, then the HML-Muni spread should be smaller when more states are included in these portfolios. This is because the distinction between states where economic conditions are expected to improve and worsen becomes less stark with more states in the extreme portfolios. Second, changing the number of states in each portfolio also ensures that the HML-Muni spread is not driven by any choice of portfolio breakpoints.

Table OA.10 in the Online Appendix reports these results. The results show that the HML-Muni spread monotonically decreases as more states are included in the extreme portfolios. In particular, the spread decreases to 0.31% (0.29%) per month when six (seven) states are sorted into each extreme portfolio. The rank-weighted portfolios also result in an economically and statistically significant spread of 0.32% per month. Thus, the baseline results are not driven by the choice of portfolio breakpoints in Section 2.1.

Rebalancing frequency. Rather than rebalancing each portfolio monthly, Table OA.11 in the Online Appendix reports the results of four alternative portfolio-rebalancing schemes. First, the results show that no return spread emerges when states are sorted into portfolios based on unconditional differences in the level of each state's municipal spread. This highlights the importance of the conditional rebalancing procedure in Section 2.1 and shows that returns are not driven by state-level fixed effects. Second, the table shows that rebalancing portfolios at the quarterly frequency (using either overlapping or non-overlapping returns) produces a return spread that exceeds 0.30% per month and remains significant at the 10% level. Finally, the results also show that the return spread remains economically and statistically significant at 0.24% per month when portfolios are constructed using (overlapping) annual holding periods. Thus, the baseline results in Table 2 are insensitive to perturbing either the portfolio rebalancing frequency or the holding period.

Alternative measures. I ensure that the results are not driven by the specific way I measure the level of the municipal spread (e.g., estimating equation (3) via OLS) by repeating the key empirical test with three alternative proxies for the level of the municipal spread.

First, I repeat the benchmark analysis without adjusting the municipal bond yields in each state for tax effects. This ensures that the results are not sensitive to the way in which the underlying municipal bond yields are scaled to account for differences in income taxes across states. Second, rather than fixing λ in equation (3), I estimate this shape parameter alongside the three yield factors via NLS. Finally, I define the level of the municipal spread as $\tilde{y}_{i,t}(240)$. This avoids the need to estimate equation (3), or variants thereof, altogether.

Panel A of Table 9 reports the results of these analyses and shows that the HML-Muni spread remains economically and statistically significant regardless of how the level of the municipal spread is measured. For instance, the HML-Muni spread earns 0.35% per month when municipal yields are not adjusted for cross-state differences in income tax rates. Furthermore, the returns of these portfolios generally remain monotonically increasing in the level of each state's municipal spread.

Yield decomposition. Section 1.1 draws on prior literature to interpret the municipal-Treasury spread — $\tilde{y}_{i,t}(m)$ in equation (2) — as largely reflecting the credit risk of state i at time t. Here, I decompose each state's municipal spread into its credit and liquidity components in the spirit of Schwert (2017) and show that the credit component drives my results. Namely, I project each state's time series of municipal spreads on the volume of municipal debt traded, the Amihud (2002) measure, the Jankowitsch, Nashikkar, and Subrahmanyam (2011) price dispersion measure, the Dick-Nielsen, Feldhütter, and Lando (2012) round-trip cost measure for the state's bonds, and the standard deviation of the previous variable. The fitted value of this regression serves as a proxy for liquidity risk, while the residual serves as a proxy for credit risk (see Section OA.2.1 in the Online Appendix for more details). Panel B of Table 9 then repeats the baseline portfolio sorts using each component of the tax-adjusted yield spread and shows that the HML-Muni spread arises only if states are sorted into portfolios based on the credit risk component of yields.

Excluding states. Figure OA.7 in the Online Appendix shows that the HML-Muni spread is not driven by any specific state in the sample, including those that have undergone (or are currently undergoing) financial distress.[19] The figure reports the annualized level of the HML-Muni spread that is obtained after removing a given state from the sample (denoted along the horizontal axis) and conducting the baseline portfolio sorts described in Section 2.1 with the remaining states. The results show that the HML-Muni spread remains economically large and statistically significant in all cases.

Sorting on related variables. Instead of sorting states into portfolios based on the level of each state's municipal spread, I form portfolios based on the short- and long-term slope of each state's term structure of municipal spreads. Here, the short-term (long-term) slope of the municipal spread is measured via $S_{i,t}$ ($C_{i,t}$) from equation (3). Table OA.13 in the Online Appendix shows that neither of these alternative yield factors predict cross-sectional variation in local stock returns. This is consistent with my primary conjecture that the level of the municipal spread is the most informative about local economic conditions, as this factor reflects the "average" degree of state-specific credit concerns embedded in yields.

[19] These distressed states include California (Vallejo filed for bankruptcy in 2008 and Stockton filed in 2012), Michigan (Detroit filed for bankruptcy in 2013), and Pennslyvania (Harrisburg filed for bankruptcy in 2011). Additionally, Illinois tends to have the lowest credit rating among the 50 states, with its bonds rated just above junk status by S&P.

5 Conclusion

This study documents that the level of a state's municipal-Treasury spread is informative about the risk exposures and expected returns of local assets. Specifically, I show that firms in states where the municipal spread is higher earn stock returns that are, on average, 0.37% per month higher than those of firms located in states where the municipal spread is lower. This return differential, which I label the high-minus-low municipal spread (or the "HML-Muni" spread), cannot be explained by limits-to-arbitrage, mispricing, differences in industry composition across states, or asset-pricing characteristics.

Why do firms located in states with a high municipal spread earn higher stock returns? I show that the answer hinges on the fact that these states have weaker fundamentals, such as lower local labor productivity. As such, the firms located in these states are more exposed to fluctuations in the business cycle, and have higher conditional risk exposures and returns. In line with this economic narrative, I show that (i) the level of a state's municipal spread is indeed positively related to the risk exposures of local firms, and (ii) the HML-Muni spread is concentrated among the most local firms, such as those whose operations are less geographically dispersed. These results are also in line with the notion that a large component of the municipal spread reflects (local) default risk.

Collectively, my results show that the municipal debt market conveys valuable information about the risks of local economies. Besides using this information to predict cross-sectional variation in excess returns, the information embedded in municipal yields can also be used in a variety of other ways, such as forecasting the revenues and expenditures of state and local governments. Additionally, while I focus on state-level economies in my analysis, the municipal spread may provide information about economic outcomes in more granular regions, such as MSAs. I leave these examinations for future research.

References

Adrian, T., Etula, E., Muir, T., 2014. Financial intermediaries and the cross-section of asset returns. The Journal of Finance 69, 2557–2596.

Amihud, Y., 2002. Illiquidity and stock returns: cross-section and time-series effects. Journal of financial markets 5, 31–56.

Ang, A., Bhansali, V., Xing, Y., 2012. Taxes on tax-exempt bonds. The Journal of Finance 65, 565–601.

Ang, A., Bhansali, V., Xing, Y., 2014. The muni bond spread: Credit, liquidity, and tax. Working paper.

Ang, A., Hodrick, R., Xing, Y., Zhang, X., 2006a. The cross-section of volatility and expected returns. The Journal of Finance 61, 259–299.

Ang, A., Piazzesi, M., 2003. A no-arbitrage vector autoregression of term structure dynamics with macroeconomic and latent variables. Journal of Monetary Economics 50, 745 – 787.

Ang, A., Piazzesi, M., Wei, M., 2006b. What does the yield curve tell us about GDP growth? Journal of Econometrics 131, 359–403.

Babina, T., Jotikasthira, C., Lundblad, C., Ramadorai, T., 2020. Heterogeneous Taxes and Limited Risk Sharing: Evidence from Municipal Bonds. The Review of Financial Studies 34, 509–568.

Belo, F., Lin, X., 2012. The inventory growth spread. The Review of Financial Studies 25, 278–313.

Belo, F., Lin, X., Bazdresch, S., 2014. Labor hiring, investment, and stock return predictability in the cross section. Journal of Political Economy 122, 129–177.

Bernanke, B., 1990. On the predictive power of interest rates and interest rate spreads. Tech. rep., National Bureau of Economic Research.

Broner, F. A., Lorenzoni, G., Schmukler, S. L., 2013. Why do emerging economies borrow short term? Journal of the European Economic Association 11, 67–100.

Carhart, M. M., 1997. On persistence in mutual fund performance. The Journal of Finance 52, 57–82.

Cestau, D., Hollifield, B., Li, D., Schürhoff, N., 2019. Municipal bond markets. Annual Review of Financial Economics 11, 65–84.

Chaney, T., Sraer, D., Thesmar, D., 2012. The collateral channel: How real estate shocks affect corporate investment. American Economic Review 102, 2381–2409.

Chun, A. L., Namvar, E., Ye, X., Yu, F., 2019. Modeling municipal yields with (and without) bond insurance. Management Science 65, 3694–3713.

Cooper, M. J., Gulen, H., Schill, M. J., 2008. Asset growth and the cross-section of stock returns. The Journal of Finance 63, 1609–1651.

Cornaggia, K. R., Hund, J., Nguyen, G., Ye, Z., 2021. Opioid crisis effects on municipal finance. Working paper.

Coval, J. D., Moskowitz, T. J., 1999. Home bias at home: Local equity preference in domestic portfolios. The Journal of Finance 54, 2045–2073.

Coval, J. D., Moskowitz, T. J., 2001. The geography of investment: Informed trading and asset prices. Journal of Political Economy 109, 811–841.

Da, Z., Warachka, M., Yun, H., 2018. Fiscal policy, consumption risk, and stock returns: Evidence from US states. Journal of Financial and Quantitative Analysis 53, 109–136.

Dagostino, R., 2022. The impact of bank financing on municipalities' bond issuance and the real economy .

Daniel, K., Grinblatt, M., Titman, S., Wermers, R., 1997. Measuring mutual fund performance with characteristic-based benchmarks. The Journal of Finance 52, 1035–1058.

Dick-Nielsen, J., Feldhütter, P., Lando, D., 2012. Corporate bond liquidity before and after the onset of the subprime crisis. Journal of Financial Economics 103, 471–492.

Diebold, F. X., Li, C., 2006. Forecasting the term structure of government bond yields. Journal of Econometrics 130, 337 – 364.

Diebold, F. X., Rudebusch, G. D., Aruoba, S. B., 2006. The macroeconomy and the yield curve: a dynamic latent factor approach. Journal of Econometrics 131, 309 – 338.

Dougal, C., Parsons, C. A., Titman, S., 2015. Urban vibrancy and corporate growth. The Journal of Finance 70, 163–210.

Eisfeldt, A. L., Papanikolaou, D., 2013. Organization capital and the cross-section of expected returns. The Journal of Finance 68, 1365–1406.

Estrella, A., Hardouvelis, G. A., 1991. The term structure as a predictor of real economic activity. The Journal of Finance 46, 555–576.

Fama, E. F., French, K. R., 1989. Business conditions and expected returns on stocks and bonds. Journal of Financial Economics 25, 23–49.

Fama, E. F., French, K. R., 1993. Common risk factors in the returns on stocks and bonds. Journal of Financial Economics 33, 3–56.

Fama, E. F., French, K. R., 2015. A five-factor asset pricing model. Journal of Financial Economics 116, 1 – 22.

Fama, E. F., MacBeth, J. D., 1973. Risk, Return, and Equilibrium: Empirical Tests. Journal of Political Economy 81, 607–636.

Fisher, R. C., Wassmer, R. W., 2014. The issuance of state and local debt during the united states great recession. National Tax Journal 67, 113–150.

Friedman, B. M., Kuttner, K. N., Bernanke, B. S., 2008. 5. Why Does the Paper-Bill Spread Predict Real Economic Activity? University of Chicago Press.

Gao, P., Lee, C., Murphy, D., 2020. Financing dies in darkness? the impact of newspaper closures on public finance. Journal of Financial Economics 135, 445–467.

Gao, P., Murphy, D., Qi, Y., 2019. Political Uncertainty and Public Financing Costs: Evidence from U.S. Gubernatorial Elections and Municipal Bond Markets. Working paper.

García, D., Norli, Ø., 2012. Geographic dispersion and stock returns. Journal of Financial Economics 106, 547 – 565.

Gertler, M., Lown, C. S., 1999. The information in the high-yield bond spread for the business cycle: evidence and some implications. Oxford Review of Economic Policy 15, 132–150.

Gilchrist, S., Zakrajšek, E., 2012. Credit spreads and business cycle fluctuations. American Economic Review 102, 1692–1720.

Goldsmith-Pinkham, P. S., Gustafson, M., Lewis, R., Schwert, M., 2021. Sea level rise exposure and municipal bond yields. Working paper.

Green, R. C., 1993. A simple model of the taxable and tax-exempt yield curves. The Review of Financial Studies 6, 233–264.

Green, R. C., Li, D., Schürhoff, N., 2010. Price discovery in illiquid markets: Do financial asset prices rise faster than they fall? The Journal of Finance 65, 1669–1702.

Grigoris, F., 2022. Municipal bond yields and local economic conditions. Working paper.

Han, B., Subrahmanyam, A., Zhou, Y., 2017. The term structure of credit spreads, firm fundamentals, and expected stock returns. Journal of Financial Economics 124, 147–171.

Harvey, C. R., 1988. The real term structure and consumption growth. Journal of Financial Economics 22, 305–333.

Hodrick, R. J., Prescott, E. C., 1997. Postwar US business cycles: an empirical investigation. Journal of Money, credit, and Banking pp. 1–16.

Hong, H., Kubik, J. D., Stein, J. C., 2008. The only game in town: Stock-price consequences of local bias. Journal of Financial Economics 90, 20–37.

Hou, K., Xue, C., Zhang, L., 2015. Digesting anomalies: An investment approach. The Review of Financial Studies 28, 650.

