The term structure of municipal bond yields, local economic conditions, and local stock returns*

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Abstract

This study shows that the municipal yield curve is informative about local economic outcomes. Controlling for Treasury yields, a flatter municipal yield curve not only predicts deteriorating local economic conditions, such as higher unemployment rates and more macroeconomic uncertainty, but also signals greater risk for locally headquartered firms. An investment strategy that exploits this fact by buying (selling) the firms located in states where municipal yield curve is relatively flat (steep) earns an excess return that exceeds 5% per annum. These novel empirical results indicate that the municipal debt market provides valuable information about the trajectories and risks of local economies.

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Municipal bonds are a key source of funding for state and local governments, and allow these entities to finance their budgets by selling debts backed by their expected future cash flows. While existing studies show that the shape of the Treasury yield curve predicts *aggregate* economic outcomes (e.g., Harvey (1988); Estrella and Hardouvelis (1991); Ang, Piazzesi and Wei (2006b)), little is known about whether municipal yield curves convey valuable information about *local* (i.e., state-level) economic outcomes. In this study I document empirically that the long-term slope of the term structure of municipal spreads (municipal yields minus Treasury yields) is informative about both local macroeconomic conditions and local asset prices.

Specifically, I define the long-term slope of the term structure of municipal spreads (referred to as the "long-term slope of the municipal spread" hereafter) as the difference between 20 year and 5 year municipal yields in excess of Treasury yields, and show that in states where this slope is flatter: (i) local economic activity, as measured by variables such as the unemployment rate, deteriorates and local economic uncertainty, as measured by the conditional volatility of economic activity, rises; and (ii) locally headquartered firms earn stock returns that are 0.43% per month higher and have higher market betas. I reconcile facts (i) and (ii) jointly by documenting that higher local uncertainty predicts higher return volatilities for local firms.

My focus on the information content of the long-term slope of the municipal spread is based on four observations. First, since the cash flows underlying municipal bonds are influenced by future economic activity, municipal yields should embed investors' expectations of future outcomes. Second, municipal spreads largely reflect default risk (Schwert, 2017), a predictor of economic activity. Third, as the slope of the Treasury yield curve predicts aggregate economic activity, a similar result may carry over to the municipal yield curve and local economic activity. Finally, unlike trading in Treasuries, trading in municipal bonds is concentrated among long-term securities (those with 10 or more years to maturity). Together, these observations suggest that the long-term slope of the municipal spread is likely to predict *local* economic outcomes.

I measure the long-term slope of the municipal spread by estimating a term structure model drawn from Diebold, Li and Yue (2008). The model first distills each state's municipal yield curve into three factors, one of which is closely related to the long-term slope of the yield curve. The model then accounts for the fact that municipal yields in each state are driven by both national and local economic forces. This is done by decomposing each yield factor into two components. One component subsumes variation in the factor that is common to all states, and the other component – the focus of this study – is *state-specific*. As a model-free alternative, I also define the long-term slope of the municipal spread as the difference between 20 year and 5 year municipal yields in excess of Treasury yields, and show that my results still hold.

Based on this decomposition, I document that economic activity deteriorates, and economic uncertainty rises, in states where the long-term slope of the municipal spread is flatter. In particular, a one standard deviation *decrease* in the long-term slope predicts (i) a 0.57% *decrease* in the growth rate of a state's real gross state product, and (ii) a 0.76% *increase* in the conditional volatility of the growth rate of a state's coincident economic activity index. I establish these results via predictive regressions that forecast local macroeconomic outcomes, such as the unemployment rate, coincident economic activity index, and real personal income, using the long-term slope of a state's municipal spread and a host of control variables, including the slope of the Treasury yield curve. I also show that the long-term slope of the municipal spread boosts the average adjusted-R^2 of these regressions by up to 7% at the one-year horizon.

Next, I show that in states where the long-term slope of the municipal spread is flatter, and macroeconomic uncertainty is expected to rise, the equity returns of local firms become more volatile. That is, increases in local economic uncertainty spillover to local firms. I demonstrate this fact by predicting the one-, three-, and 12-month ahead realized volatility of local firms using both the current volatility of these firms and the current degree of macroeconomic uncertainty in the state. The results, which control for unobserved heterogeneity across states and time with fixed effects, indicate that a one standard deviation increase in local uncertainty increases the volatility of local firms by up to 0.5% per month. This spillover of macroeconomic uncertainty has two implications for local firms: since local uncertainty rises in states where the long-term slope of the municipal spread is flatter, then the conditional (market) betas and the expected returns of firms based in these states should also rise.

Finally, I validate these two predictions by constructing an investment strategy that buys (sells) firms headquartered in states where the long-term slope of the municipal spread is flatter (steeper). I show this trading strategy, which I refer to as the flat-minus-steep (FMS) spread, (i) earns an average return that exceeds 5% per annum, and (ii) is explained by the fact that firms located in states where the municipal spread is flatter have significantly higher conditional market betas. Specifically, a conditional portfolio double sort that controls for differences in market betas across states subsumes the FMS spread. Collectively, these results highlight how municipal yield curves are also informative about the systematic risk exposures of local firms.

I conduct several robustness checks. For instance, simulation evidence indicates that the long-term slope of the municipal spread does not spuriously predict local economic outcomes. Furthermore, tests of cross-sectional heterogeneity in forecast performance show that the explanatory power of the the long-term slope varies across states in economically meaningful ways. For example, the long-term slope of the municipal spread in a given state is more useful for predicting another state's macroeconomic outcomes if the two states share closer economic ties. Here, the connections between pairs of states are measured using either the total value of freight shipped between states or a trade gravity measure (Tinbergen, 1962). Likewise, the long-term slope of the municipal spread is more informative about local economic outcomes among states that provide their residents with more tax benefits to purchase locally issued municipal debts.

The returns of the FMS spread also survive a battery of robustness tests. Specifically, the spread (i) is not driven by differences in industry composition across states; (ii) is larger in magnitude among firms whose operations are more contained within a given state (i.e., firms that are more exposed to the local economy); (iii) is insensitive to methodological variations in the portfolio formation procedure; and (iv) cannot be explained by accounting and return-based characteristics that are known to predict returns (e.g., value and momentum). These facts, among others, indicate that the FMS spread is a prominent feature of the data.

Taken together, my results show that the municipal debt market not only serves as a valuable source of funding for subnational governments, but also provides economically valuable information about the trajectories and risks of local economies.

Related literature. My study is the first to document that the term structures of municipal bond yields convey valuable information about future local economic outcomes. My analysis of the information content of municipal bond yields is motivated by the literature that examines the types of information impounded in these yields. While 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, 2019; Gao, Murphy and Qi, 2019), and local newspaper closures

(Gao, Lee and Murphy, 2018), another strand decomposes these yields into broad factors related to the tax benefits of owning municipal debt, liquidity risk, and default risk (Wang, Wu and Zhang, 2008; Ang, Bhansali and Xing, 2014; Schwert, 2017). Notably, Schwert (2017) shows that over 70% of the tax-adjusted spread between general obligation (GO) municipal and Treasury yields bond reflects the credit risk of the issuer, despite the infrequency of municipal defaults. In contrast to the studies that explore *why* municipal bond yields vary, I show that this variation in municipal yields is informative about future local economic outcomes.

My study also contributes to the literature on stock return predictabiltiy across regions of the United States. Although numerous 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 for 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 by state lines, and that trading by home biased investors impacts 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 of these explanations completely account for why stock returns differ across states. This is because the FMS spread is not driven by firms that are easy to misprice (e.g., less visible firms followed by fewer analysts) or states with countercyclical fiscal policies.

In contrast to these studies that point to differences in the *price* of risk across states, my results indicate that states are also heterogeneous with respect to the *quantity* of risk. This is in line with Tuzel and Zhang (2017) who show that the quantity of risk differs across more granularly defined metropolitan statistical areas (MSAs). I establish this fact by showing that when the long-term slope of the municipal spread is flatter, the risk exposures of local firms rise. This relation between the long-term slope of the municipal spread, local conomic uncertainty, and the systematic risk exposures of local firms reconciles the FMS spread observed in the data.

An additional possibility for differences in stock returns across the United States is that investors across geographies may underreact to cash flow relevant news, leading to future earning surprises (Smajlbegovic, 2018; Parsons, Sabbatucci and Titman, 2018). However, I find no empirical evidence that the returns to the FMS spread are explained by an underreaction to future fundamentals. For instance, future earnings surprises are statistically indistinguishable between states where the long-term slope of the municipal spread is flatter versus steeper.

Finally, my results have implications for the literature that examines the consequences of tax-induced segmentation in the municipal debt market. Pirinsky and Wang (2011) and Babina *et al.* (2019) provide evidence that this form of market segmentation, which stems from the fact that municipal bond holders are typically only exempt from paying state incomes taxes on income from municipal bonds issued in their state of residence, limits cross-state risk sharing. In contrast to these studies that identify a cost associated with this type of segmentation, a qualitative insight from my study is that this type of segmentation may have benefit. In particular, state incomes tax policies may influence the amount of information contained in the term structures of municipal bond yields. In line with this conjecture, I show the long-term slope of state's municipal spread is often a better predictor of economic activity in states that offer their residents a larger tax advantage for purchasing locally issued municipal debts.

The rest of this paper is organized as follows. Section 1 describes the data and how I define the long-term slope of the municipal spread. Section 2 uses the slope of the municipal spread to forecast local macroeconomic outcomes, while Sections 3 and 4 document the relation between the slope of the municipal yield spread and risk and returns across states. Section 5 concludes.

1 Data

My sample period spans January 2000 to December 2017. Data related to state-level general obligation (GO) municipal yields, U.S. Treasury yields, state-level macroeconomic outcomes, and stock return and accounting data are obtained from a variety of sources, outlined below.

Municipal bond yields. GO municipal yields for 19 states are drawn from Bloomberg at the end of each month. This data includes yields related to the following tenors: 3 and 6 months, and 1–5, 7, 9, 10, 12, 14, 15, 17, 19, 20, 25, and 30 years. However, data related to maturities of less than one year are excluded since very short-term bonds carry negligible default risk. Additionally, points on the yield curve with more than 20 years to maturity are also excluded because there is a steep decline in trading volume for bonds with these much longer maturities (see Figure 1, below). Thus, I retain 14 tenors that range from one year to

20 years for the analysis. This municipal yield data is described in more detail in Section 1.1.

