Municipal-Treasury spreads and local stock returns*

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January 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 a return that exceeds 0.35% 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.

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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 0.37% 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 high in states where local economic fundamentals are weak. 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). Moreover, the default risk premium for municipal debt is an order of magnitude larger than that for investment-grade corporate debt. This means that small changes in local economic conditions are likely to manifest themselves as large changes in the municipal spread. 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. Collectively, these observations suggest that the tax-adjusted municipal spread is natural and forward-looking predictor of local economic conditions.

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 monthly term structures provide a representative one- to 30-year municipal bond yield for each state and span January 1998 through September 2019. 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 the level of the tax-adjusted municipal spread does indeed predict 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 0.37% per month. The HML-Muni spread 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 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 in these states (i.e., 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 investments in firms located in states with a higher municipal spread are riskier.

Finally, I establish that firms located in states with a larger municipal spread are more exposed to risk because each state's municipal spread serves as an observable proxy of economic fundamentals to which all firms in the state are exposed. To begin, I show that the HML-Muni spread is concentrated among the firms in each state that are most sensitive to fluctuations in local economic conditions. Here, I proxy for each firm's exposure to a given location's economy using either (i) the operational dispersion measure of García and Norli (2012) or (ii) the intensity with which each firm uses labor in production. The assumption here is that geographically concentrated firms that rely more on labor are more exposed to the local economy. Next, I document that the municipal spread is higher in states where local economic fundamentals, measured using micro- and macro-level proxies of labor productivity, are weaker. This negative relation between municipal spreads and local fundamentals implies that the risk exposures of local firms are higher in states with higher municipal spreads (i.e., weaker fundamentals) provided that the firms' inputs to production, such as capital and labor, are costly to adjust (Zhang, 2005; Belo, Lin, and Bazdresch, 2014).

I rule out alternative explanations for the HML-Muni spread and conduct numerous robustness checks. For instance, I show that the spread is not driven by either the interaction between 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 indicates 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 serves as a 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 pension funds (Novy-Marx and Rauh, 2012), local 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), and climate risk (Painter, 2020; Goldsmith-Pinkham, Gustafson, Lewis, and Schwert, 2021). 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.

In contrast to these studies that explore *why* municipal bond yields vary, I show that this variation in yields is itself informative about the 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 0.37% 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.[1]

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. While this is broadly in line with Tuzel and Zhang (2017), who show that risk exposures vary across more granular

[1] 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.

metropolitan statistical areas (MSAs), the cross-sectional differences in the Tuzel and Zhang (2017) measure of "local beta" do not explain the HML-Muni spread. Rather, my results indicate that when the level of the municipal spread is high (i.e., when local credit risk is high), then state-level productivity is low, increasing the risk exposures of local firms. This suggests that risk exposures have a location-specific component that is independent of the local factor prices.

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, as proxied by 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 September 2019. Data on municipal bond yields, Treasury yields, and stock return and accounting data 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 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 1.96% (4.14%) per annum. Notably, the levels (first differences) of the yield curves I construct have an average correlation of 0.96 (0.64) with those from Bloomberg, which are available for only a subset of 19 states.[2] 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 Gürkaynak, Sack, and Wright (2007) are used to measure the monthly term structure of the nominal risk-free rate.[3]

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

[2]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.

[3]These data are available at `https://www.federalreserve.gov/data/nominal-yield-curve.htm`.

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.[4]

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

[4] 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).[5] While λ may, in principle,

[5]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, often rising around recessions (notably the 2008-2009 crash). As expected, the level of the municipal spread is countercyclical and has a correlation of -0.25 (-0.12) 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. Moreover, the significant 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 0.91% (0.77%). While the level of the municipal spread is somewhat volatile, the average spread is positive throughout the sample period, reaching a minimum (maximum) of 1.97% (8.12%). This factor is also somewhat persistent, with a one-month (12-month) autocorrelation coefficient of 0.92 (0.04). The table also reports the same summary statistics for the $S_{i,t}$ and $C_{i,t}$ factors from equation (3).

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 0.90. 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.[6] 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.[7]

2 Municipal yield spreads and local stock returns

2.1 Portfolio returns

Local stock returns. I implement the asset-pricing tests in this paper 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 headquarter (HQ) locations, supplemented with HQ location data from 10-K/Q filings.[8] I use a firm's HQ location as a proxy for the firm's location in accordance with the

[6]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 $\tilde{y}_{i,t}(360) - \tilde{y}_{i,t}(120)$.

[7]The non-zero terms in the off-diagonal elements of this correlation matrix highlight 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.

[8]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.

literature that examines the geography of stock returns and firm-level investment decisions (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 their employees in their 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 assigned to each state's portfolio. To reduce measurement error, I exclude states with fewer than five firms satisfying the aforementioned data filters at any time in the sample period.[9] This results in a time-series of local stock returns for each of the 38 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) and then sort states into portfolios based the values of $L_{i,t}$. Each portfolio is held for one month before rebalancing all portfolios at the end of month $t + 1$. This monthly rebalancing

[9]This requirement removes the following 13 states from the sample: Alaska (AK), Hawaii (HI), Idaho (ID), Maine (ME), Mississippi (MS), Montana (MT), North Dakota (ND), New Hampshire (NH), New Mexico (NM), 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 over the sample period.

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 August 2019. The low (high) portfolio includes the seven states with the lowest (highest) level of the municipal spread in the prior month, while the medium portfolio contains the remaining 24 states.[10] Since each state-level portfolio comprises many underlying firms (often hundreds), this choice of portfolio breakpoints produces three well-diversified portfolios.[11]

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. Specifically, the portfolio that buys (sells) firms located in states where the level of the municipal spread is high (low) earns an average value-weighted monthly return of 0.94% (0.55%) per month. Thus, the high-minus-low return spread, which I refer to as the "HML-Muni" spread, is 0.39% per month and statistically significant at the 5% level. Since the monthly volatility of the HML-Muni spread is 2.50%, the annualized Sharpe ratio of this trading strategy is larger than 0.50 over the sample period. This exceeds the market's Sharpe ratio of 0.43 over the same period of time.

The table also shows that, by constitution, the average level of the municipal spread monotonically increases from 2.87% to 4.45%, and there are seven states assigned to each extreme portfolio. Furthermore, as there are typically 430 (542) firms underlying the high (low) portfolio, the composition of each portfolio in terms of the number of underlying firms is similar to a composition resulting from sorts conducted at the firm level rather than the

[10]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 subsets of states.

[11]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 55% chance of remaining in the same portfolio in the next month. A state currently in the middle portfolio has about a 12% 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. 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 than state fixed effects.

state level. Finally, the results of three key robustness checks are also reported.

First, to ensure that the value-weighted returns associated with 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 0.35% 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 49 industry group from each firm's raw monthly return. The table shows that the industry-adjusted HML-Muni spread is 0.34% per month, and that this quantity is statistically significant at the 1% level.

Third, to ensure 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. The characteristic-adjusted HML-Muni spread remains economically sizable at 0.34% per month and significant at the 5% level.

Overall, Table 2 shows that variation in the level of each state's municipal spread predicts differences in stock returns across states. Stock returns are significant higher in states where the level of the municipal yield curve is higher, regardless of how portfolio returns are measured. The next sections not only show that the HML-Muni spread is not simply a manifestation of known asset-pricing characteristics and *why* the HML-Muni spread arises, but also show that there is a risk-based explanation for why firms located in states where the municipal spread is high earn higher expected returns. In short, the spread arises because firms in states with high municipal spreads are more exposed to systematic risk.