İmrohoroğlu, A., Tüzel, Ş., 2014. Firm-level productivity, risk, and return. Management Science 60, 2073–2090.

Jankowitsch, R., Nashikkar, A., Subrahmanyam, M. G., 2011. Price dispersion in otc markets: A new measure of liquidity. Journal of Banking & Finance 35, 343–357.

Jegadeesh, N., 1990. Evidence of predictable behavior of security returns. The Journal of Finance 45, 881–898.

Jegadeesh, N., Titman, S., 1993. Returns to buying winners and selling losers: Implications for stock market efficiency. The Journal of Finance 48, 65–91.

Jones, C. S., Tuzel, S., 2013. Inventory investment and the cost of capital. Journal of Financial Economics 107, 557 – 579.

Joulfaian, D., Matheson, T., 2009. The supply elasticity of tax-exempt bonds. In: *Proceedings. Annual Conference on Taxation and Minutes of the Annual Meeting of the National Tax Association*, JSTOR, vol. 102, pp. 136–142.

Keim, D. B., Stambaugh, R. F., 1986. Predicting returns in the stock and bond markets. Journal of Financial Economics 17, 357–390.

Korniotis, G. M., Kumar, A., 2013. State-level business cycles and local return predictability. The Journal of Finance 68, 1037–1096.

Litterman, R. B., Scheinkman, J., 1991. Common factors affecting bond returns. The Journal of Fixed Income 1, 54–61.

Liu, Y., Wu, J. C., 2021. Reconstructing the yield curve. Journal of Financial Economics 142, 1395–1425.

Livnat, J., Mendenhall, R. R., 2006. Comparing the post–earnings announcement drift for surprises calculated from analyst and time series forecasts. Journal of Accounting Research 44, 177–205.

Longstaff, F. A., 2011. Municipal debt and marginal tax rates: Is there a tax premium in asset prices? The Journal of Finance 66, 721–751.

Moskowitz, T. J., Ooi, Y. H., Pedersen, L. H., 2012. Time series momentum. Journal of financial economics 104, 228–250.

Nelson, C., Siegel, A. F., 1987. Parsimonious modeling of yield curves. The Journal of Business 60, 473–89.

Newey, W., West, K., 1987. A simple, positive semi-definite, heteroskedasticity and autocorrelation consistent covariance matrix. Econometrica 55, 703–08.

Novy-Marx, R., 2013. The other side of value: The gross profitability premium. Journal of Financial Economics 108, 1–28.

Novy-Marx, R., Rauh, J. D., 2012. Fiscal imbalances and borrowing costs: Evidence from state investment losses. American Economic Journal: Economic Policy 4, 182–213.

Painter, M., 2020. An inconvenient cost: The effects of climate change on municipal bonds. Journal of Financial Economics 135, 468–482.

Parsons, C. A., Sabbatucci, R., Titman, S., 2020. Geographic Lead-Lag Effects. The Review of Financial Studies 33, 4721–4770.

Pirinsky, C., Wang, Q., 2006. Does corporate headquarters location matter for stock returns? The Journal of Finance 61, 1991–2015.

Saunders, A., Spina, A., Steffen, S., Streitz, D., 2021. Corporate loan spreads and economic activity. Working paper.

Schwert, M., 2017. Municipal bond liquidity and default risk. The Journal of Finance 72, 1683–1722.

Smajlbegovic, E., 2018. Regional economic activity and stock returns. Journal of Financial and Quantitative Analysis pp. 1–32.

Stambaugh, R. F., Yuan, Y., 2017. Mispricing factors. The Review of Financial Studies 30, 1270–1315.

Tuzel, S., Zhang, M. B., 2017. Local risk, local factors, and asset prices. The Journal of Finance 72, 325–370.

Wang, J., Wu, C., Zhang, F. X., 2008. Liquidity, default, taxes, and yields on municipal bonds. Journal of Banking and Finance 32, 1133 – 1149.

Yu, W.-C., Salyards, D. M., 2009. Parsimonious modeling and forecasting of corporate yield curve. Journal of Forecasting 28, 73–88.

Zhang, L., 2005. The value premium. The Journal of Finance 60, 67–103.

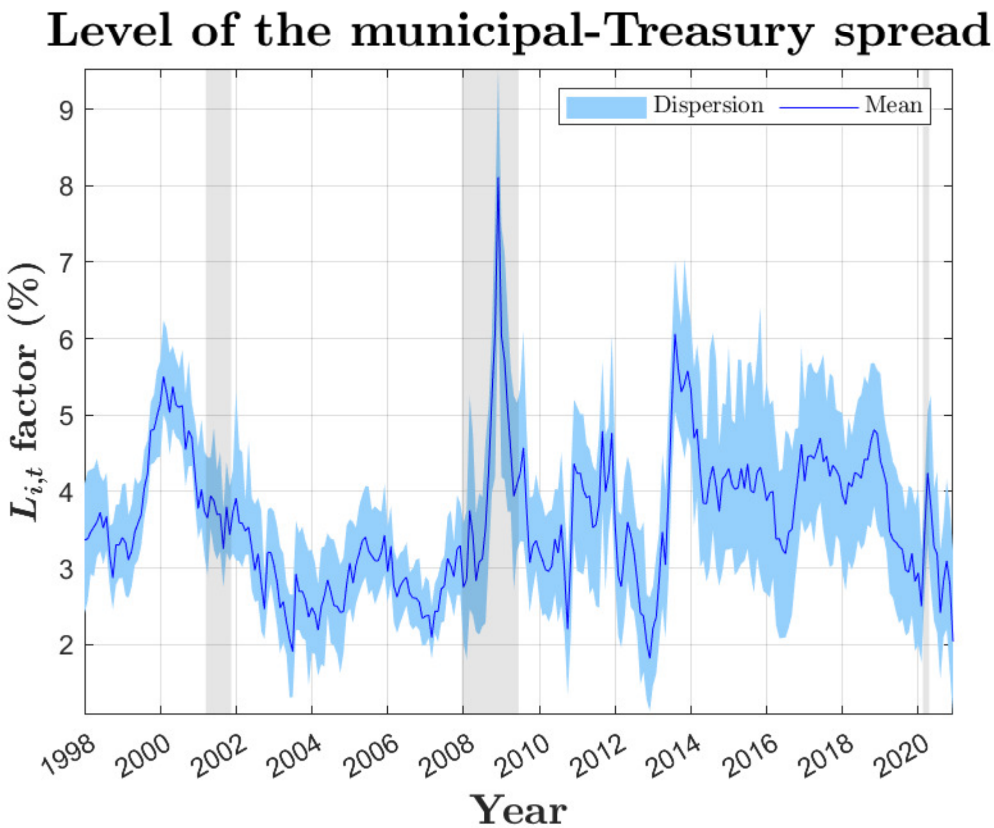

Figure 1: Level of the municipal-Treasury spread
The figure reports the monthly time series of the level of the municipal-Treasury spread obtained via equation (3). This equation is estimated on a state-by-state basis, and the average level of the tax-adjusted municipal-Treasury spread is computed by taking the gross state product (GSP) weighted-average of $L_{i,t}$ across states. This GSP-weighted average is represented by the solid blue line and the cross-sectional dispersion at each point in time is represented by the blue shaded regions. The time period for this analysis ranges from January 1998 through December 2020.

Table 1: Municipal yield factors: correlations and summary statistics
The table reports the summary statistics and the time-series correlations associated with the yield factors underlying this study. Panel A reports summary statistics associated with the Nelson-Siegel (NS) factors obtained by estimating equation (3) within each state. The summary statistics reported for each factor are the time-series mean, standard deviation (SD(TS)), minimum and maximum values, and the average cross-sectional dispersion of each factor across states (SD(CS)). The panel also reports the one-, 12-, and 30-month autocorrelation of each factor. Panel B reports the correlations between (i) each pair of NS factors, and (ii) each NS factor and the 20-year municipal spread ($\tilde{y}(240)$), 20-year minus 1-year municipal spread ($\tilde{y}(240) - \tilde{y}(12)$), and 30-year minus 10-year municipal spread ($\tilde{y}(360) - \tilde{y}(120)$). The statistics associated with the time-series dynamics of each variable are computed as the GSP-weighted average of each variable across states. Finally, the sample period ranges from January 1998 through December 2020.

Panel A: Factor summary statistics								
	Mean	SD(TS)	SD(CS)	Min	Max	$\hat{\rho}_1$	$\hat{\rho}_{12}$	$\hat{\rho}_{30}$
L	3.60	0.90	0.71	1.82	8.01	0.89	0.07	0.03
S	-2.06	0.99	0.71	-5.28	1.51	0.85	0.33	0.20
C	-3.23	2.27	2.32	-10.55	3.12	0.87	0.29	0.04

Panel B: Factor correlations						
	L	S	C	$\tilde{y}(240)$	$\tilde{y}(240) - \tilde{y}(12)$	$\tilde{y}(360) - \tilde{y}(120)$
L	1.00	-0.47	-0.72	0.88	-0.42	-0.34
S		1.00	0.10	0.38	-0.96	0.04
C			1.00	0.84	-0.44	-0.90

Table 2: Municipal spread-sorted portfolios: portfolio returns

The table reports the monthly returns of portfolios sorted on the level of each state's municipal-Treasury spread and the difference between the returns of the Low (L) and High (H) spread-sorted portfolios. Here, the level of each state's municipal spread ($L_{i,t}$) is obtained from equation (3). The portfolio formation procedure is described in Section 2.1. The average level of the municipal spread of each portfolio is denoted by "Level," while the mean and standard deviation of the value-weighted portfolio returns are represented by $\mathbb{E}[R]$ and $\sigma(R)$, respectively. $\mathbb{E}[R_{EW}]$ denotes equal-weighted portfolio returns, while N(States) and N(Firms) report the mean number of states and firms underlying each portfolio, respectively. The columns denoted $\mathbb{E}[R - R_{\text{IND}}]$ and $\mathbb{E}[R - R_{\text{DGTW}}]$ report value-weighted portfolio returns that are obtained by using each firm's return in excess of its Fama-French 10 industry group and Daniel et al. (1997) characteristic-based benchmark, respectively. Finally, parentheses report Newey and West (1987) t-statistics. The sample period is from January 1998 through December 2020.

	Level	$\mathbb{E}[R]$	$\sigma(R)$	N(Firm)	$\mathbb{E}[R_{EW}]$	$\mathbb{E}[R_{\text{IND}}]$	$\mathbb{E}[R_{\text{DGTW}}]$
Low (L)	2.98	0.74	4.71	492	1.12	0.52	-0.41
Medium	3.61	0.80	4.84	1928	1.20	0.61	-0.36
High (H)	4.31	1.10	5.52	413	1.38	0.80	-0.09
Spread (H-L)	1.33	0.36	2.71		0.26	0.27	0.33
t(Spread)		(2.23)			(1.96)	(1.93)	(2.23)

Table 3: Municipal spread-sorted portfolios: portfolio characteristics
The table reports the industry-adjusted characteristics of the portfolios sorted on the level of the municipal-Treasury spread, the difference between the characteristics of the High (H) and Low (L) portfolios (Spread (H-L)), and the Newey and West (1987) t-statistic associated with this difference (t(Spread)). Here, the level of each state's municipal spread is obtained by estimating equation (3), and portfolios are formed following the procedure outlined in Section 2.1. The characteristics of each portfolio as of each portfolio formation month are computed as follows: (1) Each firm is assigned to the relevant Fama-French 10 industry group, and the cross-sectional average industry-level characteristic is subtracted from each firm-level characteristic; (2) the value-weighed average of these characteristics is computed across all firms in a given state, and the equal-weighted average of these state-level characteristics is taken across all states assigned to each portfolio; and (3) the table reports the time-series average of each portfolio-level characteristic. Details on the construction of each variable are provided in Section OA.1 of the Online Appendix. The sample period ranges from January 1998 through December 2020.

	Low (L)	Medium	High (H)	Spread (H-L)	t(Spread)
ln(ME)	0.03	0.06	0.07	0.04	2.09
BEME	-0.24	-0.25	-0.28	-0.04	-2.07
GP (%)	0.85	0.48	0.61	-0.24	-1.85
ROA (%)	2.27	2.04	1.82	-0.45	-4.88
Leverage (%)	2.39	2.20	2.81	0.43	0.46
Asset growth (%)	3.42	3.22	2.68	-0.73	-0.87
I/A (%)	0.52	0.27	0.28	-0.24	-0.61
Hire (%)	0.79	0.93	0.07	-0.71	-2.10
ORG	-0.36	-0.39	-0.35	0.01	0.28
Momentum (%)	7.84	7.19	8.86	1.02	0.92
Reversal (%)	0.27	0.21	0.30	0.03	0.23
IVOL (%)	-1.40	-1.33	-1.14	0.26	4.21
TFP	0.36	0.36	0.33	-0.02	-0.71
β (MSA)	-1.07	-0.69	0.27	1.34	2.00

Table 4: Fama-MacBeth regressions

The table reports the results of Fama and MacBeth (1973) regressions that project future monthly state-level excess stock returns on both the current level of each state's municipal-Treasury spread and various characteristics that are known to predict returns. The level of each state's municipal spread (L) is obtained by estimating equation (3). Each other state-level characteristic is constructed by computing the value-weighted average characteristic across all firms in a given state. Here, each variable is standardized by its unconditional standard deviation. The table reports the time-series average value of the slope coefficient associated with each predictor (obtained via equation (4)), and the Newey and West (1987) t-statistic associated with each point estimate. The sample period ranges from January 1998 through December 2020.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
L	0.31	0.33	0.29	0.32	0.31	0.37	0.32	0.32	0.39	0.33
	(2.98)	(3.10)	(2.66)	(2.93)	(3.02)	(3.33)	(3.01)	(2.97)	(3.23)	(3.23)
ln(ME)		-0.03								
		(-0.48)								
ln(BEME)			0.01							
			(0.12)							
I/A				0.08						
				(1.29)						
HIRE					0.03					
					(0.53)					
ROA						0.01				
						(0.09)				
ORG							-0.02			
							(-0.51)			
TFP								0.01		
								(0.14)		
β_{MSA}									0.45	
									(0.83)	
IVOL										-0.15
										(-0.90)
$\bar{R}^2$	0.39	5.60	4.35	3.20	5.17	2.93	1.51	2.95	3.23	9.73

Table 5: Municipal spread-sorted portfolios: pricing errors and risk exposures

The table reports the pricing errors (α's) and risk exposures (β's) associated with the quarterly excess returns of portfolios sorted on the level of each state's municipal-Treasury spread. The table also reports the difference between the excess returns, alphas, and betas of the Low (L) and High (H) spread-sorted portfolios. The first set of columns reports the average excess returns associated with each spread-sorted portfolio. The next three sets of columns estimate CAPM regressions with one of three proxies for aggregate productivity: excess market returns (MKTRF), the measure of labor productivity provided by the Federal Reserve Bank of San Francisco (LP), and a tradeable proxy for labor productivity (LP^{Ret}) constructed following the approach outlined by Adrian et al. (2014). The data underlying each column is quarterly, so as to mirror the availability of the labor productivity measure. Excess returns and alphas are multiplied by four so that each of these estimates can be interpreted as an annualized return. Parentheses report Newey and West (1987) t-statistics and the sample period is from January 1998 through December 2020.