Treasury data. Treasury yield data constructed by Gürkaynak, Sack and Wright (2007) are used to measure the term structure of nominal risk-free rate. Only the Treasury yields related to the same 14 tenors mentioned above are retained for the analysis.[1]

State-level macroeconomic data. Data related to the unemployment rate, coincident and leading economic activity indexes, real personal income per capita, and real gross state product are obtained from FRED. The first three of these series are available at the monthly frequency, while the latter two series are available at the quarterly frequency. These time series are seasonally adjusted and each series, except the leading index, is transformed into a 12-month percentage change. Furthermore, local macroeconomic uncertainty is measured by applying an AR(1)-GARCH(1,1) model to the monthly growth rate of each state's coincident economic activity index, and retaining the estimated conditional volatility. Local uncertainty is measured using this particular index since Crone and Clayton-Matthews (2005) note that this index provides the most comprehensive measure of local economic activity available. Additional details are provided in both Section 2.1, below, and Section OA.1 of the Online Appendix.

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) three- and five-factor models and the Carhart (1997) four-factor model are from the data library of Kenneth French, and the q-factors of Hou, Xue and Zhang (2015) are provided by Lu Zhang.[2]

1.1 Municipal bond data

The term structures of municipal yields related to the GO bonds issued by 19 state governments are obtained from Bloomberg. The 19 states in the sample are California, Connecticut, Florida, Georgia, Illinois, Maryland, Massachusetts, Michigan, Minnesota, New Jersey, New York, North Carolina, Ohio, Pennsylvania, South Carolina, Texas, Virginia, Washington, and Wisconsin. These states account for approximately 80% of both aggregate U.S. GDP and trading activity in the secondary market for municipal debt, as measured by either the total par volume traded

[1] This data is available at `https://www.federalreserve.gov/pubs/feds/2006/200628/200628abs.html`.

[2] Thanks to Kenneth French and Lu Zhang for making this data available.

or the number of bonds traded. The remaining 31 states are excluded from the sample because they (1) prohibit the issuance of GO debt, (2) severely restrict the amount of GO debt that can be issued, (3) allow GO debt to be issued but have none outstanding, or (4) typically account for less than 1% of trading activity in the municipal debt market.[3]

Since municipal bond holders are often exempt from paying both Federal income tax on interest from municipal debt, as well as state incomes taxes on the income earned on municipal debts issued by their state of residence, there is a wedge between the yields of tax-exempt municipal bonds and taxable Treasury bonds. As a preliminary step to my analysis, I account for difference in tax treatment both between the municipal and Treasury debt market and across states by following Schwert (2017) and scaling each municipal yield by $\frac{1}{(1-\tau_{i,t})}$. Here, $1 - \tau_{i,t} = (1 - \tau_t^{Fed})(1 - \tau_{i,t}^{State})$, 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]

I focus on the yields of GO bonds because the cash flows underlying these bonds are secured by the full faith, credit, and taxing power of the issuing government. In contrast, the cash flows underlying revenue bonds, another common form of municipal debt, are secured by income from specific revenue streams (e.g., airport gate fees) rather than the credit of the issuing government. Schwert (2017) examines the tax-adjusted spread between the yields of GO and Treasury bonds and finds that over 70% of this spread captures default risk. While Ang *et al.* (2014) suggest this spread is driven by liquidity risk, both Wang *et al.* (2008) and Novy-Marx and Rauh (2012) also find the municipal spread contains a large credit risk component. Since my primary purpose is to examine whether local municipal bond yields are informative about local economic conditions, and the municipal spread largely reflects the credit spread of the issuing government, it is natural to consider whether the slope of the municipal spread predicts local economic outcomes. This is because a flat (steep) municipal spread indicates a state where

[3]The two U.S. states that are most active in the municipal debt space but are not included in this study are Arizona and Colorado. Arizona and Colorado account for approximately 1.30% (1.67%), 1.58% (1.65%) of the total par volume traded (number of trades) in the secondary market for municipal debt. Arizona is excluded from the sample because its state constitution limits outstanding GO debt to $350,000, while Colorado is excluded from the sample because its state constitution prohibits the issuance of GO debt entirely.

[4]The Federal tax rates are from the Tax Policy Center (`https://www.taxpolicycenter.org`) and the state tax rates are from the Tax Foundation (`https://taxfoundation.org`). Note, however, that column (x) of Table X and Table A7 in the Online Appendix repeat the main analyses without tax adjusting municipal bond yields. These tables show that my key results are similar to those obtained by applying this tax adjustment.

short-term credit risk is high (low) relative to long-term credit risk.

There are three advantages of using municipal yield data from Bloomberg instead of constructing term structures of municipal yields using trade data recorded by the MSRB. First, the Bloomberg yield curves account for the fact that most municipal bonds contain embedded call options (e.g., Harris and Piwowar (2006); Gao *et al.* (2018)). While some studies deal with the optionality of municipal debt by dropping bonds that include options from their analyses (e.g., Wang *et al.* (2008); Chun, Namvar, Ye and Yu (2018)), this filter eliminates a large source of variation in yields. Second, Bloomberg attempts to overcome the illiquidity of the municipal debt market by using (i) data on the recent trades of each bond; (ii) proprietary data on bid-ask quotes for each bond; and (iii) data on the recent trades of comparable bonds to construct the yield curve for each state. Third, the Bloomberg yield curves are updated frequently, and are used by market participants to price both outstanding bonds and new issues.

Figure 1 shows measures of trading activity in the secondary market for municipal debt between 2005 and 2017. The left subfigure displays the proportion of par value traded in the municipal debt market across six maturity groups, and compares these proportions to those for the Treasury debt market. Here, data on trading activity in the municipal (Treasury) market is gathered from the MSRB (Federal Reserve Bank of New York's Primary Dealer Statistics). The key takeaway from this figure is that, unlike the Treasury market, most of the par value of municipal debt traded corresponds to long-term securities. Specifically, while approximately 60% of the par value of municipal debt traded has a maturity of six years or more, only 30% of the par value of Treasury debt traded has a maturity greater than six years. The right subfigure shows the number of monthly trades in the municipal debt market for the same maturity groups. Similar to the left subfigure, the right subfigure shows that long-term municipal securities are frequently traded. In particular, there are an average of 600 thousand trades per month in municipal securities with more than six years to maturity versus only an average of 200 thousands traded per month in securities with fewer than six years to maturity.

[Insert Figure 1 about here.]

Collectively, Figure 1 suggest that the actively traded long-end of the municipal yield curve is likely to convey the most information about future local economic outcomes. Combined with the fact that the term structure of the tax-adjusted municipal spreads is approximately equal to the credit spread of the issuing state, I consider whether the long-term slope of the municipal spread is informative about local macroeconomic conditions. My focus on the slope of the municipal spread is mainly influenced by the studies that use the shape of the Treasury yield curve to predict aggregate economic outcomes (e.g., Harvey (1988); Estrella and Hardouvelis (1991); Ang *et al.* (2006b)). However, studies also show that the slope of credit default swap spreads conveys information about firm-level expected returns (e.g., Han, Subrahmanyam and Zhou (2017)) and sovereign credit risk (e.g., Augustin (2018)).

I examine the information content of the long-term slope of the municipal spread using two measures. Motivated by the large literature on term structure modeling, my main measure measure of the slope of the municipal spread is based on a reduced-form term structure model. This model, which I draw from Diebold *et al.* (2008), takes advantage of variation in yields across *all* maturities, rather than focusing on a small set of (potentially arbitrary) maturities only (see, e.g., Ang and Piazzesi (2003); Ang *et al.* (2006b); Diebold, Rudebusch and Aruoba (2006)). However, as an alternative model-free measure, I also define the long-term slope of the municipal spread as the difference between 20 year and 5 year municipal bond yields in excess of Treasury bond yields. While this alternative measure is easy to construct, its shortcoming is that this measure only exploits information contained in two specific points on the yield curve.

The key to constructing my main measure of the long-term slope of the municipal spread is to first distill each state's municipal yield curve into a low-dimensional set of municipal yield factors. Next, the Treasury yield curve is also collapsed into a low-dimensional set of Treasury yield factors that influence yields across all states. Finally, the municipal yield factor related to the long-term slope of each state's yield curve is projected on the Treasury yield factors. This final step, which is akin to subtracting the long-term slope of the Treasury yield curve from the long-term slope of the municipal yield curve, isolates variation in a state's yields that cannot be explained by variation in Treasury yields. The following section describes these steps in detail.

1.2 Constructing the long-term slope of the municipal spread

A small set of (latent) common factors drive the variation in yields across maturities (e.g., Litterman and Scheinkman (1991)). Thus, a popular way to model a term structure of interest rates is to use the Diebold and Li (2006) model, which is based on Nelson and Siegel (1987), to express a m-month to maturity yield as a maturity-dependent linear combination of three time-varying factors. While this model, which is known as the Dynamic Nelson-Siegel (DNS) model, was developed to forecast Treasury yields, the model has also been applied in other contexts. For example, the DNS model has been used to examine the joint dynamics of Treasury yields and national economic variables (Diebold *et al.*, 2006), identify common factors in global bond markets (Diebold *et al.*, 2008), model yields in emerging markets (Broner, Lorenzoni and Schmukler, 2013), and forecast corporate bond yields (e.g., Yu and Salyards (2009)). Consequently, the DNS model offers a theoretically and empirically motivated way to distill each state's municipal yield curve into a low-dimensional set of state-level yield factors as follows

$$y_{i,t}(m) = l_{i,t} + s_{i,t}\left(\frac{1-e^{-\lambda m}}{\lambda m}\right) + c_{i,t}\left(\frac{1-e^{-\lambda m}}{\lambda m} - e^{-\lambda m}\right) + v_{i,t}(m). \tag{1}$$

Here, $y_{i,t}(m)$ represents the time t yield of a municipal bond issued by state i with m months until maturity, $\{l_{i,t}, s_{i,t}, c_{i,t}\}$ is the set of state-level yield factors to be estimated, the terms multiplying these factors are the maturity-dependent loadings on each factor, λ is a shape parameter that governs the factor loadings of $s_{i,t}$ and $c_{i,t}$, and $v_{i,t}(m)$ is the pricing error. With λ fixed, the factors underlying equation (1) are estimated via a cross-sectional OLS regression at the end of each month t. While, in principal, λ may also vary across states and over time, simultaneously estimating $\{l_{i,t}, s_{i,t}, c_{i,t}, \lambda_{i,t}\}$ requires the use of nonlinear methods, such as nonlinear least squares, instead of OLS. I do not consider this generalization for two reasons: (i) Diebold and Li (2006) suggest that fixing λ achieves numerical stability without sacrificing the model's fit; and (ii) I ensure my results are not driven by the value of λ by also constructing a model-free measure of the long-term slope of the municipal yield curve. Thus, I follow both Diebold and Li (2006) and numerous subsequent studies by fixing λ in equation (1) to 0.0609.[5]

While the yield factors underlying equation (1) are often denoted the level ($l_{i,t}$), slope ($s_{i,t}$), and curvature ($c_{i,t}$) of the underlying yield curve, it is not immediately clear how changes in these factors affect the shape of the municipal yield curve. Therefore, I ascribe an economic interpretation to each factor by examining how each factor is correlated with key yields and

[5]Figure A1 in the Online Appendix plots the factor loadings underlying the DNS model with $\lambda = 0.0609$.

yield spreads. These correlations, which are computed by finding the correlation between the yields and the yield factors *within* each state, and then taking the gross state product (GSP) weighted average correlation *across* states, are reported in Panel A of Table 1.