2.2 Portfolio characteristics

Table 2 reports the key stylized fact of this study and shows that the *current* level of a state's municipal spread is informative about *future* local stock returns. With this in mind, 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 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 expected 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 49 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 size, book-to-market ratios, leverage, total asset growth (Cooper, Gulen, and Schill, 2008), return momentum (Jegadeesh and Titman, 1993), short-term reversals (Jegadeesh, 1990), and local betas, as measured by Tuzel and Zhang (2017). Thus, the HML-Muni spread cannot be explained by these common predictors of stock returns. Likewise, while there are significant differences in profitability and idiosyncratic return volatility between the low and high spread-sorted portfolios, these characteristics *cannot* explain the return spread either. This is because high profitability and low idiosyncratic volatility firms tend to earn high, not low, future returns.

There are, however, four 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 investment rates, as measured following Stambaugh and Yuan (2017); hiring rates (Belo et al., 2014); more organizational capital (Eisfeldt and Papanikolaou, 2013); and lower idiosyncratic productivity (İmrohoroğlu and Tüzel, 2014). Thus, Section 2.3 conducts Fama and MacBeth (1973) regressions and portfolio double sorts that show that these four characteristics do not reconcile the high expected 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 value, investment, profitability, 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 market equity and book-to-market ratio of firms in state i; the average investment rate; hiring rate; profitability, as measured by ROA; organizational capital; firm-level productivity; and local beta 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 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. That is, a one standard-deviation increase in a state's municipal spread in month t predicts a 0.32% higher return in month $t + 1$. Columns 2 to 9 then present bivariate regressions showing that this positive and statistically significant relation persists regardless of which additional 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 takeaways of this regression analysis by presenting the results of portfolio double sorts. The table shows that controlling for the average value of either a state's investment rate, hiring rate, organizational capital, idiosyncratic productivity, 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.

Having established that the HML-Muni spread is a distinct feature of the data, and that higher municipal spreads predict state-level risk premia, the next section proposes a risk-based explanation for this relation between municipal spreads and expected returns.

3 Municipal spreads and local returns: a risk-based explanation

This section documents a risk-based explanation for the HML-Muni spread. Specifically, I show that the HML-Muni spread arises because firms located in areas with weaker fundamentals, such as lower labor productivity, are more exposed to aggregate risks. Consequently, these riskier firms earn higher average returns. Section 3.1 begins by demonstrating that geographical differences in the risk exposures of local firms, measured using either CAPM betas or one of two proxies for labor productivity, are aligned with a state's municipal-Treasury spread. This section also shows that single-factor asset-pricing models, such as the CAPM, can explain 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* productivity of a state's economy that affects all local firms.

3.1 Risk exposures and pricing errors

Having shown that (i) the municipal spread is informative about cross-sectional differences in expected stock returns, and (ii) the HML-Muni spread is not driven by geographic variation in characteristics such as investment or profitability, I examine whether the relation between municipal spreads and expected stock returns is explained by differential exposures to macroeconomic risks. Specifically, I examine whether common asset-pricing models can explain the HML-Muni spread. This is motivated by studies including Zhang (2005), Belo and Lin (2012), and İmrohoroğlu and Tüzel (2014) that show that differences in (potentially time-varying) exposures to aggregate productivity explain a number of prominent return spreads, such as the value premium.

I start by estimating the following regression to examine the *unconditional* risk exposure of each municipal spread-sorted portfolio using one of three different proxies for aggregate productivity

$$R_{p,t} - R_{f,t} = \alpha_p + \beta_p \text{AggProd}_t + \varepsilon_{p,t}. \tag{5}$$

Here, $R_{p,t} - R_{f,t}$ 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 the given proxy for aggregate productivity. 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 following the approach of Adrian, Etula, and Muir (2014).[12] Since labor productivity data are available only quarterly, equation (5) is estimated using returns aggregated to the quarterly frequency. Consequently, α_p can be interpreted as a pricing error (e.g., the CAPM alpha) when using tradable proxies for aggregate productivity.

Table 5 shows each spread-sorted portfolio's exposure to aggregate productivity. Column (1) begins by reporting the average *excess* returns associated with each portfolio and mimics the baseline results reported in Table 2, albeit on a quarterly basis. Columns (2) and (3) then show that the CAPM beta of each portfolio is monotonically increasing with the average level of the municipal spread. Notably, the CAPM beta of the high portfolio is not only 0.13 units higher than that of the low portfolio, but this difference in CAPM betas renders the CAPM alpha of the HML-Muni spread statistically insignificant. This piece of evidence provides the first indication that there is a risk-based explanation for the HML-Muni spread.

Next, columns (4) and (5) consider both the economic underpinnings and the robustness of this result. Since Tuzel and Zhang (2017) show that the risk exposures of local firms differ in regards to the local factor markets from which these firms draw their production inputs (e.g., labor and real estate), I consider the extent to which these local firms are exposed to these more localized aspects of risk. To do so, these columns report the results of re-estimating equation (5) when using labor productivity in place of excess market returns. Column (5) once again shows that firms located in states with higher municipal-Treasury spreads are associated with higher exposures to fluctuations in (labor) productivity.

Finally, since labor productivity constructed by the BLS does not represent a tradable factor, the pricing error in Column (4) is difficult to interpret. As such, columns (6) and (7) employ a tradable version of the labor productivity factor and repeat the previous regressions. Once again, the results not only indicate that firms in states with higher municipal-Treasury

[12]Specifically, I project the non-traded measure on 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. All of these basis assets are 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.

spreads are more exposed to fluctuations in aggregate productivity, but the pricing error in Column (6) also confirms that differential exposures to aggregate risk can fully explain the HML-Muni spread. Overall, Table 5 confirms that there is a risk-based explanation for why the HML-Muni spread arises.

Time-varying exposures. Beyond showing that the CAPM explains the HML-Muni spread, 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 excess returns of local firms. The results in that section are obtained by estimating a set of panel regressions that control for both firm characteristics (e.g., profitability and idiosyncratic volatility) 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 predicts local productivity. These facts highlight that a state's municipal spread serves as an observable and high-frequency proxy for the underlying 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 results in state-level stock returns that are easy to construct, the location of a firm's HQ is only a rough proxy for the degree to which the firm is exposed 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 indeed sensitive to fluctuations in 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 first crawling the Electronic Data Gathering, Analysis, and Retrieval (EDGAR) system of the U.S. Securities and Exchange Commission, and 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 from January 1998 through September 2019. I do this by computing the average return of all firms headquartered in a given state that mention fewer than five states in their 10-Ks in the previous year.[13] 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, which I industry-adjust to account for differences in industry composition across states. Since the former (latter) set of returns is constructed with firms whose operations are more (less) concentrated in a given state, the HML-Muni spread is likely to be larger (smaller) in magnitude among more (less)

[13]Given that only a small number of locally headquartered firms satisfy this state-name count criterion in certain states (e.g. Connecticut), equal-weighted returns ensure that the state-level portfolio returns are not dominated by idiosyncratic factors related to a small number of relatively large local firms in each state.

localized firms.

The results of this test are reported in Panel A of Table 6 and show that the HML-Muni spread is 0.23% per month and statistically significant at the 10% level among the most local firms in each state. In contrast, the spread is economically small (0.05% per month) and statistically insignificant (t-statistic of 0.35) among less-local firms. Together, these results support the conjecture that the returns of firms whose operations are more localized in a given state will be more sensitive to fluctuations in 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.

I empirically examine this intuition by defining 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). Firms with an above (below) median value of labor intensity in the calendar year ending in the previous fiscal year are considered more (less) local. I then examine the HML-Muni spread among state-level portfolios whose returns are constructed using only the firms in each state with either high or low levels of industry-adjusted 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 (0.33% per month) and statistically significant (t-statistic of 2.19) 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 merely 0.15% per month.

3.2.2 State-level labor productivity

Table 5 documents an explanation for the HML-Muni: firms located in states with higher municipal-Treasury spreads are more exposed to productivity risk. Since these firms are more exposed to aggregate risk, they earn higher average returns. In line with this logic, and consistent with the notion that local factor markets shape firms' risk exposures (Tuzel and Zhang, 2017), Table 6 documents that the HML-Muni spread is indeed larger among firms that are more exposed to local economic conditions (e.g., more localized firms that rely more on localized factors of production, such as labor). Together, these results suggest that a state's municipal spread is informative about the local fundamentals that firms are differentially exposed to, depending on their geographic location in the United States.