	Raw returns	CAPM		LP		LP^{Ret}	
	$\mathbb{E}[R]$	α	β	α	β	α	β
Low (L)	9.40	-0.45	0.99	-1.62	1.05	1.60	10.39
Medium	9.96	-0.01	1.00	-1.13	1.06	1.54	11.45
High (H)	13.88	2.96	1.12	0.41	1.33	3.84	14.28
Spread (H-L)	4.29	3.22	0.13	1.89	0.27	2.10	3.80
	(2.27)	(1.58)	(2.50)	(0.73)	(1.46)	(0.92)	(1.77)

Table 6: Municipal spread-sorted portfolios: firm localization and labor intensity
The table reports the monthly returns of portfolios sorted on the level of each state's municipal-Treasury spread, as well as the difference between the returns of the Low (L) and High (H) spread-sorted portfolios. The level of each state's municipal spread ($L_{i,t}$) is obtained by estimating equation (3), and the portfolio formation procedure employed is described in Section 2.1 with the following exceptions. First, portfolios in Panel A are formed using state-level stock returns that are computed as the value-weighted average return across all firms headquartered in a given state that name five or fewer (labeled "$\leq$ 4") or more than five (labeled "$>$ 5") states in their 10-K filings in the previous calendar year (see Section 3.2.1 for details). Second, the portfolios in Panel B are formed using state-level stock returns that are computed across all firms headquartered in a particular state with labor intensity that is above (below) the cross-sectional median value of labor intensity across all firms headquartered in the state. The mean and standard deviation of the returns are represented by $\mathbb{E}[R]$ and $\sigma(R)$, respectively. The row label p (Close $>$ Far) reports the p-value from a test on the null hypothesis that the spread among more localized firms is greater than that among less localized firms. Finally, parentheses report Newey and West (1987) t-statistics. The sample period is from January 1998 through December 2020.

	Panel A: Firm localization				Panel B: Labor intensity			
	$\leq$ 5 states		$>$ 5 states		High		Low	
	$\mathbb{E}[R]$	$\sigma(R)$	$\mathbb{E}[R]$	$\sigma(R)$	$\mathbb{E}[R]$	$\sigma(R)$	$\mathbb{E}[R]$	$\sigma(R)$
Low (L)	0.52	7.25	0.85	5.50	0.78	5.27	0.77	4.78
Medium	0.93	5.84	0.82	5.14	0.82	5.44	0.75	4.74
High (H)	1.33	6.97	0.76	8.16	1.01	5.66	0.85	5.58
Spread (H-L)	0.81	7.20	-0.09	6.83	0.23	2.14	0.08	2.91
t(Spread)	(1.83)		(-0.18)		(1.94)		(0.38)	
p(Close $>$ Far)	0.08				0.19			

Table 7: State-level municipal spread and labor productivity

The table reports the association between the level of each state's municipal spread and labor productivity. The level of each state's municipal-Treasury spread ($L_{i,t}$) is obtained from equation (3), and state-level labor productivity is constructed in one of two ways. In Panel A, a quarterly macro-level measure of labor productivity is obtained by computing the ratio of quarterly gross state product and total employment. In Panel B, an annual micro-level measure of labor productivity is obtained by computing the value-weighted average ratio of the natural logarithm of sales-to-employees across all firms headquartered in a given state. Consistent with the baseline results, this micro-level measure of labor productivity is only computed for the states that have at least 10 locally headquartered firms. The slope coefficients reported in odd-numbered columns are obtained from panel regressions that include time fixed effects, whereas the slope coefficients reported in even-numbered columns are obtained from panel regressions that include both state and time fixed effects. Parentheses report t-statistics based on standard errors that are clustered by state, and the sample period is from January 1998 through December 2020.

	Panel A: GSP per employee		Panel B: Sales per employee	
	(1)	(2)	(3)	(4)
L_i,t	-0.05	-0.05	-0.12	-0.12
	(-2.21)	(-2.21)	(-2.01)	(-2.01)
Frequency	Qtr.	Qtr.	Ann.	Ann.
Time FE	Yes	Yes	Yes	Yes
State FE	No	Yes	No	Yes
$Adj. - R^2$	0.37	0.36	0.65	0.64
Obs.	3216	3216	864	864

Table 8: Municipal spread-sorted portfolios: trading costs, information environment, and visibility

The table reports the monthly returns of portfolios sorted on the level of each state's municipal-Treasury spread, as well as the spread between the returns of the Low (L) and High (H) spread-sorted portfolios. States are sorted into portfolios following the portfolio formation procedure described in Section 2.1, subject to the following exceptions. In the columns of Panel A labeled "Large ME" or "High VOL" ("Low IVOL") state-level portfolios are constructed only after excluding any firm whose market capitalization or trading volume (IVOL) is below (above) the 20^{th} (80^{th}) percentile of the cross-sectional distribution of the relevant variable in month $t-1$. Similarly, the column labeled "High PRC" constructs each state-level portfolio after removing all firms with a share price of less than \$5 per share in month $t-1$. In the columns of Panel B labeled "High Visibility," "High Analysts," or "High Institutional," state-level portfolios are constructed by removing any firm with a visibility measure of Hong et al. (2008), analyst following, or level of institutional ownership below the 20^{th} percentile of the cross-sectional distribution of the relevant variable in month $t-1$. Finally, parentheses report Newey and West (1987) t-statistics, and the sample period is from January 1998 through December 2020.

	Panel A: Trading costs		
	Large ME	High VOL	Low IVOL
Low (L)	0.61	0.52	-0.34
Medium	0.69	0.64	-0.27
High (H)	0.86	0.81	-0.11
Spread (H-L)	0.26	0.29	0.22
t(Spread)	(2.15)	(2.09)	(2.88)
	Panel B: Information and visibility		
	High Visibility	High Analysts	High Institutional
Low (L)	0.32	0.30	0.37
Medium	0.35	0.37	0.48
High (H)	0.54	0.56	0.55
Spread (H-L)	0.22	0.26	0.18
t(Spread)	(1.74)	(2.24)	(1.77)

Table 9: Municipal spread-sorted portfolios: alternative measures and yield decomposition

The table reports the monthly returns of portfolios sorted on the level of each state's municipal-Treasury spread, as well as the spread between the returns of the Low (L) and High (H) spread-sorted portfolios. States are sorted into portfolios following the procedure described in Section 2.1, with the level of each state's municipal spread in Panel A measured in one of three ways. First, the baseline analysis is repeated without adjusting municipal bond yields for differences in taxes across states (i.e., $\tau_{i,t}$ in equation (1) is set to zero for all states). Second, the common shape parameter λ in equation (3) is replaced by a state-specific shape parameter $\lambda_{i,t}$ that is estimated alongside the three yield factors via non-linear least squares (NLS). Finally, states are sorted into portfolios based on the observable value of the 20-year tax-adjusted municipal-Treasury spread (i.e., $\tilde{y}_{i,t}(240)$). Panel B then splits the level of the municipal-Treasury spread into two components associated with the liquidity and credit risk associated with each state's municipal bond yields and sorts states into portfolios based on each of these two components of the yield. Section OA.2.1 of the Online Appendix outlines this decomposition in more detail. The average and the standard deviation of the value-weighted portfolio returns are denoted by $\mathbb{E}[R]$ and $\sigma(R)$, respectively. In Panel B, the figure p(Credit $>$ Liq) reports the p-value associated with the null hypothesis that the credit-related spreads exceeds the liquidity-related spread. Finally, parentheses report Newey and West (1987) t-statistics. The sample period is from January 1998 through December 2020.

Panel A: Alternative measures						
	No tax		NLS		Obs.	
	$\mathbb{E}[R]$	$\sigma(R)$	$\mathbb{E}[R]$	$\sigma(R)$	$\mathbb{E}[R]$	$\sigma(R)$
Low (L)	0.68	4.71	0.68	4.73	0.87	4.92
Medium	0.80	4.83	0.80	4.83	0.71	4.93
High (H)	1.04	5.78	1.04	5.67	1.22	5.19
Spread (H-L)	0.36	3.01	0.42	2.84	0.35	2.79
t(Spread)	(1.91)		(2.35)		(1.95)	

Panel B: Yield decomposition				
	Credit		Liquidity	
	$\mathbb{E}[R]$	$\sigma(R)$	$\mathbb{E}[R]$	$\sigma(R)$
Low (L)	0.69	5.22	0.91	4.89
Medium	0.79	4.82	0.76	4.98
High (H)	1.05	5.33	0.96	4.80
Spread (H-L)	0.36	2.90	0.05	2.17
t(Spread)	(1.98)		(0.40)	
p(Credit>Liq.)	0.09			

OA Online Appendix

OA.1 Variable description and construction

Analyst following (Analyst). The number of analysts following a firm in year t is defined as the number of analysts that issue a forecast for firm-level EPS in the same year (I/B/E/S item NUMEST from the Historical Summary Statistics dataset).

Asset growth. Asset growth is calculated as the year-on-year annual growth rate of total assets (Compustat Annual item AT) between years $t-1$ and t Cooper et al. (2008).

Book-to-market (BEME). A firm's book-to-market ratio is constructed by following **?**. Book equity is defined as shareholders' equity minus the value of preferred stock. If available, shareholders' equity is set equal to stockholders' equity (Compustat Annual item SEQ). If stockholders' equity is missing, then common equity (Compustat Annual item CEQ) plus the par value of preferred stock (Compustat Annual item PSTK) is used instead. If neither of the two previous definitions of stockholders' equity can be constructed, then shareholders' equity is the difference between total assets (Compustat Annual item AT) and total liabilities (Compustat Annual item LT). For the value of preferred stock the redemption value (Compustat Annual item PSTKRV), the liquidating value (Compustat Annual item PSTKL), or the carrying value (Compustat Annual item PSTK), are used in that order of preference. The value of deferred taxes and investment tax credits (Compustat Annual item TXDITC) is added to, and the value of postretirement benefits (Compustat Annual item PRBA) is subtracted from, the value of book equity if either variable is available. Finally, the book value of equity in the fiscal year ending in calendar year $t-1$ is divided by the market value of common equity from December of year $t-1$.

Gross profitability (GP). Consistent with Novy-Marx (2013), gross profitability is calculated as total revenue (Compustat Quarterly item REVTQ) minus the cost of goods sold (Compustat Quarterly item COGSQ), divided by total assets (Compustat Quarterly item ATQ).

Hiring rate (Hire). The firm-level hiring rate is computed following Belo et al. (2014). In particular, the hiring rate in year t is the change in the number of employees (Compustat Annual item EMP) from year $t-1$ to year t, divided by the average number of employees over years $t-1$ and t.

Idiosyncratic productivity (TFP). Estimates of idiosyncratic (i.e., firm-level) productivity are drawn from İmrohoroğlu and Tüzel (2014).

Idiosyncratic return volatility (IVOL). Idiosyncratic volatility is computed in accordance with Ang, Hodrick, Xing, and Zhang (2006a). At the end of month t, a firm's idiosyncratic volatility over the past month is obtained by regressing its daily excess returns on the Fama and French (1993) factors, provided there are at least 15 valid daily returns in the month of interest. Idiosyncratic volatility is then defined as the standard deviation of the residuals from the aforemention regression.

Institutional ownership (Ownership). At time t, the proportion of shares outstanding owned by institutional investors is computed by scaling the shares owned by institutional investors (identified using data from SEC Form 13(f)) by the total split-adjusted shares outstanding for each security in CRSP. This procedure is implemented by following the research note on "Institutional Trades, Flows, and Turnover Ratios" written by Rabih Moussawi at WRDS.[20]

Investment rate (I/A). Following Stambaugh and Yuan (2017) the investment rate is computed as the change in gross property, plant, and equipment (Compustat Annual item PPEGT) plus the change in inventory (Compustat Annual item INVT) between years $t-1$ and t, divided by the value of total assets (Compustat Annual item AT) in year $t-1$.

Leverage. The leverage ratio is defined as the sum of total long-term debt (Compustat Annual item DLTT) and debt in current liabilities (Compustat Annual item DLC) divided by total assets (Compustat item AT).

Local beta ($\boldsymbol{\beta_{MSA}}$). The conditional risk exposures of firms located in each metropolitan statistical area (MSA) are obtained from Tuzel and Zhang (2017).

Market capitalization (ME). A firm's end of month t market capitalization is computed as the firm's end of month t stock price (CRSP Monthly item PRC) multiplied by the firm's number of shares outstanding (CRSP Monthly item SHROUT).