The results show that $l_{i,t}$ is closely related to the long-term level of the municipal yield curve, as the average correlation between $l_{i,t}$ and $y_{i,t}(240)$ across the 19 states in the sample is 0.951. 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 $y_{i,t}(60) - y_{i,t}(12)$ ($y_{i,t}(240) - y_{i,t}(60)$) yield spread, I refer to $s_{i,t}$ and $c_{i,t}$ as the "short-term slope" and "long-term slope" slope factors, respectively. This is because *increases* in $s_{i,t}$ ($c_{i,t}$) *flatten* the short-term (long-term) slope of the municipal yield curve.

[Insert Table 1 about here.]

Since municipal bonds are typically priced relative to Treasury bonds (e.g., Ang *et al.* (2014); Schwert (2017)), and equation (1) is based on the *level* of municipal yields in each state, the yield factors obtained via equation (1) vary due to changes in either the underlying Treasury rates or for state-specific reasons. Since I am primarily interested in isolating state-specific variation in municipal bond yields, I purge each municipal yield factor of the common, national, component of variation by applying the framework of Diebold *et al.* (2008). That is, I first collapse the Treasury yield curve into a set of Treasury yield factors, and then focus on the variation in each state's long-term slope factor ($c_{i,t}$) that is orthogonal to the variation in the Treasury yield factors. Here, the Treasury yield factors are obtained by estimating the following equation

$$Y_t(m) = L_t + S_t\left(\frac{1-e^{-\Lambda m}}{\Lambda m}\right) + C_t\left(\frac{1-e^{-\Lambda m}}{\Lambda m} - e^{-\Lambda m}\right) + V_t(m). \tag{2}$$

Similar to equation (1), this equation indicates that a Treasury yield with m-months to maturity at time t, denoted by $Y_t(m)$, can be expressed as a maturity-dependent linear combination of three Treasury yield factors: L_t, S_t, C_t. These factors are, once again, obtained by setting the shape parameter $\Lambda = 0.0609$ and estimating equation (2) via a series of cross-sectional OLS regression. In line with the economic interpretation of the state-level yield factors from equation (1), Panel A of Table 1 also shows that L_t, S_t, and C_t can be interpreted as the level, short-term slope, and long-term slope of the Treasury yield curve, respectively.

With a reduced-form measure of the long-term slope of each state's municipal yield curve in hand (i.e, $c_{i,t}$ from equation (1)), as well as the common factors underlying the Treasury yield curve (i.e., L_t, S_t, and C_t from equation (2)), the final step of the procedure involves stripping $c_{i,t}$ of the common, national, component of the variation in the factor. This is achieved by estimating the following time-series regression that is motivated by Diebold *et al.* (2008)

$$c_{i,t} = \alpha_i^c + \beta_i^{c,l} L_t + \beta_i^{c,s} S_t + \beta_i^{c,c} C_t + \varepsilon_{i,t}^{LTS}. \tag{3}$$

Equation (3) implies the long-term slope of a state's municipal yield curve varies due to (i) the extent to which yields in the state are exposed to the national factors driving Treasury yields, and (ii) a state-specific component represented by $\varepsilon_{i,t}^{LTS}$.[6] Given this decomposition, $\varepsilon_{i,t}^{LTS}$can be interpreted as a statistically efficient measure of the long-term slope of the municipal spread.

As an alternative model-free measure of the long-term slope of the municipal spread, I also construct this factor using observable yields. Based on the notation related to equations (1) and (2), I define this observable factor as $\{[y_{i,t}(240) - y_{i,t}(60)] - [Y_t(240) - Y_t(60)]\}$. I ensure the two measures of the long-term slope of the municipal spread are in fact related by computing the time-series correlation between these measures *within* each state, and then calculating the GSP-weighted average correlation *across* the 19 states. The results show these two variables are closely related, as the average correlation is -0.765. The negative correlation arises because an *increase* in $c_{i,t}$ is associated with a *decrease* in $y_{i,t}(240) - y_{i,t}(60)$ (recall Panel A of Table 1). Therefore, to aid in the interpretation of the upcoming analyses, I multiply $\varepsilon_{i,t}^{LTS}$ in equation (3) by -1 so that an *increase* in either measure is associated with a *steeper* municipal spread.

While $\varepsilon_{i,t}^{LTS}$ and the observable long-term slope factor are highly related, the key difference between the two measures is that the latter is identified using only two points on the yield

[6]Equations (3) is unrestricted version of that employed by Diebold *et al.* (2008), who not only impose the restrictions that that $\beta^{x,y} = 0$ for $x \neq y$ and $x, y \in \{l, s\}$ for computational simplicity and tractability but also consider a two-factor model only. However, this equation can also be extended in a number of ways, such as by including higher-order terms of the national yield factors as additional explanatory variables that absorb additional common variation driving the state-level yield factors. In the interest of parsimony, I use equation (3) as my main measure of the long-term slope of the municipal spread, but robustness tests show my results continue to hold if I either restrict this equation or expand this equation to also included higher-order terms (i.e., squares of the national factors). Likewise, while the focus of this study is on the long-term slope of the municipal spread, equation (3) can also be applied to the level and short-term slope factors obtained via equation (1). Finally, the factor exposures associated with estimating equation (3) on a state-by-state basis over the full sample period are reported in Table A3 of Section OA.3.3 of the Online Appendix.

curve, whereas the former is identified using variation related to all maturities. Therefore, to ensure my results are not simply driven by two specific points on the yield curve, I employ $\varepsilon_{i,t}^{LTS}$ as my primary measure of the slope of the municipal spread. However, robustness tests show that my main results hold if I use the alternative, model free, measure instead.

Finally, note that equation (3) can either be estimated over the full sample, or a rolling window or recursive window. While estimating equation (3) over the full sample produces more precise estimates of the state-specific factor exposures, this approach results in a measure of $\varepsilon_{i,t}^{LTS}$ that is not time-t measurable. Therefore, in the analyses that strictly require $\varepsilon_{i,t}^{LTS}$ to be time-t measurable (i.e., the portfolio sorts in Sections 3 and 4), I estimate equation (3) over a recursive window. In all other cases I estimate the equation over the full sample for simplicity.

1.2.1 Summary statistics for the long-term slope of the municipal spread

Figure 2 shows the time-series dynamics of the long-term slope of the municipal spread obtained by estimating equation (3) over the full sample period. Here, $\varepsilon_{i,t}^{LTS}$ is GSP-weighted across states and standardized. The key takeaway from this figure is that ε_{t}^{LTS} shows no relation to the economic cycle. This supports the notion that this factor state-specific captures variation in municipal yields that is orthogonal to aggregate economic conditions. For example, the correlation between ε^{LTS} and the growth rate of industrial production (excess market returns) is 0.05 (-0.10). Additionally, although Figure 2 shows that the time-series dynamics of ε_{t}^{LTS} are somewhat erratic, this likely makes detecting a relation between the municipal yield curve and future local economic activity in Section 2 more difficult.[7]

[Insert Figure 2 about here]

Summary statistics in Panel B of Table 2 show that ε_{t}^{LTS} is mean zero (by construction) and has a time-series volatility (cross-sectional dispersion) of 2.065 (0.723). While the long-term slope of the municipal spread is volatile, an augmented Dickey-Fuller test rejects the null hypothesis that this factor contains a unit root. Consequently, this factor can be included in the predictive regressions considered in Section 2 without raising concerns related to nonstationar-

[7]Figure A2 of the Online Appendix plots the time-series of the Treasury yield factors obtained from equation (2), as well as the GSP-weighted state-level yield factors obtained from equation (1) over the sample period.

ity. In the interest of completeness, Table A2 in the Online Appendix also reports the summary statistics for the state and national yield factors obtained via equations (1) and (2).

2 Forecasting state-level macroeconomic outcomes

With a measure of the long-term slope of each state's municipal spread in hand (i.e., $\varepsilon_{i,t}^{LTS}$ from equation (3)), this section considers whether the current shape of the municipal spread is informative about future local macroeconomic outcomes. Knowledge of local business conditions is important for policy makers and market participants interested in matters that include creating subnational government budgets, predicting national economic outcomes (e.g., González-Astudillo (2018)), and explaining variation in stock returns (e.g., Korniotis and Kumar (2013)).

Below, Section 2.1 examines whether information contained in the long-term slope of the municipal spread is useful for forecasting local macroeconomic outcomes. In that section, forecast gains are calculated by measuring the extent to which adding $\varepsilon_{i,t}^{LTS}$ to a predictive regression that includes no municipal yield data changes the adjusted-R^2 of the model. Similarly, Section 2.2 considers whether forecast gains vary across states in economically meaningful ways. This is done by exploring whether (1) forecast gains differ based on the tax incentives that residents of each state are offered to purchase locally issued municipal debt, and (2) the slope of one state's municipal spread is also useful for predicting business conditions in other, economically connected, states. A comprehensive set of robustness checks, including a pseudo out-of-sample forecast exercise, are reported Sections OA.2 and OA.3.4 of the Online Appendix.

Before implementing these analyses, Table 2 reports summary statistics for the six local macroeconomic variables I consider: the unemployment rate (denoted UR), the coincident economic activity index (denoted CI), which is considered the most comprehensive measure of local economic activity (Crone and Clayton-Matthews, 2005), the conditional volatility of the coincident economic activity index (denoted σ (CI)), which is my measure of local macroeconomic uncertainty, the leading economic activity index (denoted LI), real personal income (denoted PI), and real gross state product (denoted GSP). The key takeaway from this table is that there is substantial heterogeneity in local business conditions across states. For example, while the average annual growth rate in unemployment in New York is -0.53%, the average annual growth rate in unemployment in Connecticut exceeds 2.5%. Likewise, while the mean conditional volatility of the monthly growth rate of coincident economic activity ("uncertainty") in New Jersey is less than 12% per month, this quantity exceeds 30% per month in Michigan.

[Insert Table 2 about here.]