If this is indeed the case, then this common fundamental will shape the optimal investment decisions, employment decisions, and the valuations of local firms, especially if it is costly for the firm to adjust margins such as investment (Zhang, 2005), inventory (Belo and Lin, 2012; Jones and Tuzel, 2013), and hiring rates (Belo et al., 2014). That is, this geography-specific fundamental would explain why firms located in states with a high municipal spread have higher exposures to productivity risk and consequently earn higher expected returns. While Table 3 already indicates that firms in states with high municipal-Treasury spreads have lower investment and hiring rates, and Table 5 confirms that differential exposure to productivity risk can explain the HML-Muni spread, I have yet to provide a direct link between a state's municipal-Treasury spread and productivity. I provide explicit evidence for this type of link below.

I empirically establish this link by documenting that the level of a state's municipal spread is negatively correlated with various measures of labor productivity. That is, productivity tends to be low in states where the municipal-Treasury spread is high. I focus on labor productivity because, as highlighted above, labor is typically considered 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 state-level labor productivity using either (i) the quarterly growth rate of gross state product (GSP) minus the part of GSP associated with agriculture divided by total *non-farm* employment in a state, or (ii) the value-weighted average ratio of the natural logarithm of firm-level sales (Compustat Annual item SALE) to employees (Compustat Annual item EMP) across all firms in a given state. All variables are scaled by their unconditional standard deviations so that the slope coefficient ρ is interpreted as a 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.

All in all, the results show a negative and statistically robust connection between a state's municipal spread and labor productivity. That is, local firms are less productive when the state's municipal spread is higher. 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 panel regressions, indicating that the correlation is not driven by a small number of unrepresentative times during the sample period (e.g., the global financial crisis). Likewise, the negative correlation also arises when state fixed effects are included in the panel regressions, highlighting that the connection between municipal spreads and labor productivity is not influenced by a small number of states. Overall, the negative association between municipal spreads and local productivity is economically sizable and robust.

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 a given state, particularly 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. Korniotis and Kumar (2013), and ensuing 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) the wealth of local investors is concentrated in local firms and (ii) there are limits to risk sharing 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. Under this conjecture, 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 the two aforementioned mechanisms explain the HML-Muni spread. First, I construct the HML-Muni spread within the set of 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 a driver of the HML-Muni spread, as the spread remains economically large and significant among visible firms.

I also construct the HML-Muni spread among states that implement different fiscal polices. An economically smaller spread among states with countercyclical fiscal polices would suggest that the return spread is at least partially 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 spread arises in states with both procyclical and countercyclical fiscal policies.

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.

4.2 Empirical robustness

Portfolio breakpoints. The baseline portfolio sorts in Section 2.1 assign seven states to each of the low and the high spread-sorted portfolios. Here, I form portfolios by either (i) sorting either six or eight 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 larger when *fewer* states are included in these portfolios. This is because the distinction between states where economic conditions are expected to improve and worsen becomes starker with fewer states in each extreme portfolios. Second, changing the number of states in each portfolio also ensures that the HML-Muni spread is not driven by any particular choice of portfolio breakpoints.

Table OA.10 in the Online Appendix reports these results. They show that the HML-Muni spread monotonically increases as fewer states are included in the extreme portfolios. In particular, the spread increases to 0.47% (decreases to 0.31%) per month when six (eight) states are sorted into each extreme portfolio. The rank-weighted portfolios also result in an economically and statistically significant spread of almost 0.30% 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 0.36% per month and remains significant at the 5% level. Finally, the results also show that the return spread remains economically and statistically significant at 0.29% 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 (i.e., the way in which I estimate 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 0.37% 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 in that state, the Amihud (2002) 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 yield and shows that the HML-Muni spread arises only if states are sorted into portfolios based on the credit risk component of yields.

Excluding key states. Table OA.13 in the Online Appendix shows that the HML-Muni spread is not driven by specific states in the sample. The spread not only persists if California, New York, and Texas, the three economically largest states in the sample, are removed from the analysis, but also persists if five states whose municipal debt markets have recently undergone (or are currently undergoing) financial distress are excluded.[14]

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.12 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

[14]The five states removed from the analysis are Alabama (Jefferson County declared bankruptcy in 2011), 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 is also removed because the credit ratings assigned to bonds issued by that state are the lowest among the 50 states, and are rated just above junk status by S&P.

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.

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.

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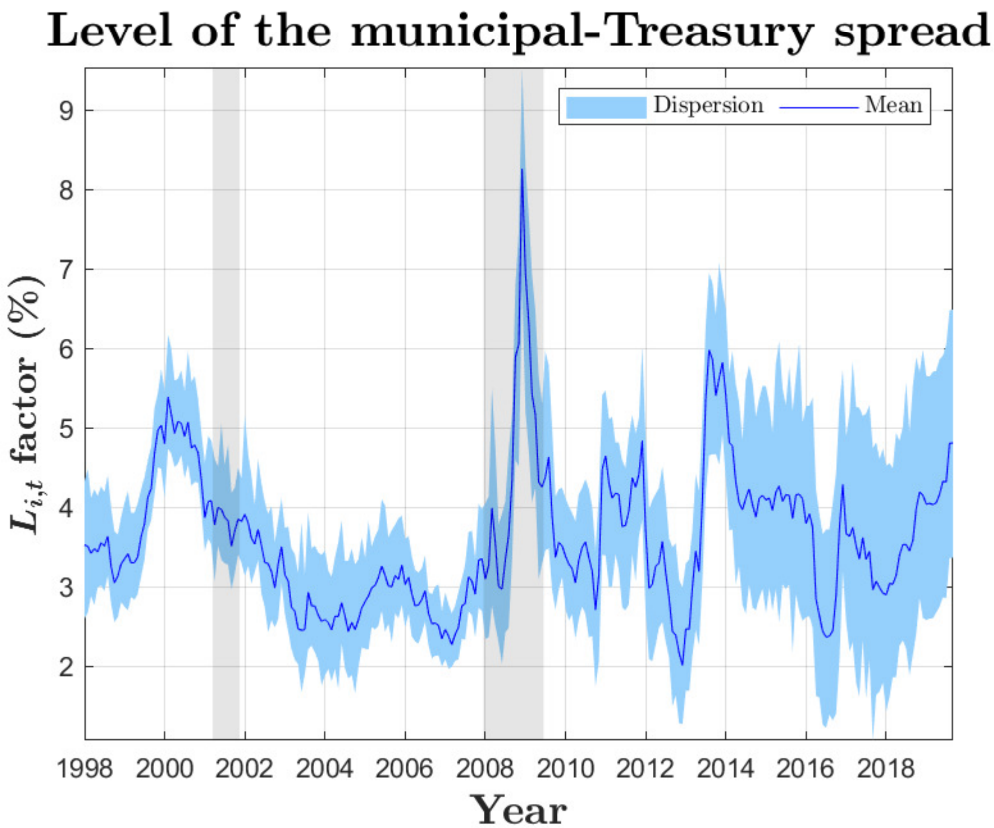

Figure 1: Level of the municipal-Treasury spread
The figure reports the monthly time series of the level of the municipal-Treasury spread obtained via equation (3). This equation is estimated on a state-by-state basis, and the average level of the tax-adjusted municipal-Treasury spread is computed by 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 September 2019.

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 September 2019.

Panel A: Factor summary statistics								
	Mean	SD(TS)	SD(CS)	Min	Max	$\hat{\rho}_1$	$\hat{\rho}_{12}$	$\hat{\rho}_{30}$
L	3.60	0.91	0.77	1.97	8.12	0.92	0.04	-0.02
S	-2.26	0.84	0.77	-5.67	-0.11	0.89	0.24	0.06
C	-3.36	1.97	2.48	-11.77	0.70	0.91	0.25	0.02

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	-0.56	-0.73	0.90	-0.54	-0.39
S		1.00	0.16	0.52	-0.98	-0.07
C			1.00	0.86	-0.42	-0.92

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 49 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 September 2019.