Momentum (MOM). A firm's past return momentum in month t is defined as its cumulative return between months $t-11$ and $t-1$ (Jegadeesh and Titman, 1993). This measure is constructed using CRSP Monthly return data that is adjusted for de-listing events.

Organizational capital (ORG). Each firm's stock of organizational capital is obtained by following the perpetual inventory method described by Eisfeldt and Papanikolaou (2013). This method recursively accumulates a firm's real selling, general and administrative expenses (Compustat Annual item XSGA) over time, and then scales the stock of organizational capital by the firm's total assets (Compustat Annual item AT).

Return on assets (ROA). Return on assets is computed as income before extraordinary items (Computat Quarterly item IBQ), minus dividends to preferred shareholders (Compustat Quarterly item DVPQ), if available, and deferred income tax credits (Compustat Quarterly item TXDCQ), if available. This sum is then divided by lagged total assets (Compustat Quarterly item ATQ).

Short-term reversal (Reversal). Consistent with Jegadeesh (1990), the short-term reversal of each firm in month t is defined as its monthly stock return in month $t-1$.

Standardized unexpected earnings 1 (SUE1). Consistent with the measures of standardized unexpected earnings (SUE) based on the seasonal random walk models in Livnat and Mendenhall (2006), SUE1 in quarter t is computed by taking the difference between split-adjusted earnings per share excluding extraordinary items (Compustat Quarterly item EPSPXQ divided by item AJEXQ) in quarters t and $t-4$, and scaling this difference by the split-adjusted price at the end of quarter t (Compustat Quarterly item PRCCQ divided by item AJEXQ).

Standardized unexpected earnings 2 (SUE2). Consistent with the measures of standardized unexpected earnings (SUE) based on the seasonal random walk models in Livnat and Mendenhall (2006), SUE2 in quarter t is computed by taking the difference between split-adjusted earnings per share excluding both extraordinary items and special items (Compustat Quarterly item EPSPXQ minus 65% of item SPIQ scaled by item CSH-

[20] This research note and the code for implementing the procedure is available at the following URL: `https://wrds-www.wharton.upenn.edu/pages/support/applications/institutional-ownership-research/institutional-trades-flows-and-turnover-ratios-using-thomson-reuters-13f-data-tr-13f/`. Thanks to Rabih Moussawi and WRDS for making this research note and the associated SAS code available.

PRQ, all divided by item AJEXQ) in quarters t and $t-4$, and scaling this difference by the split-adjusted price at the end of quarter t (Compustat Quarterly item PRCCQ divided by item AJEXQ).

Visibility. Following Hong et al. (2008), a firm's visibility is computed as the residual of the regression of the natural logarithm of the total number of common shareholders (Compustat Annual item CSHR) on the natural logarithm of market capitalization (Compustat Annual item CSHO multiplied by Compustat Annual item PRCC_F).

OA.2 Term structure of state-level municipal bond yields

I use the cross-section of yields in each state i and each month t to estimate state-specific term structures of municipal bond yields in two steps. First, I clean the historical data on municipal bond transaction prices from the Municipal Securities Rulemaking Board (MSRB) and link this data to bond- and issuer-level characteristics from the Mergent Municipal Bond Database (Mergent). Second, I use the cross-section of cleaned transaction price data in each state-month period to estimate the version of the Nelson and Siegel (1987) model proposed by Diebold et al. (2006). After estimating these state-specific municipal yield curves, I present summary statistics that show that these municipal yield curves, which can be produced for each of the 50 states and Washington, D.C., are closely aligned with the yield curves available from commercial data providers for a subset of 19 states.

Data filters. Motivated by Green, Li, and Schürhoff (2010), Schwert (2017), and Gao et al. (2020), I apply the following data filters to the historical municipal bond transactions data from the MSRB. First, I remove any transaction for which either (i) the coupon rate or the maturity date of the bond is missing and cannot be found in Mergent or (ii) the trade occurs after the maturity of the bond. I also exclude trades in bonds for which the coupon rate is greater than 20% or the maturity date either exceeds 40 years (Figure OA.1 shows that trades in very-long dated bonds are rare) or is less than six months (to avoid microstructure issues associated with bond issuance). Second, I exclude a very small number of transactions with a price less than 50% of face value or more than 150% of face value. Third, I limit my analysis to fixed-rate bonds that are neither taxable at the Federal level nor subject to alternative minimum taxation (AMT). This ensures that all bonds that remain in the sample are relatively homogeneous in regards to tax treatment, which is a key feature of the municipal debt market (see, e.g., Babina et al. (2020)). I also retain all transactions regardless of whether they are (i) inter-dealer trades, or (ii) trades between dealers and customers. Likewise, I do not filter on whether a bond is a general obligation (GO) or revenue (RV) bond. This ensures that there are a sufficient number of bonds traded within each state-month period to reliably estimate a yield curve.

Rather than excluding all callable bonds from my sample, which would remove approximately 50% of transactions in the MSRB data, I eliminate any transaction within three months of a call or a redemption date. This is because bond yields are likely to take on relatively extreme and unrepresentative values around these dates. Moreover, to ensure that the state-level yield curves are not driven by noise emanating from a large number of small retail trades, I only retain trades for which at least $20,000 of par value is traded. Finally, I aggregate the yield across all transactions in the same bond within a given month by computing the par-weighted average yield. I then link each resulting bond-month observation to the state of its issuer from Mergent.

Yield curve estimation. For each state i and each month t of the sample period, I estimate a Nelson and Siegel (1987) model using the cross-section of bond yields obtained as the result of the aforementioned filters. Letting $y_{b,i,t}(\tau)$ denote the yield of bond b in state i at time t that has τ months remaining until maturity, the Nelson and Siegel (1987) approach estimates the parameters $\{\beta_1, \beta_2, \beta_3, \gamma\}$ in the following function

$$y_{b,i,t}(\tau) = \beta_1 + \beta_2 \left[\frac{1-\exp(-\tau\gamma)}{\tau\gamma}\right] + \beta_3 \left[\frac{1-\exp(-\tau\gamma)}{\tau\gamma} - \exp(-\tau\gamma)\right] + \varepsilon_{b,i,t}(\tau), \quad \text{(OA.1)}$$

by minimizing the mean-squared pricing error (i.e., $\sum_b \varepsilon_{b,i,t}(\tau)^2$), where $\varepsilon_{b,i,t}(\tau)$ is the pricing error associated with the τ-month-to-maturity bond b in state i at time t. I estimate the parameters via nonlinear least squares (NLS) over a comprehensive grid of initial values for each parameter to ensure that the parameter estimates do not correspond to local minima of the aforementioned function. Furthermore, since my goal is to estimate a representative yield curve for each state-month period, I remove any transactions for which the yield is less than (greater than) the 2.5^{th} (97.5^{th}) percentile of the cross-section of yields in the given state-month period. Having estimated equation (OA.1), the representative term structure for state s in month t for maturities of $m \in \{1, \ldots, 360\}$ months is then given by

$$y_{i,t}(m) = \hat{\beta}_1 + \hat{\beta}_2 \left[\frac{1-\exp(-m\hat{\gamma})}{m\hat{\gamma}}\right] + \hat{\beta}_3 \left[\frac{1-\exp(-m\hat{\gamma})}{m\hat{\gamma}} - \exp(-m\hat{\gamma})\right], \quad \text{(OA.2)}$$

where $y_{i,t}(m)$ denotes the m month-to-maturity yield of a representative bond issued by state i at the end of t. The state-level yield curves represented by equation (OA.2) are then used to implement my empirical analyses in Section 1 and onwards.

Validation and summary statistics. I show that estimating state-level yield curves using the method described above, which can be applied to all 50 United States and Washington, D.C., produces term structures of municipal bond yields that are closely aligned with those from commercial data providers that are only available for a subset of states. I also present summary statistics related to these state-level yield curves.

Table OA.1 presents summary statistics associated with the state-level term structures of municipal bond yields obtained from equation (OA.2). Panel A of the table shows the abbreviated name of each state, the proportion of total gross domestic product (GDP) that each state produces, the average number of municipal bonds traded in each state-month period, and the estimated one- and 20-year municipal bond yields (denoted by $y(12)$ and $y(240)$, respectively.) The panel also reports two key correlations. First, the table reports the correlation between the level of the one- and 20-year municipal bond yields estimated above and the same maturity yields from the Bloomberg Fair Value Curves (denoted by $\rho^{BBG}_{L,12}$ and $\rho^{BBG}_{L,240}$, respectively). Second, the table also reports the correlation between the first difference of each state's one- and 20-year municipal bond yields and the first differences of these yields from the Bloomberg yield curves (denoted by $\rho^{BBG}_{\Delta,12}$ and $\rho^{BBG}_{\Delta,240}$, respectively).

Notably, while these Bloomberg Fair Value Curves are only available for a subset of 19 states, the yield curves estimated above are available for all 50 states and Washington, D.C. Finally, the table also shows the average maturity of the municipal bonds traded in each state and the average number of firms headquartered in a given state. Panel B of the table then shows the summary statistics of these variables across all states.

Panel B indicates that while the average state reflects about 1.96% of GDP, the median state is only responsible for producing around 1.13% of GDP. This highlights that the U.S. economy features a small number of very large states (e.g., CA, NY, and TX) and a large number of very small states (e.g., AK, DE, ND, SD, VT, and WY). Similar to this skewed distribution of state sizes, trading activity in the municipal debt market is also skewed towards larger states. While there are approximately 4,900 municipal bonds trade within the average state in a given month (most of which are traded within a small set of very large states), there are only about 2,600 municipal bonds traded in the median state. Robustness tests in Section 4.2 ensure that my key empirical results are not driven by any of the individual small or large states in my sample.

Panel B of the table also shows that the yield curves estimated using the methodology outlined above share very similar dynamics (both in terms of levels and first differences) to those constructed by the Bloomberg for a subset of 19 states. For instance, the average correlation between the level (first difference) of the yield curves estimated above and those from Bloomberg is 0.98 (0.63). This high correlation arises despite the fact that, unlike the proprietary approach implemented by Bloomberg, the methodology described above makes no explicit (but proprietary) adjustments for either embedded call options or illiquid bonds. These high correlations indicate that the yield curves produced above do indeed reflect the representative yield of bonds issued by each state and suggest that the methodology described above is suitable to extend to a larger cross-section of states than Bloomberg considers.[21]

Figure OA.2 complements the summary statistics reported in Table OA.1 by presenting the average term structure of municipal bond yields across all states. Notably, the figure shows that the average term structure of municipal yields is upward sloping. While the mean one-year yield is approximately 2% per annum, the average 20 year yield is roughly 4% per annum. The figure also displays the average yield curve in two states: California and North Carolina. The average yield curve in each of these states is very similar to the average yield curve across all states.

[21]Bloomberg imposes significantly more stringent filters on the MSRB transaction data to construct their Fair Value Curves. Namely, Bloomberg only considers transactions related to GO bonds (and a very small subset of RV bonds), and requires each transaction to relate to a AAA-rated tax-exempt fixed-coupon bond with an issuance size of more than $2 million in a issuance deal of more than $40 million. Only (i) inter-dealer trades of more than $500,000 or (ii) customer-to-dealer and dealer-to-customer trades of more than $1m are retained. These stringent filters mean that only 19 states are included in the Bloomberg data, and economically prominent states, such as Arizona, Colorado, Indiana, have no Bloomberg yield curves due to state-level limits on the issuance of GO debt. In contrast, the yield curves I construct are highly correlated with those from Bloomberg, and are available for all 50 states and Washington, D.C.

Table OA.1: State-level summary statistics

The table reports the characteristics of the states underlying the sample. "GDP" represents the share of total of gross domestic product attributed to each state, while "Trades" denotes the average number of trades in the municipal bonds issued by each state per month. The column labeled "$Y(1)$" ("$Y(20)$") reports the time-series average value of bonds issued in each state with one year (20 years) to maturity. The columns represented by $\rho_{L,1}^{BBG}$ and $\rho_{L,20}^{BBG}$ ($\rho_{\Delta,1}^{BBG}$ and $\rho_{\Delta,20}^{BBG}$) report the time-series correlations between the level (first difference) of the one- and 20-year municipal bond yields underlying this study, and those constructed by Bloomberg for a subset of states, respectively. The mean maturity (in years) of bonds outstanding in each state is reported in the column labeled "Mat.," while the average number of firms headquartered in each state is reported under "Firms." Panel A reports the average value of each characteristic across each state, while Panel B (Panel C) reports the value of each statistic within the five largest (smallest) states underyling the sample. Finally, the sample period ranges from January 1998 through December 2020.