2.1 Predictive regressions

A simple way to assess whether the long-term slope of the municipal spread, as constructed in Section 1.2, is informative about local business conditions is to examine whether this factor explains variation in future local macroeconomic outcomes at various forecast horizons. Specifically, if the current shape of the municipal spread is informative about local outcomes, then including this variable in a predictive regression will improve the model's adjusted-R^2 relative to a benchmark model that excludes this relevant predictor. This analysis is implemented by estimating the following predictive regression on a state-by-state basis

$$y_{i,t+h} = \alpha + \rho y_{i,t} + \boldsymbol{\beta X_t} + \gamma \varepsilon_{i,t}^{LTS} + u_{i,t+h}. \tag{4}$$

Here, $y_{i,t+h}$ represents of the six macroeconomic outcomes in state i at time $t+h$, where the forecast horizon is $h \in \{3, 6, 9, 12\}$ months, $\varepsilon_{i,t}^{LTS}$ is the long-term slope of the state's municipal spread, as defined in Section 1.2, and $\boldsymbol{X_t}$ is a matrix of asset-pricing variables related to the national economy. This matrix includes the log price-dividend ratio, term spread, and corporate bond default spread (Fama and French, 1989). If the current shape of the municipal spread is *uninformative* about macroeconomic outcomes, then the change in adjusted-R^2 obtained by adding $\varepsilon_{i,t}^{LTS}$ to the model should not only be low or negative, but the estimated value of γ should be statistically indistinguishable from zero. Therefore, I consider two (related) tests to determine whether $\varepsilon_{i,t}^{LTS}$ explains *incremental* variation in the state-level outcomes.

First, I estimate γ in equation (4) by pooling observations across states. The sign of $\hat{\gamma}$ indicates the direction in which each macroeconomic outcome is anticipated to change as the slope of the municipal spread changes. Consequently, the statistical significant of $\hat{\gamma}$ represents the reliability of this association. I assess the statistical significance of $\hat{\gamma}$ by jointly estimating the parameters underlying equations (3) and (4) – $\left[\alpha, \rho, \boldsymbol{\beta}, \gamma, \{\alpha_i^c, \beta_i^{c,l}, \beta_i^{c,s}, \beta_i^{c,c}\}_{i=1}^{19}\right]'$ – for the

19 states in the sample using GMM. Thus, the standard errors associated with $\hat{\gamma}$ account for the estimation error that arises by generating $\varepsilon_{i,t}^{LTS}$ in equation (4) via equation (3).

Second, I compare the adjusted-R^2 obtained by estimating equation (4) with γ restricted to zero to the adjusted-R^2 obtained by estimating the same equation with γ unrestricted. The incremental proportion of variance explained by the unrestricted model is denoted $\Delta\bar{R}_i^2 \equiv \bar{R}_{i,\gamma\neq 0}^2 - \bar{R}_{i,\gamma=0}^2$. At one extreme, if the slope of the municipal spread in state i explains all the variation in a given macroeconomic outcome, then $\Delta\bar{R}_i^2 = 100\%$. At the other extreme, if the municipal spread explains none of the variation in the macroeconomic outcomes of the state, then $\Delta\bar{R}_i^2 = 0\%$. Thus, for a given macroeconomic variable and forecast horizon, the average value of $\Delta\bar{R}_i^2$ across the 19 states (denoted $\Delta\bar{R}^2$) represents the average proportion of variation in an outcome that is explained by including $\varepsilon_{i,t}^{LTS}$ in equation (4).[8]

I assess the statistical significance of each value of $\Delta\bar{R}^2$ by using Monte Carlo simulations to obtain the finite sample distribution of $\Delta\bar{R}^2$. I conduct each one of the $10,0000$ simulations conducted as follows. First, I generate a time-series process that mimics the temporal dynamics of $\varepsilon_{i,t}^{LTS}$ (i.e., the standard deviation and first-order autocorrelation) reported in Panel B of Table 1. Second, I estimate the predictive regressions described about using this generated process in place of the actual long-term slope of each state's municipal spread. Third, I record the value of $\Delta\bar{R}^2$ from each simulation. Since the generated processes underlying these simulations have no economic content, a positive value of $\Delta\bar{R}^2$ can only arise by chance. Therefore, for a given macroeconomic variable and forecast horizon, I consider a value of $\Delta\bar{R}^2$ obtained using the actual long-term slope of each state's municipal spread as statistically significant if fewer than 10% of the generated regressors produce a $\Delta\bar{R}^2$ statistic that is larger.

[Insert Table 3 about here.]

The results are reported in Table 3, and are obtained by using both the estimated long-term slope (Panel A) and the observable long-term slope factor (Panel B). The results show that long-term slope of the municipal spread is both an economically valuable and a statistically reliable predictor of local macroeconomic conditions. For instance, the last row of Panel A shows that

[8]To mitigate the possibility that large forecast gains in a small subset of states are driving the results, I also the median value of $\Delta\bar{R}_i^2$ across the 19 states. These results, reported in in Table A4 of the Online Appendix, are qualitatively similar to those obtained by taking the average across states.

adding $\varepsilon_{i,t}^{LTS}$ to equation (4) increases the average adjusted-R^2 of the predictive regression by 4.70% at the 12-month horizon. As the mean adjusted-R^2 of this regression at the 12-month is only 24.60% when no municipal yield data is used to forecast local economic outcomes (see Table A5 of the Online Appendix), including $\varepsilon_{i,t}^{LTS}$ in equation (4) boosts the explanatory power of the model by close to 20%. These large forecast gains, especially at the 12-month horizon, highlight the usefulness of using municipal yield data to forecast local economic conditions.

Breaking down the forecast gains in Panel A by economic variable and forecast horizon shows that the long-term slope of the municipal spread boosts the incremental adjusted-R^2 of equation (4) in 18 out of the 24 cases. Specifically, the long-term slope of the municipal spread is particularly informative about the growth rates of local unemployment, leading economic activity, and gross state product at each of the four forecast horizons. While $\varepsilon_{i,t}^{LTS}$ is also useful for predicting the coincident economic activity index, as well as the conditional volatility of this index, the factor is generally uninformative about the growth rates of personal income per capita in each state. Table A6 of the Online Appendix considers longer-horizon forecasts, and shows that the forecast gains associated with equation (4) dissipate within approximately 30 months. This indicates that the long-term slope of the municipal spread is particularly informative about *transitory* rather than *permanent* changes in local economic conditions.

Beyond documenting that the long-term slope of a state's municipal spread explains an economically large and statistically significant proportion of the variation in local business conditions, Table 3 also documents the direction in which a change in the long-term slope factor predicts each macroeconomic outcome. That is, the table reports the value of $\hat{\gamma}$ obtained by pooling equation (4) across states. The key takeaway from this analysis is that a *decrease* in the long-term slope of the municipal spread is associated with a *deterioration* in local macroeconomic conditions. For instance, if $\varepsilon_{i,t}^{LTS}$ decreases by one standard deviation, then the expected 12-month ahead growth rate of unemployment (gross state product) rises (falls) by 4.19% (0.78%).[9] Similarly, a one standard deviation *decrease* in $\varepsilon_{i,t}^{LTS}$ is associated with a 0.76% *increase* in 12-month ahead macroeconomic uncertainty, as measured by the conditional volatility of the coincident economic activity index. Panel B confirms that these marginal effects are similar if the analysis is conducted using the observable long-term slope of the municipal

[9]Since the standard deviation of the estimated long-term slope of the municipal spread is 2.065 (see Panel B of Table 1), the change in the growth rate of unemployment (GSP) is computed as -2.03×2.065 (0.28×2.065).

spread. Thus, a flatter municipal spread signals deteriorating local economic conditions.

The intuition for these results aligns with my conjecture of why the long-term slope of the municipal spread is informative about local conditions. Specifically, since (i) local economic conditions worsen in states where the long-term slope of the municipal spread is flatter, and (ii) the municipal spread largely reflects default risk (Schwert, 2017), a flatter municipal spread likely indicates a state where short-term credit risk is elevated relative to long-term credit risk.

I conduct several robustness checks to ensure that this relation between the long-term slope of a state's municipal spread and future local economic conditions is not spurious.

Out-of-sample analysis. Section OA.2 of the Online Appendix complements the results of the in-sample predictive regressions reported in Table 3 by conducting a pseudo out-of-sample forecast analysis. The purpose of this out-of-sample analysis is to determine whether the long-term slope of the municipal spread is also a valuable predictor of local business conditions in real time. In this section the long-term slope of the municipal spread is obtained by estimating equation (3) over a recursive window, and all macroeconomic data are extracted from ALFRED to account for the fact that the reported values of macroeconomic variables are revised often. These changes ensure that the information used to produce each time $t + h$ forecast is in the information set of an agent standing at time t. The results of this out-of-sample analysis show that the long-term slope of the municipal spread also serves as a statistically significant and economically valuable predictor of local economic conditions in real time.

Sensitivity to tax adjustment. I ensure the results in Table 3 are not sensitive to the way in which I scale municipal bond yields to account for differences in income taxes across states (recall the discussion of the tax adjustment factor, $1/(1 - \tau_{i,t})$, in Section 1.1). This is accomplished by re-conducting the analysis underlying Table 3 with raw, rather than tax adjusted, municipal bond yields. Table A7 of the Online Appendix shows that the results in Table 3 are not dependent on tax adjusting municipal bond yields.

Predictive regressions with alternative yield factors. Since long-term municipal securities are traded more actively than short-term municipal securities, the yields related to these actively traded long-term securities are presumably the most informative about local economic conditions. While this observation motivates my focus on long-term municipal securities, other segments of the municipal yield curve may also convey information about local economic conditions. I examine this possibility by computing the forecast gains associated with adding either the level or the short-term slope of each state's municipal spread to equation (4) in place of $\varepsilon_{i,t}^{LTS}$. Here, the level (short-term slope) of the municipal spread is obtained by estimating equation (3) with $l_{i,t}$ ($s_{i,t}$) from equation (1) on the left-hand side of the projection. The results, reported in Table A8 of the Online Appendix, are consistent with my conjecture that the long-term slope of the municipal spread is most informative about local economic conditions. Including either the level or the short-term slope of the municipal spread in equation (4) contributes little to the model's ability to explain variation in local economic conditions.

Taken together, the results in this section establish two novel facts: (i) a decrease in the long-term slope of a state's municipal spread signals a deterioration in local economic conditions, such as higher unemployment rates and more macroeconomic uncertainty, and (ii) the long-term slope of a state's municipal spread help to explain economically large (and statistically significant) proportions of the variation in local business conditions. Section 2.2 complements these results by examining how the explanatory power of the long-term slope of the municipal spread varies across states. For instance, the section consider whether the average forecast gains documented in Table 3 interact with state-level income tax policies that may influence the amount of information contained in the municipal yield curve. Furthermore, the section considers whether variation related to one state's municipal yield curve is also informative about local economic conditions in other, economically connected, states.