	Level	$\mathbb{E}[R]$	$\sigma(R)$	N(State)	N(Firm)	$\mathbb{E}[R_{EW}]$	$\mathbb{E}[R_{\text{IND}}]$	$\mathbb{E}[R_{\text{DGTW}}]$
Low (L)	2.87	0.55	4.59	7	542	0.84	-0.15	-0.47
Medium	3.60	0.73	4.67	24	2001	1.06	-0.07	-0.27
High (H)	4.45	0.94	5.46	7	430	1.19	0.19	-0.12
Spread (H-L)	1.58	0.39	2.50			0.35	0.34	0.34
t(Spread)		(2.33)				(2.65)	(2.75)	(2.43)

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 49 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 September 2019.

	Low (L)	Medium	High (H)	Spread (H-L)	t(Spread)
ln(ME)	1.98	1.96	1.94	-0.04	-1.01
BEME	-0.21	-0.20	-0.19	0.02	0.98
GP (%)	0.74	0.50	0.66	-0.07	-0.61
ROA (%)	1.70	1.46	1.51	-0.19	-2.55
Leverage (%)	1.63	1.76	2.06	0.43	0.62
Asset growth (%)	4.51	3.70	3.56	-0.95	-1.24
I/A (%)	1.32	0.72	0.27	-1.06	-1.94
Hire (%)	1.31	1.00	0.33	-0.98	-3.29
ORG	-0.35	-0.34	-0.28	0.08	2.69
Momentum (%)	7.28	6.95	7.36	0.09	0.12
Reversal (%)	0.22	0.31	0.22	-0.00	-0.01
IVOL (%)	-0.97	-0.96	-0.92	0.05	2.84
TFP	0.24	0.21	0.21	-0.03	-1.71
β (MSA)	-0.01	-0.01	0.00	0.01	1.57

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 and state-level returns are industry-adjusted. These industry-adjusted returns are obtained by first computing each firm's return in excess of it's Fama-French 49 industry group, and then finding the value-weighting average of these industry-adjusted returns across all firms in a given state. 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 September 2019.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
L	0.32	0.34	0.26	0.29	0.28	0.33	0.33	0.32	0.40
	(2.22)	(2.22)	(2.17)	(2.17)	(1.91)	(2.39)	(2.26)	(2.19)	(2.42)
ln(ME)		-0.04							
		(-0.41)							
ln(BEME)			0.01						
			(0.15)						
I/A				0.08					
				(1.38)					
HIRE					-0.05				
					(-0.83)				
ROA						-0.03			
						(-0.30)			
ORG							-0.02		
							(-0.43)		
TFP								0.05	
								(0.78)	
β_{MSA}									0.42
									(1.02)
$\bar{R}^2$	0.26	3.93	3.54	1.98	5.70	2.39	-0.14	2.54	2.41

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 September 2019.

	Raw returns	CAPM		LP		LP^{Ret}	
	$\mathbb{E}[R]$	α	β	α	β	α	β
Low (L)	6.85	-1.67	0.96	-2.95	0.98	1.42	2.63
Medium	9.02	0.07	1.02	-0.43	0.93	3.26	2.88
High (H)	11.64	2.25	1.09	-0.74	1.30	5.03	3.51
Spread (H-L)	4.67	3.80	0.13	2.02	0.33	3.50	0.87
	(2.21)	(1.58)		(0.75)		(1.54)	

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 equal-weighted and industry-adjusted average stock return across all firms headquartered in a given state that name four or fewer (labeled "≤ 4") or five or more (labeled "> 4") 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 as the industry-adjusted and value-weighted average returns 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. Finally, parentheses report Newey and West (1987) t-statistics. The sample period is from January 1998 through September 2019.

	Panel A: Firm localization				Panel B: Labor intensity			
	≤ 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)	-0.02	1.50	0.99	6.40	-0.23	1.70	-0.04	1.26
Medium	0.22	1.36	1.08	6.33	-0.03	1.38	-0.02	0.84
High (H)	0.21	1.52	1.04	6.77	0.10	2.15	0.12	1.86
Spread (H-L)	0.23	2.14	0.05	2.46	0.33	2.34	0.15	1.91
t(Spread)	(1.75)		(0.35)		(2.19)		(1.26)	

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 (excluding the component of gross state product associated with agriculture) and total non-farm 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. 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 September 2019.

	Panel A: GSP per employee		Panel B: Sales per employee	
	(1)	(2)	(3)	(4)
$L_{i,t}$	-0.06	-0.06	-0.07	-0.07
	(-2.12)	(-2.11)	(-1.88)	(-1.77)
Time FE	Yes	Yes	Yes	Yes
State FE	No	Yes	No	Yes
Adj.-R^2	0.29	0.28	0.66	0.65
Obs.	2832	2832	792	792

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 $t-1$. Moreover, the state-level stock returns underlying all columns are constructed by computing the industry-adjusted average stock return across all firms in a particular state. Finally, parentheses report Newey and West (1987) t-statistics, and the sample period is from January 1998 through September 2019.

Panel A: Trading costs				
	Large ME	High PRC	High VOL	Low IVOL
Low (L)	-0.09	-0.02	-0.10	-0.03
Medium	-0.05	0.02	-0.06	0.02
High (H)	0.14	0.25	0.13	0.20
Spread (H-L)	0.23	0.27	0.23	0.23
t(Spread)	(2.33)	(2.30)	(2.28)	(2.28)
Panel B: Information and visibility				
	High Visibility	High Analysts	High Institutional	
Low (L)	-0.08	-0.15	-0.03	
Medium	-0.05	-0.06	-0.02	
High (H)	0.19	0.18	0.21	
Spread (H-L)	0.27	0.33	0.24	
t(Spread)	(2.58)	(3.08)	(2.35)	

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. Finally, parentheses report Newey and West (1987) t-statistics. The sample period is from January 1998 through September 2019.

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)	0.52	4.53	0.52	4.50	0.73	4.75
Medium	0.75	4.68	0.75	4.71	0.66	4.81
High (H)	0.90	5.50	0.90	5.43	0.99	4.80
Spread (H-L)	0.37	2.43	0.37	2.54	0.26	2.39
t(Spread)	(2.46)		(2.28)		(1.84)	

Panel B: Yield decomposition				
	Credit		Liquidity	
	$\mathbb{E}[R]$	$\sigma(R)$	$\mathbb{E}[R]$	$\sigma(R)$
Low (L)	0.71	4.69	0.84	4.75
Medium	0.68	4.76	0.64	4.74
High (H)	0.94	5.13	0.93	4.98
Spread (H-L)	0.23	2.45	0.09	1.99
t(Spread)	(1.72)		(0.71)	

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) betweens years $t-1$ and t (Cooper et al., 2008).

Book-to-market (BEME). A firm's book-to-market ratio is constructed by following Daniel and Titman (2006). 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.[15]

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 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-

[15]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).

Standardized unexpected earnings 3 (SUE3). Consistent with the measure of standardized unexpected earnings (SUE) based on analyst expectations in Livnat and Mendenhall (2006), SUE in quarter t is computed by taking the difference between actual EPS from the I/B/E/S unadjusted files and the median analyst forecast of EPS for the same point in time (I/B/E/S Unadjusted item MEDEST), divided by the share price on the release date (I/B/E/S Unadjusted item PRICE).