State	GDP	Trades	$y(1)$	$y(20)$	$\rho_{L,1}^{BBG}$	$\rho_{L,20}^{BBG}$	$\rho_{\Delta,1}^{BBG}$	$\rho_{\Delta,20}^{BBG}$	Mat.	Firms
Panel A: State-level statistics										
AK	0.32	746	1.84	3.99	-	-	-	-	6.75	1
AL	1.16	2572	1.89	4.04	-	-	-	-	8.27	14
AR	0.68	1237	1.82	4.05	-	-	-	-	8.68	14
AZ	1.67	5062	1.78	3.89	-	-	-	-	7.42	42
CA	13.57	37526	1.71	4.01	0.97	0.95	0.57	0.62	8.50	567
CO	1.75	3973	1.79	3.89	-	-	-	-	7.68	83
CT	1.54	5471	1.71	3.87	0.98	0.97	0.53	0.66	7.66	65
DC	0.00	939	1.80	3.88	-	-	-	-	7.73	8
DE	0.39	590	1.75	3.86	-	-	-	-	7.44	11
FL	5.04	12246	1.87	3.98	0.95	0.94	0.59	0.64	8.03	125
GA	2.89	4484	1.74	3.91	0.98	0.97	0.56	0.60	7.28	76
HI	0.45	1289	1.76	3.74	-	-	-	-	7.37	4
IA	0.96	1734	1.77	4.05	-	-	-	-	7.34	13
ID	0.37	453	1.75	3.96	-	-	-	-	7.41	6
IL	4.55	8172	1.97	4.18	0.92	0.86	0.42	0.62	7.54	128
IN	1.90	3000	1.80	3.96	-	-	-	-	6.22	33
KS	0.86	2267	1.74	3.98	-	-	-	-	7.40	15
KY	1.11	2604	1.83	4.10	-	-	-	-	7.68	14
LA	1.50	2284	1.96	4.04	-	-	-	-	8.32	17
MA	2.71	8470	1.67	3.77	0.98	0.96	0.58	0.67	7.82	176
MD	2.02	4364	1.63	3.79	0.98	0.97	0.45	0.68	7.38	46
ME	0.34	1000	1.66	3.99	-	-	-	-	7.38	4
MI	2.84	6217	1.89	4.05	0.97	0.94	0.59	0.60	7.51	53
MN	1.85	4594	1.70	3.94	0.98	0.96	0.55	0.58	7.27	92
MO	1.72	3393	1.81	3.94	-	-	-	-	7.74	42
MS	0.63	1051	1.87	4.05	-	-	-	-	7.89	5
MT	0.25	351	1.75	4.11	-	-	-	-	8.14	2
NC	2.75	4725	1.69	3.88	0.98	0.97	0.59	0.63	7.49	55
ND	0.25	466	1.79	4.15	-	-	-	-	7.22	1
NE	0.62	1559	1.68	4.20	-	-	-	-	8.02	13
NH	0.43	758	1.70	3.91	-	-	-	-	7.73	10

Continued on the next page...

Table OA.1 – Continued from the previous page

State	GDP	Trades	$y(1)$	$y(20)$	$\rho^{BBG}_{L,1}$	$\rho^{BBG}_{L,20}$	$\rho^{BBG}_{\Delta,1}$	$\rho^{BBG}_{\Delta,20}$	Mat.	Firms
NJ	3.34	12172	1.76	3.90	0.97	0.94	0.55	0.66	7.84	122
NM	0.55	1207	1.70	4.00	-	-	-	-	6.49	1
NV	0.83	1955	1.89	4.08	-	-	-	-	7.73	25
NY	8.04	31911	1.71	3.80	0.98	0.97	0.59	0.63	8.08	239
OH	3.55	6755	1.72	3.88	0.98	0.96	0.59	0.66	6.97	96
OK	1.03	1659	1.77	3.97	-	-	-	-	6.82	23
OR	1.10	2939	1.70	3.83	-	-	-	-	7.57	30
PA	4.01	10948	1.81	3.97	0.96	0.94	0.64	0.63	7.72	119
RI	0.33	901	1.83	4.01	-	-	-	-	7.28	9
SC	1.13	3092	1.73	3.99	0.97	0.94	0.47	0.63	7.87	11
SD	0.25	311	1.83	4.16	-	-	-	-	7.03	3
TN	1.77	2934	1.76	3.82	-	-	-	-	7.57	42
TX	8.44	23259	1.80	3.94	0.98	0.95	0.54	0.67	8.45	281
UT	0.78	1424	1.69	3.90	-	-	-	-	6.92	27
VA	2.70	5206	1.68	3.83	0.98	0.97	0.54	0.69	7.66	75
VT	0.17	406	1.72	3.91	-	-	-	-	7.99	2
WA	2.49	6120	1.76	3.84	0.98	0.96	0.54	0.67	7.56	58
WI	1.72	3688	1.79	3.97	0.98	0.95	0.61	0.61	6.68	44
WV	0.44	457	1.90	4.31	-	-	-	-	7.43	3
WY	0.23	94	1.81	4.43	-	-	-	-	6.59	1
Panel B: Summary statistics										
Mean	1.96	4922	1.77	3.97	0.97	0.95	0.55	0.64	7.54	57
$p25$	0.44	1012	1.71	3.89	0.97	0.94	0.54	0.62	7.30	8
Median	1.13	2604	1.76	3.97	0.98	0.96	0.56	0.63	7.56	25
$p75$	2.65	5170	1.82	4.05	0.98	0.97	0.59	0.67	7.84	72

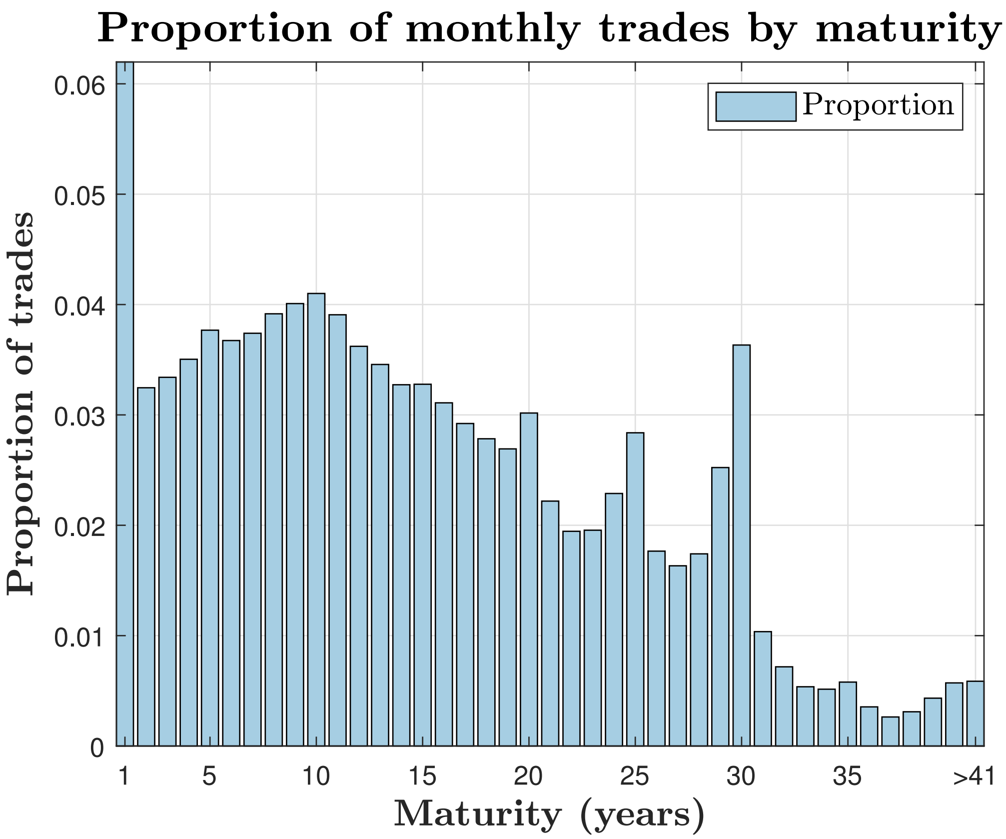

Figure OA.1: Proportion of average monthly trading volume by maturity
The figure displays the average proportion of monthly trading volume in the municipal debt market by maturity. The figure is constructed using transaction-level municipal bond data from the Municipal Securities Rulemaking Board (MSRB), supplemented with bond characteristics from the Mergent Municipal Bond Database. The sample period ranges from January 1998 through September 2019.

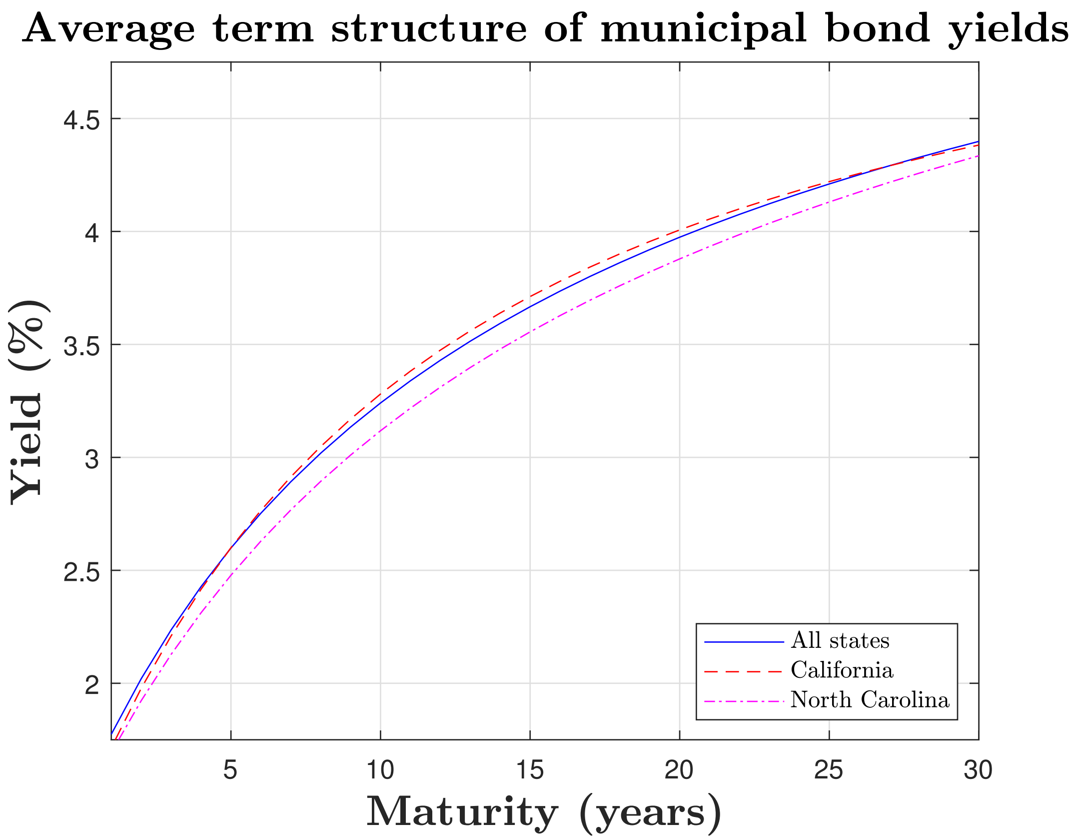

Figure OA.2: Average term structures of municipal bond yields
The figure displays the average term structure of municipal bond yields, obtained by following the procedure described in Section OA.2 of the Online Appendix, for all states, California, and North Carolina. The average term structure across all states is obtained by computing the mean yield for each maturity across all states and time periods. The average term structures for California and North Carolina are obtained by computing the time-series mean yield for each maturity in each state. The data underlying this figure ranges from January 1998 through December 2020.

OA.2.1 Yield decomposition

Beyond constructing the term structure of municipal bond yields in each state, I decompose these state-level yields into components related to liquidity and credit risk. This decomposition is motivated by equation (1) in the main text that shows that the tax-adjusted municipal bond yield of state i at time t with m-months to maturity (i.e., $y_{i,t}(m)/(1-\tau_{i,t})$) in excess of the maturity-matched Treasury yield at the same point in time (i.e., $Y_{i,t}(m)$) reflects a state-specific component of the yield: $\tilde{y}_{i,t}(m)$ from equation (2) in the main text. In turn, this state-specific component of the yield reflects a combination of the liquidity risk of the bonds trading in state i, which I will denote by $\lambda_{i,t}(m)$, and the credit risk of the state, which I will denote by $\psi_{i,t}(m)$ (see, e.g., Wang et al. (2008); Schwert (2017); Chun et al. (2019); Ang et al. (2014)).

To split the tax-adjusted municipal-Treasury spread into the components driven by liquidity risk and credit risk, I first estimate the following time-series regression in each state

$$\tilde{y}_{i,t}(m) = +\boldsymbol{\beta}_i \boldsymbol{\Lambda}_{i,t}^T + \varepsilon_{i,t}. \tag{OA.3}$$

Here, $\tilde{y}_{i,t}(m)$ follows the definition of this term from equation (2) and $\boldsymbol{\Lambda}_{i,t}$ is a vector of liquidity-related controls associated with the municipal bonds in state i at time t. In the spirit of Dick-Nielsen et al. (2012) and Schwert (2017), this vector of controls includes the state-specific values of (i) the natural logarithm of the number of bonds traded at each time t, (ii) the average Amihud (2002) ratio of the bonds outstanding at time t, (iii) the average value of price dispersion, computed in accordance with Jankowitsch et al. (2011), for each state's bonds at time t, (iv) the month t average value of the roundtrip cost, computed in accordance with Dick-Nielsen et al. (2012), and (v) the month t standard deviation of the roundtrip cost. With this regression in hand, I measure the liquidity component of state-level municipal bond yields using the fitted value of this regression (i.e., $\hat{\lambda}_{i,t}(m) = \hat{\beta}_{i,0} + \hat{\boldsymbol{\beta}}_i \boldsymbol{\Lambda}_{i,t}^T$) and I define the credit component of the state's m-month-to-maturity municipal-Treasury spread as the residual from this regression (i.e., $\hat{\psi}_{i,t}(m) = \hat{\varepsilon}_{i,t}$).

OA.3 Conditional risk exposures: state- and firm-level evidence

This section shows further evidence of the fact that risk exposures are higher in states where the municipal spread is higher. Specifically, I show that the current level of a state's tax-adjusted municipal-Treasury spread (obtained by estimating $L_{i,t}$ in equation (3) of the main text) predicts both (i) a state's conditional exposure to aggregate productivity, as proxied by the CAPM beta of each state-level portfolio of stock returns, and (ii) the conditional CAPM betas and future excess stock returns of local firms.