2.2 Heterogeneity in forecast performance across states

The predictive regressions in the previous section show that the long-term slope of the municipal spread is informative about future local economic outcomes at various forecast horizons. Specifically, when the municipal yield curve is flat relative to the Treasury yield curve, local economic conditions deteriorate and local macroeconomic uncertainty rises. Since "the municipal [bond] market may be thought of as numerous loosely integrated state markets for municipal bonds," (Schultz, 2012, p. 494), this section examines whether the previously documented forecast gains vary across states in economically meaningful ways. Two possibilities are considered. First, that forecast gains are related to the tax benefits of owning locally issued municipal debt. Second, that the slope of the municipal spread associated with a given state is also informative about macroeconomic outcomes in other, economically connected, states.

Differences in tax privilege across states. Pirinsky and Wang (2011) and Babina *et al.* (2019) indicate that the municipal bond market is segmented by state lines due to the asymmetric tax treatment of income earned on bonds issued in-state versus out-of-state. With this in mind, I examine whether information content of the slope of the municipal spread interacts with the tax benefits of owning locally issued municipal debt. I conjecture that if municipal bonds issued by high tax privilege states are more closely held by in-state residents, who are presumably better informed about local economic conditions than out-of-state investors, then the forecast gains in the previous section will be concentrated within these high tax privilege states. Here, the tax privilege of owning locally issued municipal debt is from Babina *et al.* (2019). This variable is defined as the difference between the highest state income tax rate applicable to income from municipal bonds issued by the home state and the state income tax rate applied to income from municipal bonds issued by other states.

I examine this conjecture by computing $\Delta\bar{R}^2$ across the groups of states that provide their residents with a high and low tax privilege to buy locally issued municipal debt. Here, a state is assigned to the high (low) tax privilege group if the tax privilege offered by the state is grater (less) than 5.47%, which is the median value of tax privilege across the states in my sample.[10]

The results are reported in Panel A of Table 4, and show that forecast gains are qualitatively larger among high tax privilege states in 13 of the 24 cases considered. For instance, the ΔR^2 statistic obtained by forecasting one-year ahead unemployment among high tax privilege states is almost 1% larger than that obtained among low tax privilege states. However, the small cross-section of states make it difficult to establish whether these differences in $\Delta\bar{R}^2$ are statistically distinguishable between low and high tax privilege states.

[Insert Table 4 about here.]

Overall, these results support the conjecture that asymmetry in the tax treatment of income earned on municipal bonds purchased in-state versus out-of-state interacts with the informativeness of the municipal yield curve. In particular, $\varepsilon_{i,t}^{LTS}$ is often a better predictor of local macroeconomic outcomes in states that offer their residents with a higher tax privilege to purchase locally issued municipal debts. Thus, while state income taxes can limit cross-state risk

[10]This data on state-level tax privilege is available in Table 2 of Babina *et al.* (2019).

sharing in the municipal bond market (Pirinsky and Wang, 2011; Babina *et al.*, 2019), the same tax policies may also influence the extent to which municipal bond yields convey forward-looking information about local economic conditions.

Cross-state spillovers. If the current shape of the term structure of municipal spreads in a given state is informative about the future business conditions of that state, then this same information may also help to explain macroeconomic outcomes in other, economically connected, states. For example, since the economies of South Carolina and North Carolina (Washington) are relatively connected (disconnected), the shape of the municipal spread in North Carolina (Washington) is more (less) likely to also convey information about economic conditions in South Carolina. I examine this possibility by modifying equation (4) and repeating a similar analysis to that described in Section 2.1. Here, the predictive regression I use is

$$y_{i,t+h} = \alpha + \rho y_{i,t} + \boldsymbol{\beta X_t} + \gamma \varepsilon_{i,t}^{LTS} + \delta \varepsilon_{i \neq j,t}^{LTS} + u_{i,t+h}, \tag{5}$$

where $\varepsilon_{i \neq j,t}^{LTS}$ is the slope of the municipal spread in a state j that is economically connected to (disconnected from) state i, and the forecast gain obtained by including $\varepsilon_{i \neq j,t}^{LTS}$ in equation (5) is defined as $\Delta \bar{R}_i^2 \equiv \bar{R}_{i,\delta \neq 0}^2 - \bar{R}_{i,\delta=0}^2$. The values of $\Delta \bar{R}_i^2$ obtained by using yield data from economically connected (disconnected) states to forecast macroeconomic outcomes are then averaged and compared. Comparing these $\Delta \bar{R}^2$ statistics indicates whether municipal yield data from economically connected states is, on average, more useful for forecasting local economic outcomes than municipal yield data from economically disconnected states.

I implement this analysis by measuring the economic connections between pairs of states in two complementary ways. My first proxy for economic connectedness is based on novel data produced by the Freight Analysis Framework that records the value of freight shipped between pairs of states.[11] Using this data, I consider state i as economically connected to (disconnected from) state j if state i transports the largest (smallest) value-weighted proportion of its freight to state j. My second proxy for economic connectedness is based on the gravity measure proposed by Tinbergen (1962). This measure approximates trade flows between pair of states by computing the product of each state's GSP and dividing this product by the distance between each state's capital. Accordingly, I consider state i as economically connected to (disconnected

[11] This data is available at: `https://faf.ornl.gov/fafweb/Default.aspx`.

from) state j if the gravity measure for this pair of states is maximized (minimized).

The results of these analyses are reported in Panels B and C of Table 4. The forecast gains obtained by using the slope of the municipal spread from an economically connected state to predict local economic outcomes are qualitatively larger than those obtained by the slope of the municipal spread from an economically disconnected state. This occurs in at least 20 out of the 24 cases considered, and holds holds regardless of whether the the economic connections between states are measured using the value of freight shipped between states or trade gravity. Overall, these results highlight that the slope of the municipal spread does in fact contain economically relevant and valuable information about future macroeconomic economic activity.

3 Municipal bond yields and local stock returns

The key takeaway from the previous section is that the *current* shape of the municipal yield curve conveys valuable information about *future* state-level macroeconomic outcomes. In particular, when the long-term slope of a state's municipal spread is flatter: (i) local economic activity, as measured by variables such as gross state product, deteriorates and local macroeconomic uncertainty, as measured by the conditional volatility of the coincident economic activity index, rises. Since the long-term slope of the municipal spread signals changes in local macroeconomic uncertainty, this section examines whether changes in local economic uncertainty impact the risks and returns of local firms. This examination of a link between local economic uncertainty and firm-level risk is motivated by the growing literature that show that a number of firm-level attributes and outcomes depend on a firm's location (e.g., Dougal, Parsons and Titman (2015); Tuzel and Zhang (2017); Engelberg, Ozoguz and Wang (2018)).

I implement the asset-pricing tests in this section by constructing a set of local (i.e., state-level) stock returns. Specifically, I value weight the monthly returns of all firms headquartered in a given state according to Compustat. I use a firm's headquarter location as my proxy for the primary location the firm's investors and operations since this is the convention in the 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 *et al.* (2015)). The firms included in these portfolios are restricted to common stocks (CRSP SHRCD code

10 or 11) listed on NYSE/AMEX/NASDAQ, excluding financial firms and utilities.[12][13] I also construct the realized volatility of each state-level portfolio by computing the value-weighted average stock return volatility across all firms headquartered in a given state. Here, I define firm-level volatility as the standard deviation of the daily returns of each firm in each month t.

Below, Section 3.1 examines whether higher local economic uncertainty predicts an increase in the realized volatilities of local firms, and shows that this is the case. This spillover of local uncertainty has implications for the risks and expected returns of local firms: since local uncertainty rises in states where the long-term slope of the municipal spread is flatter, the conditional (market) betas and average returns of firms located in these states should be higher. Sections 3.2 and 3.3 show that both of these predictions are supported by the data. Thus, the results in these sections highlight how the long-term slope of a state's municipal spread is also informative about the systematic risk exposures of local firms. Finally, Section 3.4 considers other explanations for why stock returns may vary across regions of the United States, and a comprehensive set of robustness checks is reported in Section 4.

3.1 Spillovers in local macroeconomic uncertainty

In this section I examine whether changes in local macroeconomic uncertainty spillover to the realized stock return volatilities of local firms. While my ultimate goal is to understand whether local uncertainty impacts the systematic risk exposures (and expected returns) of local firms, exploring the potential spillover from macroeconomic uncertainty to stock return volatility provides a useful starting point. To see why, consider a simple model for the returns of a firm f located in state i at time t (denoted $R_{f,i,t}$)

$$R_{f,i,t} = R_{i,t} + \epsilon_{f,t}, \tag{6}$$

where $R_{i,t}$ is the location-specific component of returns, and $\epsilon_{f,t}$ is the firm-specific component. The presence of $R_{i,t}$ in equation (6) reflects how firm-level returns depend, at least partially,

[12] To minimize measurement error, South Carolina is removed from the analysis below because there are typically fewer than 15 firms headquartered in South Carolina that satisfy these data filters.

[13] In Section 4 I ensure my main results are robust to this definition of local stock returns by also constructing state-level portfolios using an approach motivated by García and Norli (2012). There, I group firms into portfolios based on the geographic scope of each firm's operations as elicited from the firm's 10-K filings.

on the local economy. This is not only because certain factors of production, such as labor and real estate, are location specific (e.g., Tuzel and Zhang (2017)), but also because aspects of productivity, such as synergies between co-located firms, vary geographically. Thus, if local economic uncertainty is tied to the volatility of this location-specific component of returns, then an increase in local uncertainty will be associated with an increase in the systematic risk exposures of local firms. This can be seen by writing the conditional market beta of firm f as

$$\beta_{f,i,t} = \frac{\text{Cov}_t\left(R_{f,i,t}, R_{m,t}\right)}{\text{Var}_t\left(R_{M,t}\right)} \approx \rho_{f,i,t}\left[\frac{\sigma_t\left(R_i\right) + \sigma_t\left(\epsilon_f\right)}{\sigma_t\left(R_M\right)}\right]. \tag{7}$$

highlights that, holding all else constant, $\beta_{f,i,t}$ will increase as $\sigma_t\left(R_i\right)$ increases. Here, $R_{M,t}$ denotes the time t market return, $\rho_{f,i,t}$ is the conditional correlation between firm f's returns and the market's returns, $\sigma_t\left(R_i\right)$ $\left(\sigma_t\left(\epsilon_f\right)\right)$ is the conditional volatility of the location-specific (firm-specific) component of returns, and $\sigma_t\left(R_{M,t}\right)$ is the volatility of the market's returns.