Visibility. Following Hong et al. (2008), a firm's visibility is computed as the residual of the a 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 this cleaned transaction price data to estimate the representation of the Nelson and Siegel (1987) model proposed by Diebold et al. (2006) using the cross-section of municipal bond yields within each state-month period. Finally, 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 those 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 the coupon rate or maturity date of the bond is missing and cannot be found in Mergent, or 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 (as Figure OA.1 shows that trades in very-long dated bonds are relatively rare) or is less than six months. 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 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 the same month by computing the par-weighted average yield, and 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 $\{\beta_1, \beta_2, \beta_3, \gamma\}$ underlying 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 $\left(\sum_b \varepsilon_{b,i,t}(\tau)^2\right)$, 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 the parameter estimates do not correspond to local minima. 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

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

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. These state-level yield curves represented by equation (OA.2) are then used to implement my empirical analyses in Section 1 and onwards.

Next, I show that estimating these 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.

Summary statistics. 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 4,400 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 2,300 municipal bonds traded in the median state. Robustness tests in Section 4.2 ensure that my key empirical results are neither driven by the small set of very large states nor the large set of very small states.

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 states. For instance, the average correlation between the level (first difference) of the yield curves estimated above and those from Bloomberg is 0.96 (0.64). This high correlation arises despite the fact that, unlike the proprietary approach implemented by Bloomberg, the methodology described above above makes no explicit 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.[16]

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.

[16]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 within each state-month period. The column labeled "$y(12)$" ("$y(240)$") reports the time-series average yield in each state with one year (20 years) to maturity (obtained via equation (OA.2)). The columns represented by $\rho^{BBG}_{L,1}$ and $\rho^{BBG}_{L,20}$ ($\rho^{BBG}_{\Delta,1}$ and $\rho^{BBG}_{\Delta,20}$) 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 time-series average value of each characteristic within each state, while Panel B value of each statistic across the states underyling the sample. Finally, the sample period ranges from January 1998 to September 2019.

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
				Panel A: State-level statistics						
AK	0.32	685	2.00	4.17	-	-	-	-	6.71	0
AL	1.16	2238	2.06	4.26	-	-	-	-	8.06	14
AR	0.68	1052	1.98	4.28	-	-	-	-	8.56	14
AZ	1.67	4652	1.95	4.05	-	-	-	-	7.25	49
CA	13.57	32927	1.87	4.19	0.97	0.95	0.58	0.61	8.29	542
CO	1.75	3456	1.96	4.08	-	-	-	-	7.38	88
CT	1.54	4927	1.87	4.07	0.98	0.97	0.52	0.67	7.52	61
DC	0.00	790	1.95	4.11	-	-	-	-	7.52	6
DE	0.39	543	1.94	4.02	-	-	-	-	7.20	9
FL	5.04	11570	2.02	4.16	0.95	0.96	0.60	0.64	7.87	136
GA	2.89	4016	1.91	4.11	0.98	0.97	0.55	0.59	7.07	90
HI	0.45	1112	1.93	3.91	-	-	-	-	7.15	4
IA	0.96	1444	1.93	4.26	-	-	-	-	7.12	12
ID	0.37	402	1.94	4.18	-	-	-	-	7.15	5
IL	4.55	7536	2.13	4.40	0.92	0.85	0.43	0.62	7.39	135
IN	1.90	2534	1.98	4.16	-	-	-	-	6.14	33
KS	0.86	2002	1.90	4.20	-	-	-	-	7.22	15
KY	1.11	2287	2.00	4.31	-	-	-	-	7.48	16
LA	1.50	2059	2.12	4.22	-	-	-	-	8.16	14
MA	2.71	7542	1.84	3.97	0.98	0.96	0.58	0.67	7.60	184
MD	2.02	3819	1.80	3.97	0.98	0.97	0.45	0.68	7.12	47
ME	0.34	862	1.83	4.20	-	-	-	-	7.17	2
MI	2.84	5667	2.07	4.24	0.97	0.95	0.58	0.60	7.25	54
MN	1.85	3990	1.87	4.15	0.98	0.96	0.55	0.59	7.11	89
MO	1.72	2989	1.98	4.14	-	-	-	-	7.54	42
MS	0.63	939	2.03	4.28	-	-	-	-	7.70	3
MT	0.25	294	1.96	4.25	-	-	-	-	7.93	1
NC	2.75	4226	1.85	4.05	0.98	0.98	0.60	0.63	7.28	66
ND	0.25	381	1.93	4.35	-	-	-	-	7.05	1
NE	0.62	1348	1.82	4.30	-	-	-	-	7.91	11
NH	0.43	696	1.88	3.98	-	-	-	-	7.47	11

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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	10960	1.92	4.08	0.97	0.94	0.55	0.66	7.71	127
NM	0.55	1079	1.87	4.19	-	-	-	-	6.36	0
NV	0.83	1730	2.05	4.24	-	-	-	-	7.49	27
NY	8.04	28327	1.87	3.97	0.98	0.97	0.59	0.64	7.93	219
OH	3.55	6107	1.88	4.08	0.98	0.96	0.59	0.66	6.80	95
OK	1.03	1387	1.92	4.16	-	-	-	-	6.66	22
OR	1.10	2609	1.88	4.00	-	-	-	-	7.25	30
PA	4.01	9624	1.97	4.14	0.97	0.94	0.64	0.63	7.51	119
RI	0.33	808	2.00	4.14	-	-	-	-	7.05	10
SC	1.13	2835	1.89	4.22	0.98	0.95	0.47	0.63	7.79	11
SD	0.25	250	2.03	4.32	-	-	-	-	6.84	3
TN	1.77	2633	1.94	3.97	-	-	-	-	7.30	45
TX	8.44	19377	1.96	4.12	0.98	0.96	0.54	0.67	8.27	310
UT	0.78	1218	1.87	4.09	-	-	-	-	6.59	26
VA	2.70	4630	1.86	4.00	0.98	0.98	0.54	0.69	7.42	82
VT	0.17	357	1.87	4.07	-	-	-	-	7.85	1
WA	2.49	5482	1.92	4.04	0.98	0.97	0.55	0.67	7.36	59
WI	1.72	3038	1.96	4.07	0.98	0.96	0.61	0.62	6.42	46
WV	0.44	387	2.07	4.66	-	-	-	-	7.05	2
WY	0.23	81	1.98	4.52	-	-	-	-	6.37	0
Panel B: Summary statistics										
Mean	1.96	4351	1.94	4.16	0.97	0.96	0.55	0.64	7.34	58
$p25$	0.44	881	1.87	4.07	0.97	0.95	0.54	0.62	7.08	6
Median	1.13	2287	1.94	4.15	0.98	0.96	0.55	0.64	7.30	26
$p75$	2.65	4646	1.98	4.24	0.98	0.97	0.59	0.67	7.67	78