State-level evidence. To establish the positive relation between the level of a state's municipal spread and the conditional risk exposures of the state's equity returns, I first need to measure the conditional risk exposure of each state-level portfolio. To this end, I estimate the following rolling window time-series regressions for each state i and each state t using the previous 60 months of state-level return data

$$R^e_{i,t-60\to t} = \beta_{0,i,t} + \beta_{1,i,t} MKTRF_{t-60\to t} + \varepsilon_{i,t-60\to t}. \tag{OA.4}$$

Here, $R^e_{i,t-60\to t}$ denotes the value-weighted average excess stock return across all firms located in state i, as constructed in Section 2.1, $MKTRF$ denotes the excess returns of the market portfolio, and $\beta_{1,i,t}$ is the conditional CAPM beta of state i at time t. This process results in a monthly panel of CAPM betas for each state between January 2003 and December 2020. Next, I estimate panel regressions that project each state's conditional CAPM betas on the level of the state's municipal spread and a host of state-level characteristics observable at time t. These panel regressions also include combinations of both state and time fixed effects that capture common shocks across time and states (e.g., recessions or state-specific risks). The panel regressions I estimate are represented by

$$\beta_{1,i,t} = \gamma_i + \beta_L L_{i,t} + \boldsymbol{\beta} \boldsymbol{X}'_{i,t} + \varepsilon_{i,t}, \tag{OA.5}$$

where $L_{i,t}$ represents the level of state i's municipal spread in month t, β_L captures the average relation between the state's municipal spread and conditional risk exposures, and $\boldsymbol{X_{i,t}}$ is a matrix of other state-level characteristics related to risk exposures. These additional control variables include the average size, book-to-market ratio, investment rate, profitability, leverage, hiring rate, idiosyncratic productivity, exposure to aggregate risk, idiosyncratic volatility, momentum, and organizational capital-to-assets ratio of all local firms in a given state. Each independent variable is standardized by its unconditional standard deviation and γ_i denotes state fixed effects.

The results obtained by estimating equation (OA.5) are presented in Table OA.2. The tables shows that there is a positive and statistically significant relation between the level of a state's municipal spread and the state's exposure to aggregate risk regardless of whether no fixed effects are included in the regression (columns one and three) or state fixed effects are included in the regression (columns two and four). This conclusion also holds regardless of whether additional control variables are excluded (columns one and three) or the full set of control variables is included (columns three and four). Overall, the table highlights a clear link between the level of the state's municipal spread and the average risk exposure of the firms located in that state. Specifically, firms located in states where the municipal spread is high are riskier.

Table OA.2: Conditional risk exposures: state-level evidence

The table reports the relation between state-level conditional risk exposures, the level of a state's municipal spread, and other state-level characteristics. The analysis underlying this table is implemented in two steps. First, the conditional CAPM betas of state i at time t is obtained by projecting the excess monthly returns of the state on excess market returns via equation (OA.4) using the past 60 months of returns. Second, these state-level conditional market betas are projected on (i) the current level of each state's municipal spread, as obtained from equation (3), and a host of other state-level characteristics as control variables. The panel regression used to estimate this second-stage regression is given by equation (OA.5). All independent variables included in the panel regressions are standardized by their unconditional standard deviations prior to estimating the regressions. Columns one and three report the results of panel regressions that feature no fixed effects, while columns two and four report the results of panel regression that feature state fixed effects. Parentheses report t-statistics based on standard errors that are clustered by time and state. Finally, the sample period is from January 2003 through December 2020.

	(1)	(2)	(3)	(4)
Level	0.05	0.04	0.05	0.03
	(1.85)	(1.93)	(2.33)	(2.10)
ln(Size)			-0.13	0.00
			(-2.91)	(0.02)
ln(BEME)			-0.01	0.02
			(-0.41)	(0.58)
I/A			-0.03	-0.01
			(-1.21)	(-0.47)
GP			-0.08	-0.05
			(-2.56)	(-3.01)
Leverage			0.00	-0.03
			(0.01)	(-2.58)
Hire			0.06	-0.03
			(2.14)	(-1.39)
TFP			0.06	-0.04
			(1.55)	(-1.22)
β (MSA)			-0.01	0.00
			(-0.52)	(0.33)
IVOL			0.12	0.04
			(3.27)	(2.21)
Momentum			0.26	0.07
			(3.93)	(1.24)
ORG			-0.00	0.01
			(-0.20)	(0.28)
State FE	No	Yes	No	Yes
R2	0.03	0.57	0.34	0.60
Obs.	6665	6665	6665	6665

Firm-level evidence. Having demonstrated that the level of a state's municipal spread is informative about the extent to which a *portfolio* of local firms is exposed to aggregate risk, the following analyses shows that the same results hold at the firm level. That is, there is a positive association between the level of a state's municipal spread and the conditional CAPM betas of the *individual firms* located in that state. These analyses are implemented by following the same broad steps as those described above. However, rather than estimating equation (OA.4) for each state i, the same time-series regressions are estimated using the excess monthly returns of each firm i in the CRSP/Compustat universe (subject to the filters described in Section 2.1). I estimate the following panel regression for the firm-level analysis:

$$y_{i,j,k,t} = \gamma_{k,t} + \beta_L L_{j,t} + \boldsymbol{\beta} \boldsymbol{X}'_{i,t} + \varepsilon_{i,t}. \tag{OA.6}$$

Here, $y_{i,j,k,t}$ represents a firm-level outcome variable associated with firm i in state j that operates in industry k at time t. Specifically, I consider the case in which $y_{i,j,k,t}$ is either the conditional CAPM beta of the firm or the one-quarter ahead excess return of the firm. β_L is the parameter of interest and captures the association between the level of a state's municipal spread, denoted by $L_{j,t}$, and the firm's current conditional CAPM betas or future excess returns. Moreover, $\boldsymbol{X}_{i,t}$ is a matrix of time-varying and firm-specific controls that includes each firm's size, book-to-market ratio, investment rate, and profitability. Finally $\gamma_{k,t}$ denotes industry-by-time fixed effects.

The results of the aforementioned panel regression are reported in Table OA.3. Panel A of the table shows that there is a positive and statistically significant association between the current level of a state's municipal spread and conditional CAPM betas. That is, the panel shows that firms located in states with a higher municipal spread are more exposed to aggregate risk, even when controlling for a host of prominent firm-level covariates and industry-by-time fixed effects.

Similarly, and in line with the results in Panel A, Panel B shows that firms located in states where the municipal spread is currently high earn higher *future* excess returns. This is consistent with the notion that the level of a state's municipal spread is informative about both conditional risk exposures and firm-level risk premia. All in all, this evidence shows that firms operating in states where municipal spread is high are risky.

Table OA.3: Conditional risk exposures: firm-level evidence

The table reports the relation between firm-level conditional risk exposures (Panel A) and risk premia (Panel B), the level of the state's municipal spread, and other firm-level characteristics. The analysis underlying this table is implemented in two steps. First, the conditional CAPM betas of firm i at time t is obtained by projecting the excess monthly returns of the firm on excess market returns via equation (OA.4) using the past 60 months of returns. Second, these firm-level conditional market betas (or quarterly excess returns between months t and $t+2$) are projected on (i) the current level of each state's municipal spread, as obtained from equation (3), and firm-level size, book-to-market ratios, investment rates, and profitability as control variables. The panel regression used to estimate this second-stage regression is given by equation (OA.6). All independent variables included in the panel regressions are standardized by their unconditional standard deviations prior to estimating the regressions. Columns one and two of the table report the results of regressions in which the independent variable is a firm's conditional CAPM beta (Panel A), whereas columns three and four report the results in which the independent variable is the firm's the quarterly excess return between months t and $t+2$ (Panel B). All columns of the table feature industry-by-time fixed effects. Parentheses report t-statistics based on standard errors that are clustered by firm. Finally, the sample period is from January 2003 (Panel A) or March 1998 (Panel B) through December 2020.

	Panel A: Firm-level betas		Panel B: Firm-level excess returns	
	(1)	(2)	(3)	(4)
Level	0.05	0.04	0.44	0.40
	(3.20)	(2.98)	(2.21)	(2.01)
ln(Size)		0.04		-1.73
		(2.90)		(-12.26)
ln(BEME)		0.03		0.02
		(1.97)		(0.15)
I/A		0.03		0.64
		(2.44)		(4.72)
GP		-0.09		0.00
		(-5.66)		(0.03)
β (MSA)		0.02		0.22
		(2.10)		(2.37)
Industry-by-Time FE	Yes	Yes	Yes	Yes
R2	0.29	0.30	0.16	0.17
Obs.	17185	17185	34554	34554

OA.4 Supplemental tables and figures

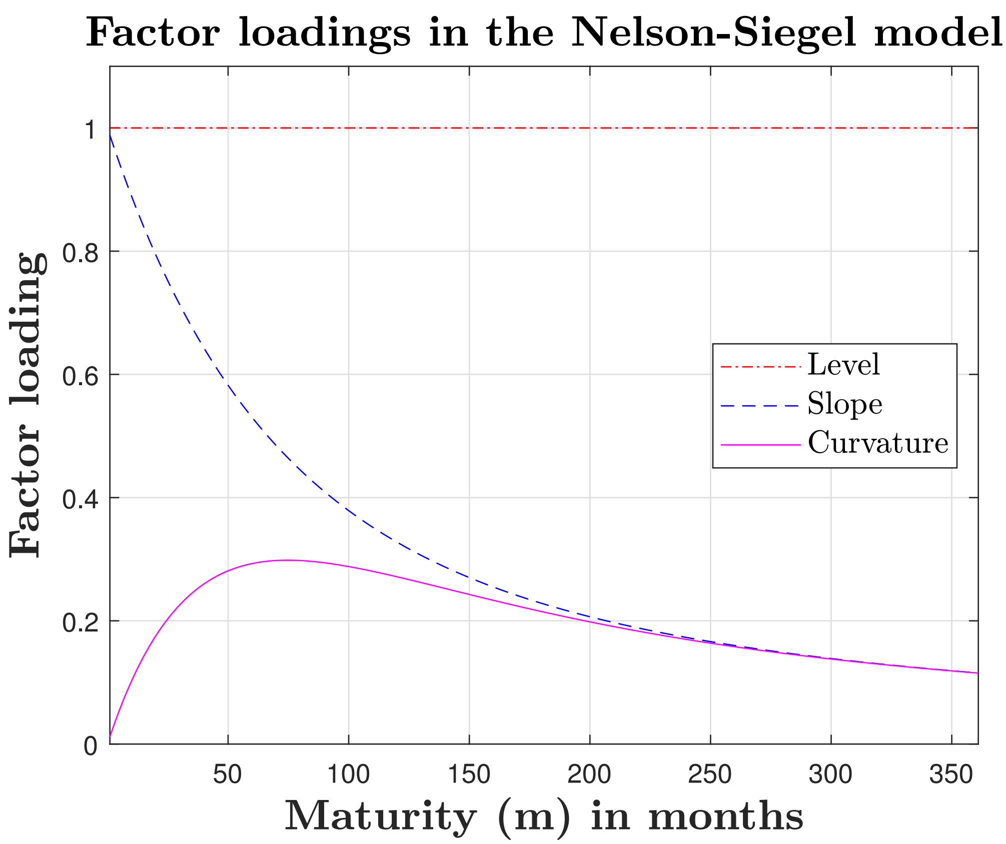

Figure OA.3: Factor loadings underlying the Nelson-Siegel model
The figure displays the factor loadings underlying the Nelson-Siegel model proposed by Diebold and Li (2006) when the shape parameter (i.e. λ in equation (3) of the main text) is set to 0.0240. In this figure the loadings associated with the "Level", "Slope", and "Curvature" factor refer to the coefficients of $L_{i,t}$, $S_{i,t}$, and $C_{i,t}$ in equation (3) of the main text.

OA.4.1 Municipal yields and stock returns

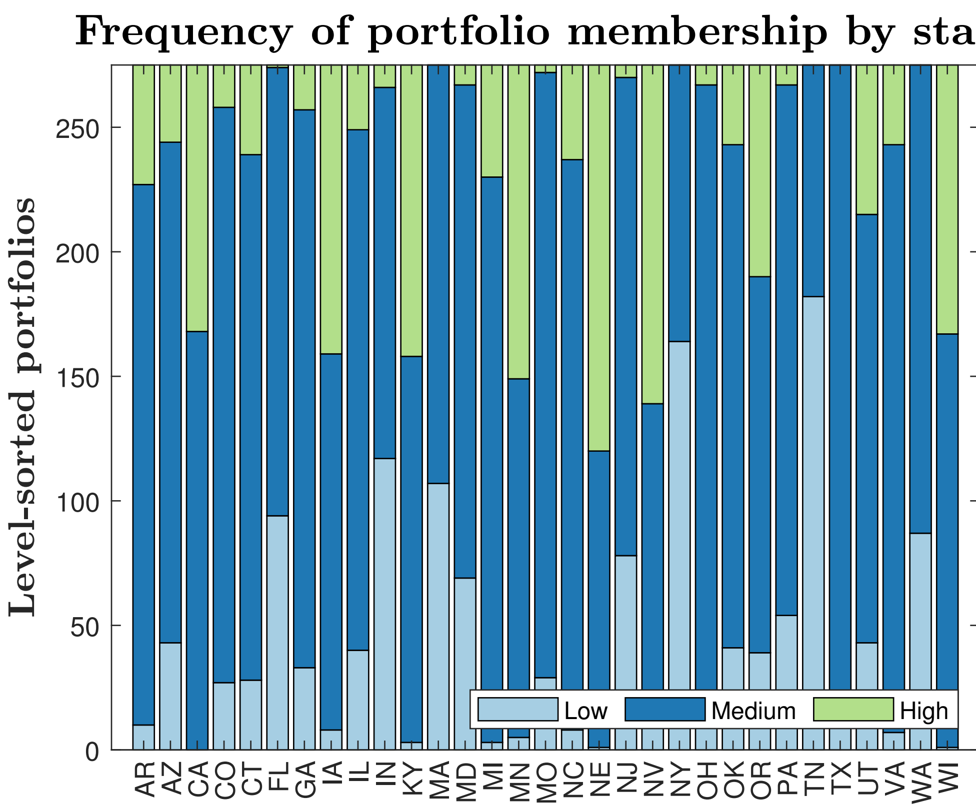

Figure OA.4: Frequency of portfolio membership by state
The figure reports the number of months each state is sorted into the low, medium, and high spread-sorted portfolio. States are sorted into portfolios at the end of each month following the portfolio formation procedure described in Section 2.1. The sample period ranges from January 1998 through December 2020.