My first step is to examine whether an increase in local macroeconomic uncertainty predicts an increase in $\sigma_t\left(R_i\right)$, the realized volatility of the portfolio associated with state i. I investigate this possibility by estimating the following predictive regression

$$\sigma_t\left(R_i\right) = \alpha + \beta\sigma_{t-h}\left(R_i\right) + \gamma\sigma_{t-h}\left(\text{CI}_i\right) + \text{Time FE} + \text{State FE} + u_{i,t}. \tag{8}$$

Here, the forecast horizons I consider are $h \in \{3, 6, 12\}$ months, each regression includes time fixed effects, and select regressions also include state fixed effects to control for unobserved differences in the relation between return volatility and economic uncertainty across states. I add the lagged value of realized volatility in each state as a regressor to account for the persistence of volatility. Finally, the standard errors associated with equation (8) are clustered at the state level. The results of these predictive regression are reported in Table 5.

[Insert Table 5 about here.]

Table 5 shows there is an economically and statistically significant association between local macroeconomic uncertainty and realized stock return volatility. For instance, as the unconditional standard deviation of local economic uncertainty is 7.32% per month, a one standard deviation increase in local uncertainty increases the one- and three-month ahead realized volatility of local stock returns by approximately 0.30% per month. Likewise, a one standard deviation increase in local uncertainty in month t is associated with a 0.50% per month increase in realized volatility in month $t + 12$. Thus, these regressions show that changes in local economic uncertainty have an *incremental* impact on the realized volatility of local firms.

Given the results in Table 5, and the expression for a firm's conditional market beta in equation (7), two testable predictions emerge: firms located in states where economic uncertainty is anticipated to increase should (i) earn higher expected stock returns, and (ii) have higher conditional market betas. In Sections 3.2 and 3.3 I test these predictions in the cross-section of stock returns by sorting states into portfolios based on the long-term slope of each state's municipal spread. I test these predictions using the municipal spread rather than my measure of economic uncertainty for two reasons. First, the forecasting results in Section 2 show that a flatter municipal spread is associated with an *increase* in local economic uncertainty. Second, while I can observe the long-term slope of the municipal spread in real time, my measure of local economic uncertainty is obtained by applying an AR(1)-GARCH(1,1) model to the monthly growth rates of each state's coincident economic activity index over the full sample period. This means that portfolios formed on the basis of the long-term slope of the municipal spread are tradable, whereas those formed on the basis of macroeconomic uncertainty are not.

3.2 Portfolio returns

In this section I test the first prediction from Section 3.1. That is, I examine whether firms located in states where the long-term slope of the municipal spread is flatter, which are the states where economic uncertainty is expected to rise, earn higher average stock returns.

Portfolio formation. The relation between the *current* slope of a state's municipal spread and *future* stock returns is evaluated by sorting the cross-section of states into portfolios based on each state's long-term slope in month $t-1$. I obtain the long-term slope by recursively estimating equation (3) using data available up to the end of month $t-1$.[14] This ensures this investment strategy is tradable, as the yield data underlying equation (3) are publically available as of the portfolio formation dates. Each portfolio then is held for one month, at which point in

[14]Table A12 of the Online Appendix confirms that the results of the upcoming portfolio sorts also hold if I sort portfolios based on the observable, rather than the estimated, long-term slope factor.

time equation (3) is re-estimated, and all portfolios are rebalanced. This rebalancing captures conditional variation in the term structure of each state's municipal spread.[15]

Three portfolios are formed at the start of each month beginning in January 2002. The flat (steep) portfolio includes the states whose long-term slope factor is at or below (above) the 10^{th} (90^{th}) percentile of the cross-sectional distribution of the factor in the prior month. The medium portfolio contains the remaining states. These breakpoints imply that each extreme portfolio contains two states. Given each state portfolio is comprised of many underlying firms (often hundreds), this choice of breakpoints produces three well-diversified portfolios.[16]

Portfolio returns. Table 6 reports the monthly returns of portfolios formed on the long-term slope of each state's municipal spread. The results show that there is an economically and statistically significant spread between the returns of the flat and steep slope-sorted portfolios. Specifically, the portfolio that buys (sells) firms located in states where the long-term slope of the municipal spread is flatter (stepper) earns an average value-weighted monthly return of 1.02% (0.60%) per month. Thus, the flat-minus-steep return spread, which I refer to as the FMS spread, is 0.43% per month, and is statistically significant at better than the 1% level. Since the monthly standard deviation of the FMS spread is 2.63%, the annualized Sharpe ratio of this trading strategy is larger than 0.60 over the sample period. This quantity exceeds the Sharpe ratio of investing in the market portfolio over the same time period.

The table also shows that, by construction, there are two states sorted into each extreme portfolio, and the average long-term slope factor underlying each portfolio monotonically increases from -1.10 to 1.35. Furthermore, as there are typically 313 (354) firms underlying the flat (steep) portfolio, the composition of each portfolio in terms of the number of underlying firms is similar to that which would arise if the sorts were conducted at the firm level rather than the state level. Finally, the table also reports the results of three key robustness checks.

[15]Table A11 of the Online Appendix shows that no spread emerges when sorting states into portfolios based on *unconditional* differences in the long-term slope of each state's municipal spread.

[16]Table A10 in the Online Appendix reports the transition matrix associated with this portfolio formation procedure. The table shows that a state sorted into either extreme long-term slope portfolio has a 50% probability of remaining in the same portfolio in the next month. A state currently in the middle portfolio has about a 7% chance of transitioning into either extreme portfolios in the following month. Additionally, Figure A3 in the Online Appendix displays the frequency of portfolio membership by state, and shows that all states are sorted into each of the portfolios over the sample period. Combined, these results suggests that the portfolio formation procedure is picking up conditional variation in the long-term slope factor rather than state fixed effects.

First, to account for the fact that the value-weighted returns associated with each portfolio may be 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 FMS spread by equal-weighting the firms underlying each state-level portfolio. The results show the equal-weighted FMS spread remains sizable at 0.29% per month, and statistically significant at the 10% level.

Second, to account for differences in industry composition across states differs (e.g. oil and gas extraction dominates the Texas portfolio while chemical manufacturing is prevalent in the North Carolina portfolio), I construct the FMS spread using industry-adjusted portfolio returns. Here, industry-adjusted 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 FMS spread is 0.34% per month, and that this quantity is statistically significant at the 1% level.

Third, to make sure the FMS 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, whereas manufacturing firms in Michigan are growth oriented), I also construct a characteristic-adjusted FMS spread. This adjustment is implemented by subtracting the appropriate Daniel, Grinblatt, Titman and Wermers (1997) benchmark return from the firm's raw monthly return. The characteristic-adjusted FMS spread remains economically sizable at 0.31% per month and significant at the 5% level.

[Insert Table 6 about here.]

Overall, Table 6 shows that variation in the long-term slope of each state's municipal spread is economically valuable for predicting differences in stock returns across states. Regardless of how portfolio returns are measured, stock returns are significant higher in states where the long-term slope of the municipal yield curve is flatter. That is, in states where local economic uncertainty is expected to rise. This confirms the first prediction from Section 3.1.

3.3 Portfolio characteristics and double sorts

Table 6 reports one of the key stylized facts of this study, and shows that the *current* shape of a state's municipal spread is informative about *future* local stock returns. The purpose of this section is twofold. First, I report the characteristics of the firms underlying each slope-sorted portfolio to make sure the FMS spread is not driven by any firm-level characteristics that are known to predict returns. Second, I test the second prediction from Section 3.1, and examine whether the conditional market betas of locally headquartered firms are higher in states where the long-term slope of the municipal spread is flatter. That is, in states where economic uncertainty is expected to increase.

Portfolio characteristics. To ensure the FMS spread does not simply arise due to differences in key firm-level characteristics, such as profitability and investment, across states, Table 7 reports the average industry-adjusted characteristics underlying each slope-sorted portfolio. Here, characteristics are industry-adjusted to account for the effects of industry agglomeration. I compute these industry-adjusted characteristics in three steps: (1) I assign each firm to the appropriate Fama-French 49 industry group, and subtract each value-weighted industry-level characteristic from each firm-level characteristic; (2) I compute the value-weighted average of each firm-level characteristic across all firms headquartered 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 7 then reports the time-series average of each portfolio-level characteristic, as well as the spread in each characteristic, between the extreme slope-sorted portfolios.

[Insert Table 7 about here.]

Table 7 shows that there are no statistically significant differences between the long-term slope portfolios in terms of firm size, book-to-market ratios, profitability, measured using each of ROA, ROE, or gross profitability (Novy-Marx, 2013), return momentum (Jegadeesh and Titman, 1993), total accruals (Sloan, 1996), total asset growth (Cooper, Gulen and Schill, 2008), or investment-to-asset ratios (Stambaugh and Yuan, 2017). Thus, the returns of the FMS spread cannot be explained by these common predictors of stock returns. However, there are statistically significant differences between the market betas and idiosyncratic return volatilities (IVOL, hereafter) of the slope-sorted portfolios.

On the one hand, the fact that the market betas of the firms located in states where the municipal spread is flatter are significantly higher than those of the firms located in states where the municipal spread is steeper is consistent with the second prediction in Section 3.1. This is because market beta is expected to be higher in states where the municipal spread is flatter, and economic uncertainty rises (i.e., equation (7)). On the other hand, since Ang, Hodrick, Xing and Zhang (2006a) show that firms with low IVOL earn higher returns, the FMS spread may be driven by differences in IVOL between states rather than differences in conditional market betas. Therefore, I conduct conditional portfolio double sorts to determine whether the FMS spread is explained by the differences in either IVOLs or market betas across states.

Portfolio double sorts. I implement the conditional portfolio double sorts as follows. First, at the end of each month from December 2001, the cross-section of states is sorted into three portfolios based on the cross-sectional distribution of either IVOL or beta at that point in time. Here, the 20^{th} and 80^{th} percentiles of the cross-sectional distribution of each characteristic (market beta or IVOL) are used to determine the membership of each portfolio. Next, within each of these three characteristic-sorted portfolios, states are further sorted into three additional portfolios based on the 20^{th} and 80^{th} percentiles of the cross-sectional distribution of the long-term slope factor at the same point in time. This process results in nine portfolios that are held until the end of the month, at which point in time all portfolios are rebalanced.

Table 8 reports the results of this analysis. Panel A shows that within one of the three IVOL-sorted portfolios, the FMS spread remains economically large at 0.45% per month, and significant at close to the 1% level. While the FMS spread is insignificant within the remaining two IVOL-sorted portfolios, a joint test on the null hypothesis that the FMS spread is statistically indistinguishable from zero across the three IVOL-sorted portfolios is rejected at the 5% level. This indicates that firms located in states where the long-term slope of the municipal spread is flatter do not simply earn higher stock returns because they have lower IVOLs. In other words, there is economically valuable variation in the long-term slope factor that is independent of the relation between IVOL and future stock returns.