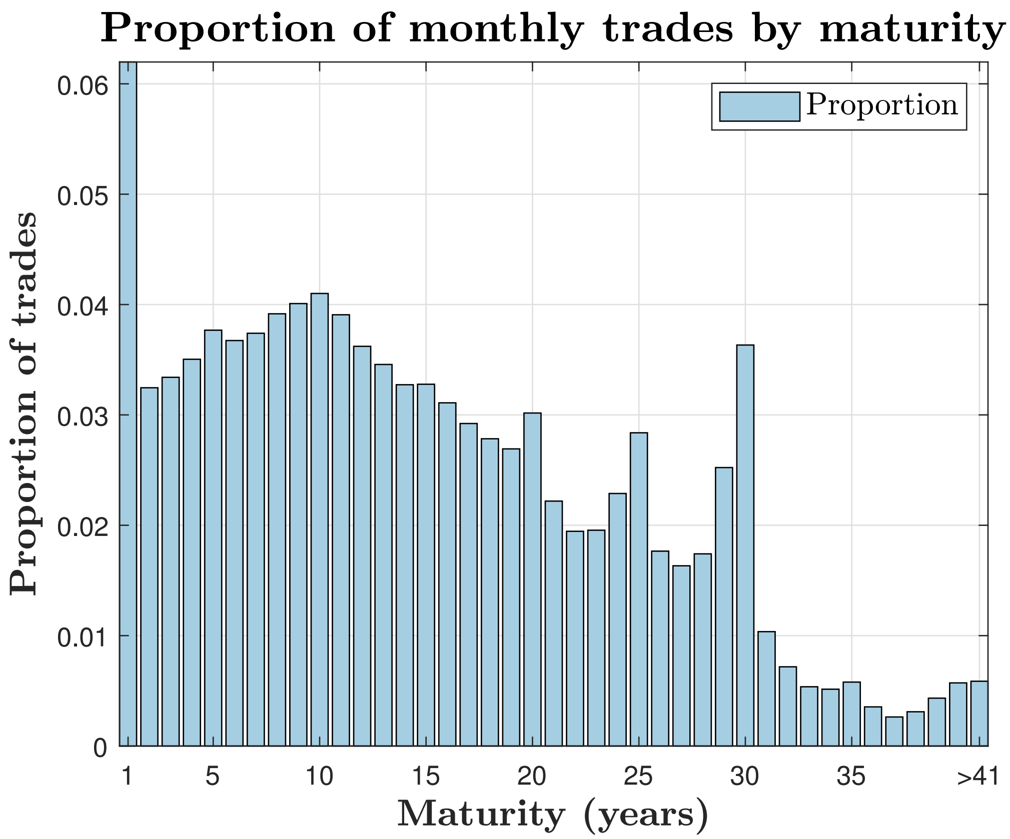

Figure OA.1: Proportion of average monthly trading volume by maturity
The figure displays the average proportion of monthly trading volume in the municipal debt market by maturity. The figure is constructed using transaction-level municipal bond data from the Municipal Securities Rulemaking Board (MSRB),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

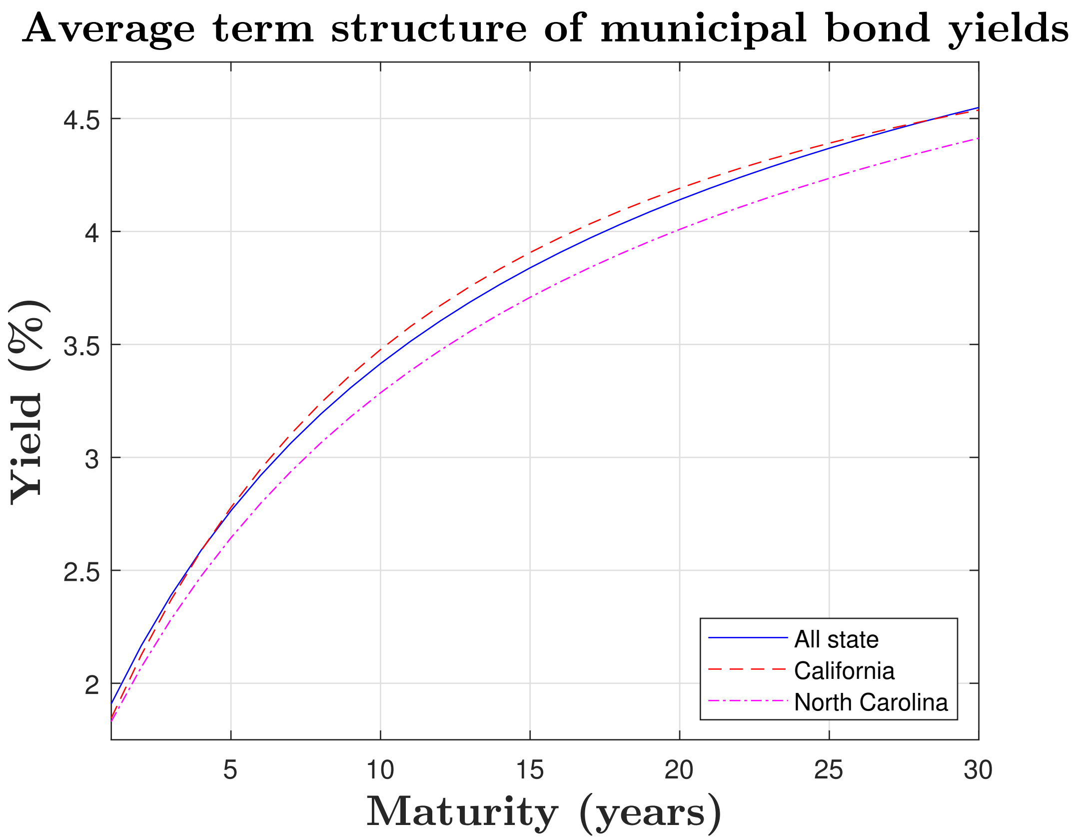

Figure OA.2: Average term structures of municipal bond yields
The figure displays the average term structure of municipal bond yields, obtained by following the procedure described in Section OA.2 of the Online Appendix, for all states, California, and North Carolina. The average term sturcture across 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.

OA.2.1 Yield decomposition

Beyond constructing the term structure of municipal bond yields in each state, I consider a simple decomposition of these state-level yields into the components related to liquidity and credit risk. This decomposition is motivated by equation (1) that shows that the tax-adjusted municipal bond yield of state i at time t with m-months to maturity (or $y_{i,t}(m)/(1-\tau_{i,t})$) in excess of the maturity-matched Treasury yield at the same point in time (or $Y_{i,t}(m)$) reflects a state-specific component of the yield: $\tilde{y}_{i,t}(m)$ from equation (2). In turn, this state-specific component of the yield reflects 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, Feldhütter, and Lando (2012) and Schwert (2017), this vector of controls includes the average Amihud (2002) ratio of the bonds outstanding within each state at time t, the cross-sectional standard deviation of the Amihud (2002) ratio at time t, and the natural logarithm of the number of bonds traded in each state. 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., $\lambda_{i,t}(m) = \hat{\beta}_{i,0} + \hat{\boldsymbol{\beta}}_i \boldsymbol{\Lambda}_{i,t}^T$) 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., $\psi_{i,t}(m) = \hat{\varepsilon}_{i,t}$).

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

I document 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)) 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

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

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 September 2019. 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

$$\beta_{1,i,t} = \gamma_i + \delta_t + \beta_L L_{i,t} + \boldsymbol{\beta} \boldsymbol{X}'_{i,t} + \varepsilon_{i,t}, \quad \text{(OA.5)}$$

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 and δ_t denote the state and time fixed effects, respectively.

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 two), time fixed effects are included in the regression (columns three and four), or state fixed effects are included in the regression (columns five and six). This conclusion also holds regardless of whether only a small set of prominent controls is included in columns one, three, and five, or whether the full set of control variables is included in columns two, four, and six. 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 two report the results of panel regressions that feature no fixed effects, while columns three and four (five and six) report the results of panel regression that feature time (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 to September 2019.

	(1)	(2)	(3)	(4)
Spread	0.05	0.04	0.03	0.03
	(2.64)	(2.52)	(2.00)	(2.12)
ln(Size)	-0.13	-0.12	-0.01	-0.01
	(-3.46)	(-3.35)	(-0.22)	(-0.15)
ln(BEME)	-0.02	-0.03	0.01	0.01
	(-1.05)	(-1.39)	(0.59)	(0.48)
Invest	-0.01	-0.03	-0.01	-0.02
	(-0.58)	(-1.51)	(-0.80)	(-0.92)
Profit	-0.09	-0.09	-0.03	-0.03
	(-3.10)	(-3.66)	(-1.80)	(-2.10)
β_{MSA}	-0.00	-0.00	0.01	0.01
	(-0.00)	(-0.20)	(1.60)	(1.22)
TFP	0.00	0.00	-0.01	-0.00
	(0.04)	(0.22)	(-0.37)	(-0.27)
ORG	-0.01	0.00	0.01	0.01
	(-0.18)	(0.14)	(0.42)	(0.52)
IVOL		0.05		0.01
		(2.46)		(0.43)
Leverage		-0.02		-0.03
		(-1.36)		(-2.19)
MOM		0.03		0.01
		(3.24)		(0.93)
HIRE		0.02		0.00
		(1.23)		(0.23)
State FE	No	No	Yes	Yes
Adj.-R^2	0.19	0.22	0.55	0.55
Obs.	7632	7632	7632	7632

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 is 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). Additionally, instead of estimating the panel regression outlined in equation (OA.5), I estimate the following panel regression

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

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 market 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) to September 2019.