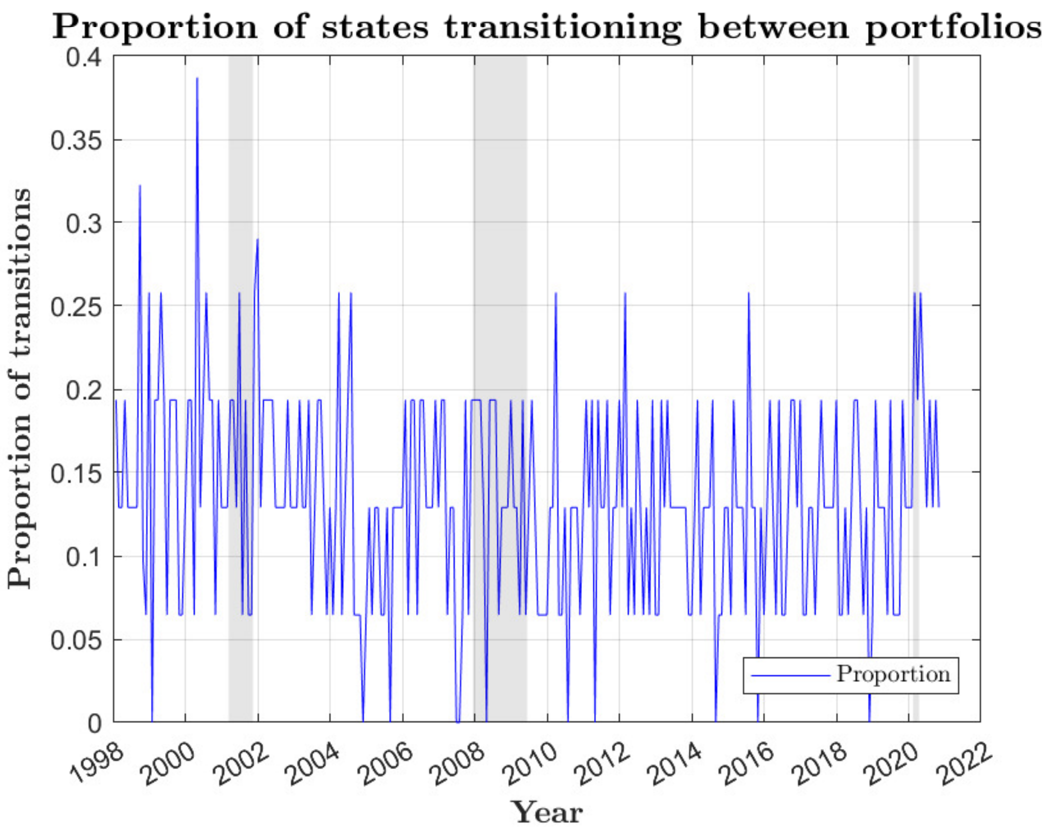

Figure OA.5: Proportion of portfolio transitions over time
The figure reports the proportion of states in each month t that have transitioned into a different portfolio since month $t-1$. States are sorted into portfolios at the end of each month following the portfolio formation procedure described in Section 2.1. The sample period ranges from January 1998 through December 2020.

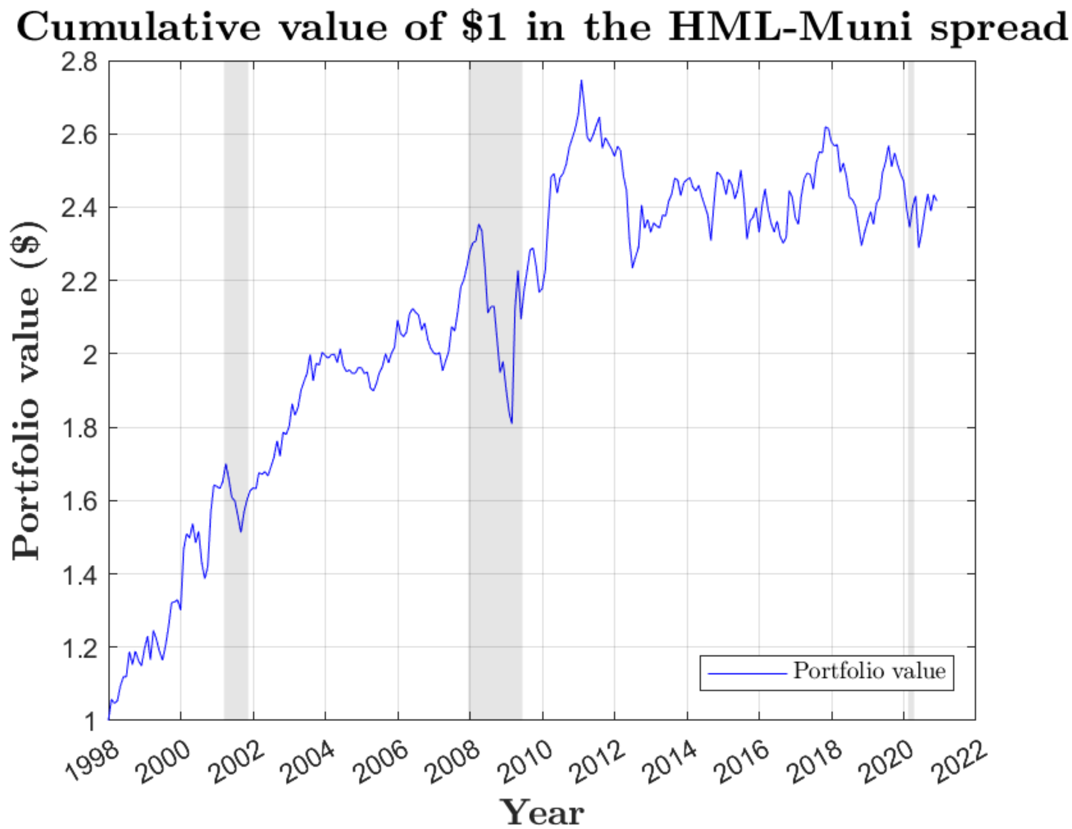

Figure OA.6: Cumulative value of investment in the HML-Muni portfolio
The figure reports the cumulative value earned by investing $1 in the HML-Muni spread at the beginning of the sample period and reinvesting all proceeds of this investment into the same portfolio at the end of each month. States are sorted into portfolios at the end of each month following the portfolio formation procedure described in Section 2.1. The sample period ranges from January 1998 through December 2020.

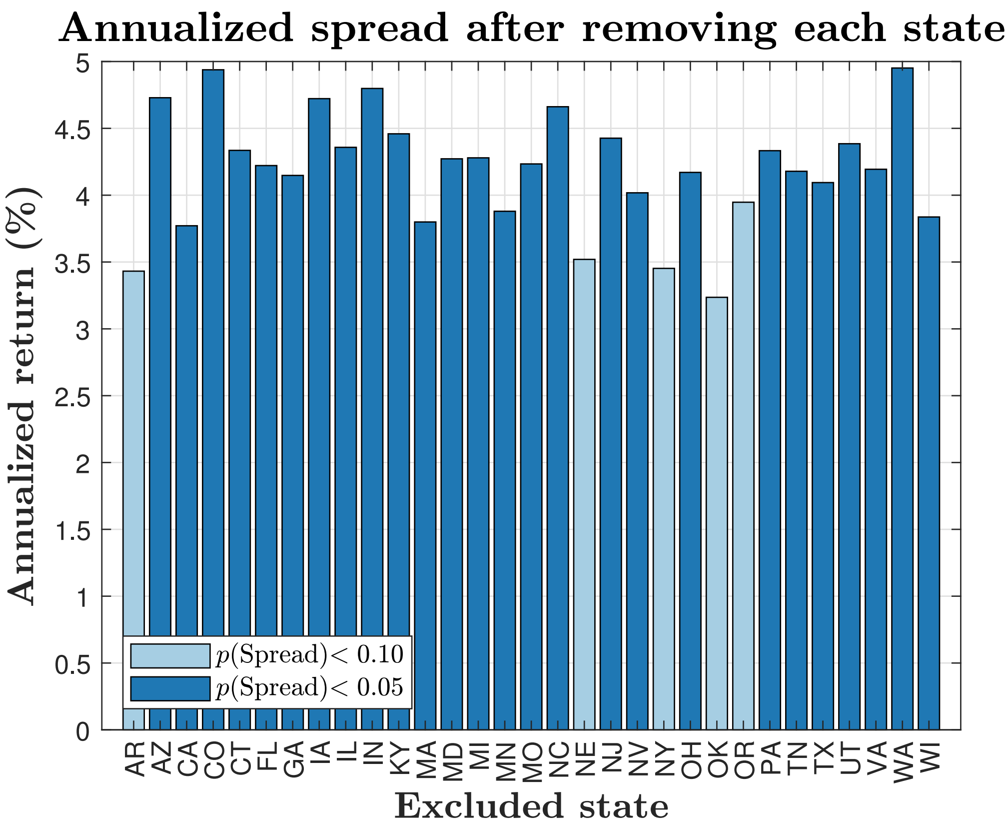

Figure OA.7: Municipal spread-sorted portfolios: excluding individual states
The figure reports the annualized return spread obtained by sorting portfolios on the level of each state's municipal-Treasury spread. Here, the level of each state's municipal spread ($L_{i,t}$) is obtained from equation (3) and the portfolio formation procedure follows that described in Section 2.1 with one exception: each bar in the figure represents the annualized spread that is obtained after excluding a given state (denoted by the horizontal axis) from the analysis. The color of each column represents the statistical significance of the resulting spread, computed using Newey and West (1987) standard errors. A dark (light) blue shaded bar denotes a spread that is statistically significant at the 5% (10%) level. Finally, the sample period is from January 1998 through December 2020.

Table OA.4: Transition matrix between the municipal spread-sorted portfolios
The table shows the probability that a state sorted into portfolio $i \in$ {Low, Medium, High} in month t, where i is the row index, is sorted into portfolio $j \in$ {Low, Medium, High} in month $t + 1$, where j is the column index. States are sorted into portfolios at the end of each month following the portfolio formation procedure described in Section 2.1. The sample period ranges from January 1998 through December 2020.

Portfolio in	Portfolio in month $t + 1$		
month t	Low	Medium	High
Low	0.804	0.196	0.001
Medium	0.047	0.901	0.052
High	0.001	0.218	0.781

Table OA.5: Double-sorted portfolios

The table reports value-weighted portfolio returns from a conditional double-sort procedure in which the control variable (i.e., the first-stage sorting variable) in Panel A and Panel B is the industry-adjusted systematic risk exposure of each firm's headquarter MSA (β_{MSA}) or hiring rate (HIRE), respectively. The second-stage sorting variable is the level of a state's municipal spread ($L_{i,t}$) from equation (3). The sorts are conducted as follows. First, at the end of each month beginning in January 1998, the cross-section of states is sorted into three portfolios on the basis of the control variable, such that eight states are included in each of the low and high control-sorted portfolios. Next, within each of these characteristic-sorted portfolios, the cross-section of states is further sorted into three additional portfolios based on the level of each state's municipal spread, such that two states are included in each of the high and low spread-sorted portfolios. This process produces nine portfolios that are held for one month, at which point in time all portfolios are rebalanced. The table reports the average returns of each portfolio, the spread between the returns of the high (H) and low (L) spread-sorted portfolios, and the Newey and West (1987) t-statistic associated with this spread (t(Spread)). Additionally, the last row of each panel reports the p-value from a joint test on the null hypothesis that the HML-Muni spread across all three characteristic-sorted portfolios is greater than zero. The sample period ranges from January 1998 through December 2020.

	Panel A: β_{MSA}			Panel B: HIRE		
	Low β_{MSA}	Medium	High β_{MSA}	Low HIRE	Medium	High HIRE
Low (L)	0.61	0.52	0.61	0.91	0.57	0.74
Medium	0.92	0.74	0.72	0.76	0.75	0.86
High (H)	1.03	1.05	0.66	1.08	1.11	1.14
Spread	0.41	0.53	0.05	0.17	0.54	0.40
t(Spread)	(1.45)	(1.74)	(0.21)	(0.65)	(2.39)	(1.34)
p(Joint)		0.05			0.02	

Table OA.6: HML-Muni spread and unconditional factor models

The table reports the results of time-series regressions of the value-weighted HML-Muni spread (the portfolio that buys firms located in states where the level of the municipal-Treasury spread is high and shorts firms located in states where the level of the municipal-Treasury spread is low) on a number of asset-pricing factors. Parameter estimates are obtained by regressing monthly excess returns on each set of monthly risk factors, and each reported α is expressed in percentage points per month by multiplying the corresponding point estimate by 12. MKTRF is the excess return of the market portfolio. SMB is the size factor of the corresponding model, HML is the value factor of the Fama and French (1993) three-factor or Fama and French (2015) five-factor model, and MOM is the momentum factor of Carhart (1997). Profit and Invest refer to the appropriately defined profitability and investment factors of the Fama and French (2015) five-factor model or the Hou et al. (2015) q-factor model, respectively. Newey and West (1987) t-statistics are reported in parentheses, and the sample period ranges from January 1998 through December 2020.