Panel B of Table 8 reports the results after first controlling for differences in market betas across states, and leads to a different conclusion. Panel B not only shows that the FMS spread is statistically indistinguishable from zero *within* each beta-sorted portfolio, the joint test also fails to reject the null hypothesis that the FMS spread is zero *across* the beta-sorted portfolios. Thus, controlling for *conditional* differences in market beta across regions of the U.S., the long-term slope of the municipal spread no longer predicts local stock returns. Economically, this means that the long-term slope of the municipal spread conveys informative about the systematic risk exposures of locally headquartered firms, as suggested by equation (7). Thus, the second prediction in Section 3.1 is also supported by the data.

[Insert Table 8 about here.]

Taken together, the results contained within Table 6 and Table 7 support the two predictions outlined in Section 3.1. That is, in states where the long-term slope of the municipal spread is flatter, and local economic uncertainty is anticipated to rise: (i) local firms earn higher average stock returns, and (ii) local firms have higher exposures to systematic risk, as measured by the conditional market beta. This indicates that the FMS spread can be explained by time-varying differences in the quantity of risk across regions of the United States.[17]

3.4 Alternative explanations for the flat-minus-steep spread

The previous section shows that, as predicted, there is a risk-based explanation for the FMS spread: firms located in states where the long-term slope of the municipal spread is flatter have a higher *quantity* of risk than those located in states where the long-term slope of the municipal spread is steeper. This indicates that variation in stock returns across states of the U.S. can be explained by cross-sectional variation in systematic risk exposures. This is in line with Tuzel and Zhang (2017), who show that risk exposures differ across MSAs. Since my study is not the first study to document that average stock returns vary across the United States, this sections considers some alternative explanations for why the FMS may arise.

Most prominently, Korniotis and Kumar (2013) and ensuing studies, such as Da *et al.* (2018), suggest that geographic variation in the *price* of risk explains why local stock returns covary with local business conditions. These studies posit that the investments of local investors are concentrated in local firms. Consequently, if local economic conditions worsen (improve), and local investors become more (less) risk averse, then these investors will sell (buy) the equity of

[17]Consistent with the notion that the long-term slope of each state's municipal spread is informative about the conditional risk exposures of locally headquartered firms, Table A14 of the Online Appendix shows that the time-series variation in the FMS spread is not explained by five unconditional empirical asset-pricing models. The models I consider are the CAPM, the Fama and French (1993) three-factor model, the Carhart (1997) four-factor model, the Fama and French (2015) five-factor model, and the Hou *et al.* (2015) q-factor model.

local firms. This causes firms located in states undergoing a relative recession (expansion) to 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 these differences in discount rates across states. This means that the stock prices of 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 have lower expected returns. This because when the local economy is undergoing a relative recession, these countercyclical fiscal policies reduce the consumption risks of local investors.

I conduct two tests to examine whether the mechanisms proposed by Korniotis and Kumar (2013) and Da *et al.* (2018) explain the FMS spread. I begin by partitioning my sample into the groups of firms that have either high or low visibility, and constructing the FMS within each group of firms. If, as Korniotis and Kumar (2013) indicate, geographic variation in stock returns is largely induced by mispricing, then the FMS spread should be smallest in magnitude amongst the most visible (i.e., most difficult to misprice) firms. Here, I measure firm-level visibility using the viability proxy of Hong *et al.* (2008), the number of analysts following each firm, and the amount of equity in each firm that is owned by institutional investors. I also construct the FMS spread within the set of states that implement procyclical and countercyclical fiscal polices. Following Da *et al.* (2018), finding that the FMS spread is smaller in magnitude among the states that implement countercyclical fiscal polices suggests, once again, that the FMS spread is driven by differences in discount rates across states. The results are reported in table 9.

[Insert Table 9 about here.]

Contrary to these possibilities, Table 9 shows that the returns of the FMS spread are neither concentrated among firms that are less visible to investors nor states that implement countercyclical fiscal policies. These results indicate that, while the price of risk may vary across the U.S., geographical variation in discount rates does not explain the FMS spread.

Another potential explanation for geographic variation in stock returns is that investors may underreact to news about future cash flows (Smajlbegovic, 2018; Parsons *et al.*, 2018).

For example, if firms located in states where economic conditions are expected to deteriorate cut expenses and expand into new markets to increase their operating profits, and market participants do not anticipate these changes, then the future cash flows of these firms will be higher than expected. Thus, the high average stock returns in the states where the municipal spread is flatter may arise due to the future earnings surprises of the underlying firms.

I examine this possibility by computing the *future* industry-adjusted accounting characteristics associated with each long-term slope portfolio. Specifically, Table 10 reports the characteristics associated with each portfolio 12 months after the portfolio formation date. The premise of this analysis is that if the long-term slope of the municipal spread predicts changes in expected cash flows, then then these differences in expected cash flows are most likely reflected in the *future* earnings and fundamentals of the underlying firms.

[Insert Table 10 about here.]

The results in Table 10 show that there are no differences in the future industry-adjusted characteristics of the firms located in states with flat and steep municipal spreads. Differences in investment intensity, as measured by asset growth and investment-to-asset, book-to-market, and profitability, as measured by ROA, ROE, and gross profitability, are statistically indistinguishable from zero. Furthermore, none of the three measures of earnings surprise considered by Livnat and Mendenhall (2006), and referred to as SUE1, SUE2, and SUE3, respectively, are different between firms located in low- and high-slope states. This latter finding suggests that, contrary to the firm-level evidence in Smajlbegovic (2018), financial analysts do not systematically misjudge the future earnings of firms located in states where economic conditions are expected to deteriorate relative to those located in states where economic conditions are expected to improve. Collectively, these results suggests that the FMS is not driven by an underraction to news about future cash flows.

4 Empirical robustness

Finally, this section examines the robustness of the FMS spread along several dimensions related to the portfolio formation procedure described in Section 3.2.

Alternative portfolio breakpoints. The benchmark portfolio formation procedure uses the 10^{th} and 90^{th} percentiles of the cross-sectional distribution of the long-term slope of the municipal spread as portfolio breakpoints. These breakpoints imply that two states are included in each extreme portfolio. Here, I alter these portfolio breakpoints to include between one and five states in the extreme portfolios. This serves two purposes. First, if local stock returns are sensitive to the changing local economic conditions, as predicted by municipal bond yields, then the FMS spread should be greater in magnitude when *fewer* states are included in the extreme portfolios. This is because the distinction between states where business conditions are expected to improve and worsen becomes starker when fewer states are in the extreme portfolios. Second, changing the number of states in the extreme portfolios also ensures that the FMS is not driven by this particular choice of breakpoints.

[Insert Figure 3 about here.]

The results of this analysis, which are reported in Figure 3, show that the FMS spread monotonically increases as fewer states are included in the extreme portfolios. In particular, the spread increases to over 0.80% per month when only one state is sorted into each extreme portfolio. Additionally, the spread is larger than 0.20% per month, and statistically significant at the 10% level or better, provided four or fewer states are included in the extreme portfolios. Thus, the baseline results are not driven by the choice of portfolio breakpoints in Section 3.2.

Limits to arbitrage. Table 11 reports the FMS spread after removing firms that are difficult to trade from the analysis. This ensures the FMS spread is not concentrated among firms that face considerable limits to arbitrage. Specifically, the table reports the FMS spread among stocks with larger market capitalizations, higher stock prices, lower idiosyncratic return volatilities, higher trading volumes. In each case, the FMS spread remains economically large and statistically significant. Thus, limits to arbitrage cannot explain the FMS spread.

[Insert Table 11 about here.]

Placebo test one: Randomizing the cross-section of states. If the long-term slope of the municipal spread is an economically meaningful predictor of local stock returns, then the slope associated with state i should not serve as a reliable predictor of stock returns in state j. I evaluate whether this is the case by once again sorting the cross-section of states into portfolios based on the long-term slope of each state's municipal spread. However, I randomize the stock returns associated with each state (e.g., the returns related to Texas are switched with those of Michigan). This randomization breaks the link between municipal yields and the future stock returns of local firms. The randomization is repeated 10,000 times, and the resulting distribution of the FMS spread is reported in the top panel of Figure 4.

The figure shows that randomizing the cross-section of states produces an average FMS spread that is essentially zero in magnitude. The magnitude of the FMS spread observed in the data, represented by the dashed red line, exceeds the 99^{th} percentile of the simulated distribution, represented by the solid black line. This is consistent with the conjecture that the long-term slope of a state's municipal spread is more useful for predicting *local* stock returns.

[Insert Figure 4 about here.]

Placebo test two: Sorting on random variables. I conduct an additional set of 10,000 simulations to ensure the relation between the long-term slope of the municipal spread and local stock returns is not spurious. In each of these simulations I first generate a random variable that mimics the temporal properties of each state's long-term slope factor (reported in Panel B of Table 2). I then sort the cross-section of states into portfolios based on these random variables, which have no economic content, and construct a pseudo FMS spread. The bottom panel of Figure 4 plots the distribution of these pseudo FMS spreads across these simulations. The figure shows that the average returns associated with the FMS spread are unlikely the result of chance. Specifically, the FMS spread observed in the data (the dashed red line) exceeds the 99^{th} percentile of the pseudo FMS spread across the simulations (the solid black line).

Alternative measures of long-term slope. In the main analysis I measure the long-term slope of each state's municipal spread using equation (3). To ensure my results are not driven by the specific way I estimate this factor, five alternative methods are considered.

First, I repeat the benchmark analysis *without* adjusting the municipal bond yields in each state for tax effects. This ensures 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, to minimize the estimation errors associated with fitting equation (3) over a recursive estimation window, I estimate this equation over the full sample period and form portfolios based on these full-sample residuals. However, since this approach requires the use of out-of-sample information, the resulting portfolios are not tradable. Third, in line with the model in Diebold *et al.* (2008), I obtain the long-term slope of each state's municipal spread by regressing the state-level DNS long-term slope factor ($c_{i,t}$) on the national DNS long-term slope factor (C_t) only. Fourth, I account for potential nonlinearities in the relation between the state and national DNS factors by extending equation (3) to also include the square of each national DNS factor. Finally, I directly apply equation (1) to the tax-adjusted municipal spread, and sort states into portfolios using the third factor from this regression.