	Panel A: Firm-level betas		Panel B: Firm-level excess returns	
	(1)	(2)	(3)	(4)
Spread	0.05	0.05	0.35	0.32
	(3.53)	(3.55)	(2.21)	(2.01)
$\ln(Size)$		0.08		-1.65
		(5.75)		(-12.26)
$\ln(BEME)$		0.05		0.02
		(4.30)		(0.15)
Invest		0.01		0.62
		(1.54)		(4.72)
Profit		-0.07		0.00
		(-7.59)		(0.03)
β_{MSA}		0.02		0.22
		(2.11)		(2.37)
Industry-by-Time FE	Yes	Yes	Yes	Yes
Adj.-R^2	0.28	0.29	0.16	0.17
Obs.	19444	19444	34554	34554

OA.4 Supplemental tables and figures

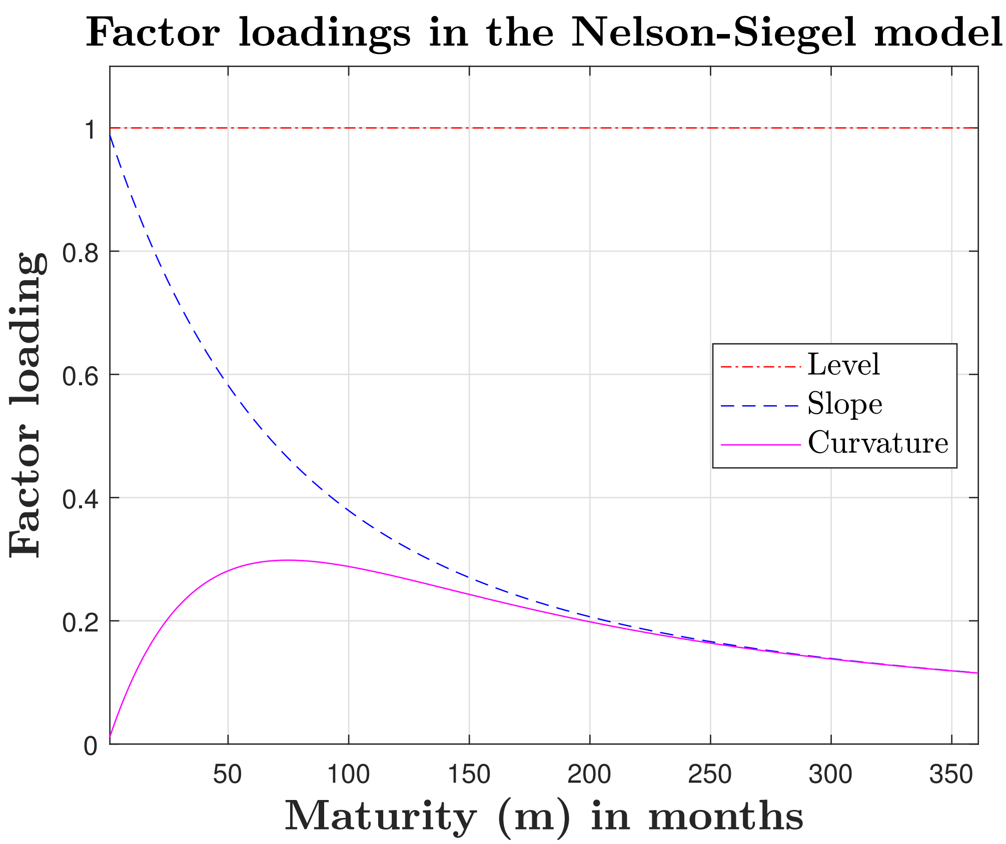

Figure OA.3: Factor loadings underlying the Nelson-Siegel model
The figure displays the factor loadings underlying the Nelson-Siegel model proposed by Diebold and Li (2006) when the shape parameter (i.e. λ in equation (3) of the main text) is set to 0.0240. In this figure the loadings associated with 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

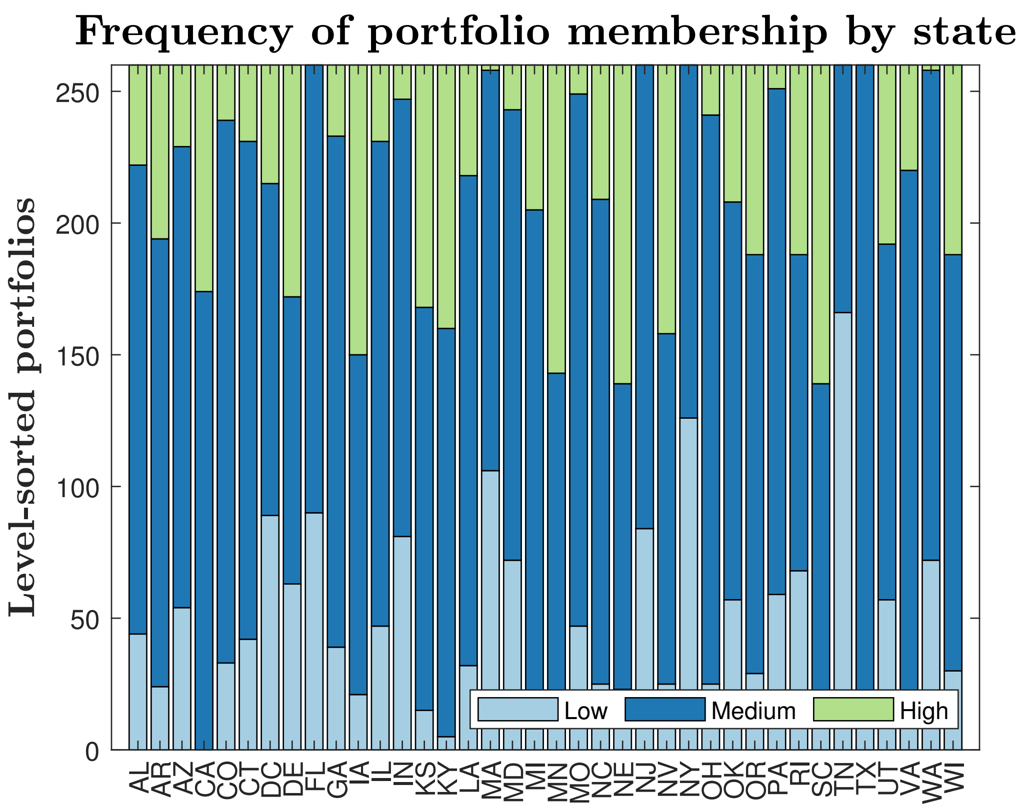

Figure OA.4: Frequency of portfolio membership by state
The figure reports the number of months each state is sorted into the low, medium, and high spread-sorted portfolio. States are sorted into portfolios at the end of each month following the portfolio formation procedure described in Section 2.1. The sample period ranges from January 1998 to September 2019.

Table OA.4: Transition matrix between the municipal spread-sorted portfolios
The table shows the probability that a state sorted into portfolio $i \in \{\text{Low, Medium, High}\}$ in month t, where i is the row index, is sorted into portfolio $j \in \{\text{Low, Medium, High}\}$ 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 to September 2019.

Portfolio in month t	Portfolio in month $t+1$		
	Low	Medium	High
Low	0.570	0.402	0.028
Medium	0.118	0.764	0.118
High	0.025	0.408	0.567

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, Panel B, Panel C, Panel D, and Panel E is the industry-adjusted investment rate (I/A), hiring rate (HIRE), idiosyncratic productivity (TFP), organizational capital-to-asset ratio (ORG), or systematic risk exposure of each firm's headquarter MSA (β_{MSA}), 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 10 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 leave 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) portfolios, and the Newey and West (1987) p-value associated with this spread (p(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 to September 2019.