	FF3F	FF4F	FF5F	q
MKTRF	0.10	0.07	0.10	0.00
	(2.25)	(1.69)	(1.97)	(1.79)
SMB	0.11	0.12	0.12	0.00
	(1.43)	(1.48)	(1.53)	(1.43)
HML	0.16	0.13	0.16	
	(2.17)	(1.95)	(2.28)	
UMD		-0.07		
		(-0.99)		
Profit.			0.00	-0.00
			(0.00)	(-0.65)
Invest.			-0.04	0.00
			(-0.41)	(1.16)
α	0.28	0.32	0.28	0.26
	(1.77)	(1.99)	(1.68)	(1.53)
$\bar{R}^2$	0.08	0.09	0.07	0.07

Table OA.7: Municipal spread-sorted portfolios: heterogeneity over the business cycle The table reports the monthly returns of portfolios sorted on the level of each state's municipal-Treasury spread, as well as the difference between the returns of the Low (L) and High (H) spread-sorted portfolios. Here, the level of each state's municipal spread ($L_{i,t}$) is obtained from equation (3), and the portfolio formation procedure employed is described in Section 2.1. The average monthly returns obtained from this portfolio formation procedure over economic expansions and contractions are then reported. Here, an economic contraction is defined as a portfolio formation month in which the cyclical component from a Hodrick and Prescott (1997) filter applied to the logarithm of monthly industrial production is 1.5 standard deviations below its mean value, and economic expansions capture all other times. In each case, a smoothing parameter of $129,600$ is applied to the industrial production data. Beyond showing the mean value-weighted portfolio returns over each stage of the business cycle, the table also reports the number of months classified as economic expansions and contractions. Finally, parentheses report Newey and West (1987) t-statistics. The sample period is from January 1998 through December 2020.

	Expansions	Contractions
Months	258	17
Low (L)	0.43	3.06
	(4.30)	(4.30)
Medium	0.46	3.44
	(1.59)	(4.40)
High (H)	0.73	4.28
	(0.73)	(3.02)
Spread (H-L)	0.30	1.22
t(Spread)	(1.98)	(1.44)

Table OA.8: Municipal spread-sorted portfolios: heterogeneity in fiscal policy and tax privilege

The table reports the monthly returns of portfolios sorted on the level of each state's municipal-Treasury spread, as well as the difference between the returns of the Low (L) and High (H) spread-sorted portfolios. Here, the level of each state's municipal spread ($L_{i,t}$) is obtained from equation (3). The portfolio formation procedure employed is described in Section 2.1 with the following two exceptions. In Panel A, the column denoted "Countercyclical" ("Procyclical") limits the cross-section of states to those that tend to implement more countercyclical (procyclical) fiscal policies. Here, I measure the cyclicality of each state's fiscal policies using the fiscal policy betas from Table 1 of Da et al. (2018). I refer to a state as a countercyclical (procyclical) state if its fiscal policy beta is below (above) the median value of this variable across all states. In Panel B, the column denoted "Low" ("High") limits the cross-section of states to those with low tax privileges for holding municipal debt. I refer to a state as having a low (high) tax privilege if its tax privilege from Table 2 of Babina et al. (2020) is below the median value. The average and the standard deviation of the returns are denoted by $\mathbb{E}[R]$ and $\sigma(R)$, respectively. The value of $p(\mathbb{E}[R_1] = \mathbb{E}[R_2])$ reports the p-value from a test on the null hypothesis that the two spreads reported within each panel are equal. Finally, parentheses report Newey and West (1987) t-statistics. The sample period is from January 1998 through December 2020.

	Panel A: Fiscal policy				Panel B: Tax privilege			
	Countercyclical		Procyclical		Low		High	
	$\mathbb{E}[R]$	$\sigma(R)$	$\mathbb{E}[R]$	$\sigma(R)$	$\mathbb{E}[R]$	$\sigma(R)$	$\mathbb{E}[R]$	$\sigma(R)$
Low (L)	0.71	4.64	0.66	5.12	0.72	5.33	0.73	4.23
Medium	0.74	4.82	1.01	5.17	0.63	5.54	0.85	4.53
High (H)	1.00	6.07	1.04	5.01	1.01	6.43	1.05	4.68
Spread (H-L)	0.29	3.08	0.38	2.54	0.29	3.07	0.31	2.25
t(Spread)	(1.40)		(2.65)		(1.64)		(2.16)	
$p(\mathbb{E}[R_1] = \mathbb{E}[R_2])$	0.74				0.93			

Table OA.9: Municipal spread-sorted portfolios: future characteristics

The table reports the month $t+12$ accounting characteristics of the portfolios sorted on the level of each state's municipal-Treasury spread, the spread between the characteristics of the High (H) and Low (L) portfolios (Spread (H-L)), and the Newey and West (1987) t-statistic associated with this difference (t(Spread)). Here, the level of each state's municipal spread is obtained by estimating equation (3), and portfolios are formed following the procedure outlined in Section 2.1. The characteristics are computed as follows. First, each firm in the sample is assigned to the relevant Fama-French 10 industry group, and the mean industry-level characteristic is subtracted from the firm-level characteristic. Next, the value-weighed average of these characteristics is computed across all firms in a given state, and the equal-weighted average of these state-level characteristics is taken across all states assigned to each portfolio. Finally, the table reports the time-series average of each portfolio-level characteristic. Details on the construction of each variable are provided in Section OA.1 of the Online Appendix. The sample period ranges from January 1998 through December 2020.

	Low (L)	Medium	High (H)	Spread (H-L)	t(Spread)
GP (%)	0.88	0.45	0.60	-0.28	-2.36
ROA (%)	2.30	2.01	1.84	-0.46	-3.84
Asset growth (%)	3.52	3.39	1.81	-1.71	-1.91
I/A (%)	1.24	0.06	0.52	-0.72	-1.89
SUE1 (%)	0.42	0.03	-0.14	-0.56	-2.20
SUE2 (%)	0.35	-0.00	0.12	-0.23	-1.21

Table OA.10: Municipal spread-sorted portfolios: alternative breakpoints

The table reports the monthly returns of portfolios sorted on the level of each state's municipal-Treasury spread, as well as the difference between the returns of the Low (L) and High (H) spread-sorted portfolios. Here, the level of each state's municipal spread ($L_{i,t}$) is obtained from equation (3). The portfolio formation procedure employed is described in Section 2.1, with two exception. First, the Low and High portfolios in the columns labeled "Seven states" ("Eight states") are required to include either seven or eight states each, respectively. For ease of comparison, the column labeled "Five states" repeats the baseline portfolio sort analysis in which five states are sorted into each Low and High spread-sorted portfolio each period. Second, the column labeled "Rank-weighted" reports the portfolio returns associated with a procedure in which the states assigned to the Low and High portfolios in each period are weighted according to the degree to which the level of the municipal-Treasury in a given state differs from the cross-sectional mean municipal-Treasury spread across all states (in the spirit of Moskowitz et al. (2012)). As such, states in the Low (High) portfolio that have a municipal-Treasury spread that is far below (above) the mean municipal-Treasury spread contribute a greater weight towards the returns of the Low (High) portfolio. Since all states are assigned to either the Low or the High portfolio in this exercise, there is no Medium portfolio return. The average and the standard deviation of the value-weighted portfolio returns are denoted by $\mathbb{E}[R]$ and $\sigma(R)$, respectively. Finally, parentheses report Newey and West (1987) t-statistics. The sample period is from January 1998 through December 2020.

	Five states		Six states		Seven states		Rank-weighted	
	$\mathbb{E}[R]$	$\sigma(R)$	$\mathbb{E}[R]$	$\sigma(R)$	$\mathbb{E}[R]$	$\sigma(R)$	$\mathbb{E}[R]$	$\sigma(R)$
Low (L)	0.74	4.71	0.76	4.70	0.76	4.68	0.73	4.60
Medium	0.80	4.84	0.79	4.85	0.79	4.79	-	-
High (H)	1.10	5.52	1.07	5.43	1.04	5.56	1.05	5.43
Spread (H-L)	0.36	2.71	0.31	2.48	0.29	2.52	0.32	2.15
t(Spread)	(2.23)		(2.09)		(1.79)		(2.37)	

Table OA.11: Municipal spread-sorted portfolios: alternative rebalancing frequencies
The table reports the monthly returns of portfolios sorted on the level of each state's municipal-Treasury spread, as well as the difference between the returns of the Low (L) and High (H) spread-sorted portfolios. Here, the level of each state's municipal spread ($L_{i,t}$) is obtained from equation (3). The portfolio formation procedure employed is described in Section 2.1, with one exception. On the left-hand side of the table, portfolios are either (i) never rebalanced, meaning that each state is permanently assigned to the first portfolio it is sorted into (in the column denoted "Unconditional"), or (ii) rebalanced at the end of each March, June, September, and December only, and (in the column denoted "Quarterly"). On the right-hand side of the table, portfolios are formed monthly, but are held for either (i) one quarter (in the column denoted "Quarterly") or (ii) one year (in the column denoted "Annual"). In the case of overlapping returns, the portfolio return in month t is the equal-weighted average monthly return across all overlapping portfolios. The average and the standard deviation of the value-weighted portfolio returns are denoted by $\mathbb{E}[R]$ and $\sigma(R)$, respectively. Finally, parentheses report Newey and West (1987) t-statistics. The sample period is from January 1998 through December 2020.

	Non-overlapping returns				Overlapping returns			
	Unconditional		Quarterly		Quarterly		Annual	
	$\mathbb{E}[R]$	$\sigma(R)$	$\mathbb{E}[R]$	$\sigma(R)$	$\mathbb{E}[R]$	$\sigma(R)$	$\mathbb{E}[R]$	$\sigma(R)$
Low (L)	0.79	5.90	0.71	4.74	0.74	4.69	0.72	4.64
Medium	0.83	4.60	0.77	4.82	0.78	4.83	0.80	4.83
High (H)	0.80	5.66	1.13	5.81	1.05	5.63	0.96	5.50
Spread (H-L)	0.00	3.30	0.42	3.09	0.31	2.68	0.24	2.34
t(Spread)	(0.02)		(2.21)		(1.83)		(1.74)	

Table OA.12: Correlation between municipal-Treasury spread and state-level CDS yield

The table reports the monthly correlation between the change in the level of each state's municipal-Treasury spread ($L_{i,t}$), obtained from equation (3), and the change in the CDS spread associated with each state's general obligation municipal bonds, obtained from Bloomberg. These CDS data are only available for a subset of 23 states and are only available from December 2007. The correlation coefficient is represented by ρ and the Newey and West (1987) t-statistic associated with each coefficient is denoted by $t(\rho)$.

State	β	$t(\beta)$
CA	0.46	3.59
CT	0.35	4.57
DE	0.18	2.36
FL	0.41	3.76
IL	0.37	4.68
MA	0.39	3.46
MD	0.15	1.75
MI	0.34	4.70
MN	0.33	3.34
MS	0.76	6.84
NC	0.33	3.89
NJ	0.45	4.03
NV	0.19	2.60
NY	0.26	3.29
OH	0.37	5.85
PA	0.31	3.43
RI	0.17	2.55
SC	0.23	3.16
TX	0.43	5.08
UT	-0.08	-0.73
VA	0.16	1.65
WA	0.19	2.56
WI	0.06	0.84

Table OA.13: Short-term and long-term slope-sorted portfolios

The table reports the monthly returns of portfolios sorted on the short-term slope (Panel A) and long-term slope (Panel B) of each state's term structure of municipal-Treasury spreads, as well as the difference between the returns of the Low (L) and High (H) portfolios. Here, the short-term (long-term) slope of each state's municipal spread, denoted by $S_{i,t}$ ($C_{i,t}$), is obtained from equation (3). The portfolio formation procedure employed is described in Section 2.1. The average short-term (long-term) slope of each portfolio is denoted by S (C), while the mean and standard deviation of the value-weighted portfolio returns are represented by $\mathbb{E}[R]$ and $\sigma(R)$, respectively. $\mathbb{E}[R_{EW}]$ denotes equal-weighted portfolio returns, while N(States) and N(Firms) report the mean number of states and firms, respectively, underlying each portfolio. The columns denoted $\mathbb{E}[R - R_{\text{IND}}]$ and $\mathbb{E}[R - R_{\text{DGTW}}]$ report value-weighted portfolio returns that are obtained by subtracting the mean return from each Fama-French 10 industry group and Daniel et al. (1997) characteristic-based benchmark from the return of each firm underlying each portfolio. Finally, parentheses report Newey and West (1987) t-statistics. The sample period is from January 1998 through December 2020.

Panel A: Slope-sorted portfolios							
	S	$\mathbb{E}[R]$	$\sigma(R)$	N(Firm)	$\mathbb{E}[R_{EW}]$	$\mathbb{E}[R_{\text{IND}}]$	$\mathbb{E}[R_{\text{DGTW}}]$
Low (L)	-2.70	1.04	5.12	629	1.39	0.81	-0.11
Medium	-2.03	0.80	4.82	1822	1.20	0.59	-0.36
High (H)	-1.48	0.80	5.15	382	1.14	0.58	-0.38
Spread (H-L)	1.22	-0.24	2.45		-0.25	-0.22	-0.27
t(Spread)		(-1.64)			(-1.55)	(-1.45)	(-2.17)
Panel B: Curvature-sorted portfolios							
	C	$\mathbb{E}[R]$	$\sigma(R)$	N(Firm)	$\mathbb{E}[R_{EW}]$	$\mathbb{E}[R_{\text{IND}}]$	$\mathbb{E}[R_{\text{DGTW}}]$
Low (L)	-5.57	0.83	6.14	293	1.32	0.77	-0.40
Medium	-3.37	0.88	4.76	1961	1.21	0.61	-0.30
High (H)	-1.29	0.68	4.59	579	1.16	0.56	-0.35
Spread (H-L)	4.28	-0.15	3.39		-0.16	-0.21	0.05
t(Spread)		(-0.81)			(-1.29)	(-1.52)	(0.33)