	Panel A: I/A			Panel B: HIRE		
	Low I/A	Medium	High I/A	Low HIRE	Medium	High HIRE
Low (L)	0.14	-0.10	-0.19	0.09	-0.21	0.04
Medium	-0.12	-0.15	-0.00	-0.06	-0.02	-0.20
High (H)	0.10	0.30	0.20	0.19	0.19	-0.08
Spread	-0.04	0.40	0.40	0.10	0.41	-0.12
(H-L)	(-0.16)	(2.38)	(2.12)	(0.43)	(2.37)	(-0.54)
p(Joint)		0.05			0.05	
	Panel C: TFP			Panel D: ORG		
	Low TFP	Medium	High TFP	Low ORG	Medium	High ORG
Low (L)	0.10	-0.23	-0.09	-0.06	-0.28	0.23
Medium	-0.05	-0.03	-0.17	-0.13	-0.08	-0.03
High (H)	0.17	0.24	-0.00	0.03	0.35	-0.03
Spread	0.06	0.47	0.09	0.09	0.63	-0.26
(H-L)	(0.26)	(2.28)	(0.43)	(0.31)	(2.98)	(-1.08)
p(Joint)		0.04			0.00	
	Panel E: β_{MSA}					
	Low β_{MSA}	Medium	High β_{MSA}			
Low (L)	-0.00	-0.01	-0.32			
Medium	0.04	-0.05	-0.14			
High (H)	0.04	0.29	0.19			
Spread	0.04	0.29	0.51			
(H-L)	(0.17)	(1.68)	(2.04)			
p(Joint)		0.05				

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 to September 2019.

	FF3F	FF4F	FF5F	q
MKTRF	0.14	0.12	0.16	0.15
	(2.82)	(2.95)	(2.96)	(3.12)
SMB	0.10	0.11	0.12	0.12
	(1.38)	(1.43)	(1.65)	(1.70)
HML	0.26	0.25	0.19	
	(3.18)	(3.27)	(2.44)	
UMD		-0.03		
		(-0.52)		
Profit.			0.05	-0.02
			(0.40)	(-0.17)
Invest.			0.09	0.25
			(0.85)	(1.87)
α	0.28	0.30	0.23	0.22
	(1.83)	(1.95)	(1.53)	(1.48)
$\bar{R}^2$	0.16	0.16	0.15	0.12

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 to September 2019.

	Expansions	Contractions
Months	246	14
Low (L)	0.24	2.84
	(0.80)	(3.04)
Medium	0.42	2.81
	(1.40)	(2.91)
High (H)	0.56	4.18
	(0.01)	(2.43)
Spread (H-L)	0.32	1.34
t(Spread)	(1.91)	(1.53)

Table OA.8: Municipal spread-sorted portfolios: heterogeneity in fiscal policy
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. First, in the column denoted "Countercyclical" ("Procyclical") the cross-section of states is limited 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. Second, given the smaller cross-sections of states underlying these analysis, the high and low spread-sorted portfolios each contain four states. The average and the standard deviation of the industry-adjusted 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 to September 2019.

	Countercyclical		Procyclical	
	$\mathbb{E}[R]$	$\sigma(R)$	$\mathbb{E}[R]$	$\sigma(R)$
Low (L)	-0.13	1.69	-0.15	2.31
Medium	-0.06	0.92	-0.03	1.63
High (H)	0.18	2.66	0.23	3.01
Spread (H-L)	0.30	3.02	0.38	3.50
t(Spread)	(1.71)		(1.90)	

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 49 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 to September 2019.

	Low (L)	Medium	High (H)	Spread (H-L)	t(Spread)
GP (%)	0.67	0.54	0.62	-0.05	-0.45
ROA (%)	1.65	1.48	1.47	-0.18	-2.84
Asset growth (%)	4.85	3.59	2.92	-1.93	-2.64
I/A (%)	1.46	0.40	0.38	-1.08	-1.94
SUE1 (%)	0.11	0.03	0.17	0.06	0.29
SUE2 (%)	0.09	0.05	0.05	-0.04	-0.28
SUE3 (%)	0.02	0.07	0.09	0.07	0.58

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 "six states" ("Eight states") are required to include either six or eight states each, respectively. For ease of comparison, the column labeled "Seven states" repeats the baseline portfolio sort analysis in which seven 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 to September 2019.

	Six states		Seven states		Eight 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)	0.50	4.59	0.55	4.59	0.62	4.57	0.67	4.43
Medium	0.73	4.70	0.73	4.67	0.70	4.69	-	-
High (H)	0.96	5.50	0.94	5.46	0.93	5.34	0.93	5.20
Spread (H-L)	0.47	2.90	0.39	2.50	0.31	2.30	0.26	2.03
t(Spread)	(2.52)		(2.33)		(2.09)		(2.06)	

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 to September 2019.

	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)	0.67	5.60	0.56	4.64	0.54	4.52	0.61	4.50
Medium	0.74	4.54	0.71	4.68	0.74	4.64	0.72	4.65
High (H)	0.75	4.91	0.98	5.42	0.90	5.41	0.90	5.28
Spread (H-L)	0.08	2.72	0.42	2.78	0.36	2.26	0.29	1.93
t(Spread)	(0.47)		(2.46)		(2.51)		(2.53)	

Table OA.12: 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 49 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 to September 2019.

Panel A: Slope-sorted portfolios								
	S	$\mathbb{E}[R]$	$\sigma(R)$	N(State)	N(Firm)	$\mathbb{E}[R_{EW}]$	$\mathbb{E}[R_{\text{IND}}]$	$\mathbb{E}[R_{\text{DGTW}}]$
Low (L)	-3.03	0.84	4.90	7	623	1.15	0.05	-0.19
Medium	-2.22	0.73	4.71	24	1956	1.04	-0.04	-0.27
High (H)	-1.50	0.63	4.95	7	394	0.94	-0.13	-0.42
Spread (H-L)	1.53	-0.21	2.22			-0.21	-0.18	-0.23
t(Spread)		(-1.53)				(-1.40)	(-1.52)	(-2.08)
Panel B: Curvature-sorted portfolios								
	C	$\mathbb{E}[R]$	$\sigma(R)$	N(State)	N(Firm)	$\mathbb{E}[R_{EW}]$	$\mathbb{E}[R_{\text{IND}}]$	$\mathbb{E}[R_{\text{DGTW}}]$
Low (L)	-6.31	0.84	5.49	7	321	1.19	0.09	-0.21
Medium	-3.55	0.72	4.72	24	2081	1.05	-0.06	-0.27
High (H)	-0.89	0.67	4.51	7	571	0.89	-0.09	-0.41
Spread (H-L)	5.42	-0.18	2.77			-0.30	-0.19	-0.19
t(Spread)		(-1.07)				(-2.46)	(-1.55)	(-1.36)

Table OA.13: Municipal spread-sorted portfolios: excluding groups of states

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: The column labeled "Excluding large" excludes the three largest states in the sample (as measured by gross state product) from the analysis, whereas the column labeled "Excluding distressed" excludes five states whose municipal debt markets were tested by municipal defaults during the sample period. 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 to September 2019.

	Excluding large: CA,NY,TX		Excluding "Distressed:' AL,CA,IL,MI,PA	
	$\mathbb{E}[R]$	$\sigma(R)$	$\mathbb{E}[R]$	$\sigma(R)$
Low (L)	0.61	4.68	0.52	4.61
Medium	0.72	4.67	0.75	4.64
High (H)	0.90	5.47	0.93	5.41
Spread (H-L)	0.29	2.52	0.41	2.71
t(Spread)	(1.73)		(2.33)	