The results of these five analyses are reported in Table 12. The table shows that no matter of how I measure the long-term slope factor, the resulting FMS spread is approximately 0.40% per month and statistically significant at the 5% level in all cases. Overall, these results show that the FMS spread is robust to the particular way in which the long-term pf each state's municipal spread is measured. Furthermore, the returns of these portfolios remain monotonically decreasing in the long-term slope of each state's municipal spread.

[Insert Table 12 about here.]

Heterogeneity in firm localization. The portfolio sorts in Section 3.2 employ state-level portfolios that are constructed by assigning each firm to a state based on the location of the firm's headquarters in Compustat. While this approach yields state-level stock returns that are easy to construct using CRSP/Compustat data, the location of a firm's headquarters is only a rough proxy for the degree to which the firm is exposed to local business conditions. Therefore, if the long-term slope of the municipal spread predicts local business conditions, and the returns of locally headquartered firms are in fact sensitive to fluctuations in the local business cycle, then the FMS spread should be concentrated among firms that are both headquartered in a given state *and* whose operations are also more contained in the same state.

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

As a concrete example of the intuition underlying this conjecture, 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 long-term slope of Minnesota's municipal yield spread predicts business conditions in the state, this factor is more likely to predict the future returns of ELSE, whose investor base and cash flows are likely concentrated in Minnesota, than the future returns of TGT, whose investor base and cash flows are likely dispersed across the United States. A test of this intuition is implemented as follows.

In each month beginning in January 2002, the firm-level state-name counts from EDGAR are used to construct the more granular measure of local stock returns. This is done by computing the equal-weighted average return of all firms headquartered in a given state that mention five or fewer states in their 10-Ks in the previous year.[18] A complementary set of returns is also produced using the firms that mention six or more states in their 10-Ks. I then repeat the portfolio sorts described in Section 3.2 using each set of returns. Since the former (latter) set of returns is constructed with firms whose operations are more (less) likely concentrated in a given state, the FMS spread is likely to be larger (smaller) in magnitude within the group of more (less) localized firms. The results of this test are reported in Table 13.

Table 13 shows that the FMS spread is 0.46% per month and statistically significant at the 5% level among more localized firms. Furthermore, the spread is statistically indistinguishable from zero among less localized firms. Overall, these results support the conjecture that, to the extent that the long-term slope of each state's municipal spread predicts local macroeconomic outcomes, the returns of firms whose operations are more localized in a given state will be more sensitive to these fluctuations in the local business cycle. That is, the long-term slope factor is better at predicting the stock returns of more localized firms.

[Insert Table 13 about here.]

[18]Given 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.

Sorting on related variables. Instead of sorting states into portfolios based on the long-term slope of each state's municipal spread, I sort portfolios according to the level and short-term slope of the municipal spread. Here, the level (short-term slope) of the municipal spread is obtained by estimating equation (3) with $l_{i,t}$ ($s_{i,t}$) from equation (1) on the left-hand side of the projection. Table A11 of the Online Appendix reports these results and shows that neither of these alternative factors predicts cross-sectional variation in local stock returns. This is consistent with my primary conjecture that the long-term slope of the municipal spread is the most informative about local macroeconomic outcomes.

Excluding key states. Table A13 in the Online Appendix shows that the FMS 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 four states whose municipal debt markets have recently undergone (or are currently undergoing) financial distress are excluded from the sample.[19]

5 Conclusion

In this study I am the first to show that the *current* shape of a state's municipal yield curve conveys valuable information about *future* local macroeconomic and financial market outcomes. This analysis is motivated by the fact that, since the cash flows underlying municipal bonds are influenced by future economic activity, municipal bond yields should embed investors' expectations of future economic outcomes. Specifically, I focus on the information content of the long-term slope of each state's term structure of municipal spread (municipal bond yields minus Treasury bond yields), and establish two novel facts.

First, I document that when the long-term slope of a state's municipal spread gets flatter, future local economic activity deteriorates and local macroeconomic uncertainty rises. I establish this fact by estimating a series of predictive regressions that forecast local economic outcomes using lagged macroeconomic data, national financial market data, such as the slope

[19]The four states removed from the analysis are California (Stockton, CA, filed for bankruptcy in 2012), Michigan (Detroit, MI, filed for bankruptcy in 2013), Pennsylvania (Harrisburg, PA, filed for bankruptcy in 2011). Additionally, Illinois is also removed due to the fact that the credit ratings assigned to bonds issued by Illinois are the lowest across the states of the U.S., and are rated just above junk status by S&P.

of the Treasury yield curve, and the long-term slope of each state's municipal spread. Including the long-term slope factor in these regressions helps to explain an average of 5% of the variation in local economic conditions at the 12-month horizon. These forecast gains do not arise by chance, and vary across states in economically meaningful ways. Taken together, these results indicate that the long-term slope of the municipal spread is a *statistically useful* and an *economically informative* predictor of the local business cycle.

Second, I show that the long-term slope of the municipal spread is also an *economically valuable* predictor of local economic conditions. Specifically, a trading strategy that buys (sells) the firms located in states where the municipal spread is flatter (steeper), which are the states where local business conditions are anticipated to deteriorate (improve), earns an excess return that exceed 5% per annum. I refer to the returns of this strategy as the flat-minus-steep (FMS) spread, and show that the FMS spread survives a battery of robustness tests. For instance, the spread is not driven by differences in industry composition between states or limits-to-arbitrage. However, the FMS spread can be explained by the fact that the conditional market betas of local firms are higher (lower) in states where the municipal spread is flatter (steeper).

I propose and empirically validate a simple explanation for why the conditional market betas of local firms are higher in states where the long-term slope of the municipal spread is flatter. Since local macroeconomic uncertainty tends to rise when the long-term slope of the municipal spread gets flatter, this rise in economic uncertainty spills over to, and increases, the return volatilities of local firms. Consequently, this spillover in economic uncertainty increases the systematic risk exposures of local firms and gives rise to the FMS spread.

Collectively, my results show that the municipal debt market conveys valuable information about the trajectories and risks of local economies. Besides using this information to predict time-series variation in local economic conditions, and cross-sectional variation in expected stock returns, the information embedded in municipal yields can also be used in other ways. For instance, this information may help forecast the revenues and expenditures of subnational governments. This, in turn, may help relax the financial constraints many of these entities face and boost economic growth. Additionally, while I focus on state-level economies, the methods I use in this study could also be applied to examine the information content of municipal yields within more granular regions, such as MSAs. I leave these examinations for future research.

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Table 1: Yield factors: correlations and summary statistics

The table reports the time-series correlations and the summary statistics associated with the yield factors underlying this study. Panel A reports the correlations between the state-level dynamic Nelson-Siegel (DNS) factors (obtained by estimating equation (1) within each state) and the 20 year municipal yield, the 5 year minus 1 year municipal yield spread, and the 20 year minus 5 year municipal yield spread. The panel also reports the correlations between the national DNS factors (obtained by estimating equation (2)) and the same yield and two yield spreads from the Treasury market. Panel B reports summary statistics for two measures of the long-term slope of the municipal spread: the estimated factor (obtained by estimating equation (3) on a state-by-state basis) and the observable factor (the difference between 20-year and 5-year municipal yields in excess of Treasury yields). The summary statistics reported for each measure are the time-series mean, standard deviation (SD(TS)), minimum, and maximum, as well as the average cross-sectional dispersion of each factor across states (SD(CS)). The table also reports the one-, 12-, and 30-month autocorrelation of each factor, alongside an augmented Dickey-Fuller (ADF) unit root test statistic and its associated p-value. In each panel the statistics associated with the state-level variables are obtained by GSP-weighting each variable across states. Finally, the sample period is from January 2000 to December 2017.

Panel A: Time-series correlations between the yield factors and underlying yields

	State DNS			National DNS		
Yields	l	s	c	L	S	C
y(240)	0.951	-0.200	0.191	0.969	-0.063	0.171
y(60)-y(12)	0.455	-0.995	-0.433	0.245	-0.998	-0.438
y(240)-y(60)	0.197	-0.678	-0.968	0.102	-0.742	-0.935

Panel B: Summary statistics of the long-term slope of the municipal spread

Factor	Mean	SD(TS)	SD(CS)	Min.	Max.	$\hat{\rho}(1)$	$\hat{\rho}(12)$	$\hat{\rho}(30)$	ADF	p(ADF)
Estimated (ε^{LTS})	-0.001	2.065	0.723	-6.662	7.544	0.758	0.287	-0.072	-5.643	0.001
Observable	1.486	0.593	0.195	0.348	3.397	0.909	0.607	0.301	-1.334	0.169

Table 2: Summary statistics of state-level macroeconomic dynamics
The table reports the mean and standard deviation of the growth rates of the state-level unemployment rate (UR), coincident economic activity index (CI), leading economic activity index (LI), real personal income per capita (PI), and real gross state product growth (GSP). Each series, except LI, is transformed into a 12-month change. The table also reports the conditional volatility of eachh state's coincident economic activity index (σ (CI)). All series are expressed as percentages, and the underlying data is extracted from FRED. Details on each macroeconomic variable are provided in Section OA.1 of the Online Appendix. The range of each statistic is reported in the final row of the table, and the sample period spans January 2000 to December 2017.

State	Macroeconomic dynamics (%)											
	UR		CI		$\sigma(CI)$		LI		PI		GSP	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
CA	-0.51	17.87	2.63	3.39	14.53	3.21	1.40	1.57	3.72	3.09	2.15	2.57
CT	2.69	18.39	1.64	2.81	18.39	1.53	0.93	1.17	3.25	3.00	-0.12	2.70
FL	0.37	22.89	3.01	2.48	14.17	8.06	1.59	1.08	2.80	3.46	0.76	3.09
GA	1.06	18.54	2.68	2.09	12.76	1.78	1.49	0.85	2.57	2.39	1.14	2.39
IL	0.73	18.98	1.58	3.10	16.83	1.15	0.87	1.31	3.01	2.65	0.69	1.73
MA	0.87	19.26	2.27	3.88	23.30	1.90	1.25	1.76	3.67	2.68	1.89	1.75
MD	0.82	16.98	2.22	3.22	24.00	3.19	1.25	1.24	3.40	2.05	1.42	1.51
MI	1.25	20.65	0.38	6.03	32.69	17.14	0.58	2.14	2.73	2.64	0.15	4.13
MN	1.23	16.04	2.36	2.42	17.63	1.15	1.35	1.03	3.21	2.72	1.11	2.20
NC	1.97	21.75	2.42	1.99	12.86	7.10	1.34	0.81	2.70	3.18	1.44	2.58
NJ	0.14	20.48	1.77	2.25	11.83	1.36	0.96	0.92	3.10	2.47	0.52	1.99
NY	-0.53	17.01	1.76	2.57	16.64	0.89	0.93	1.04	3.39	2.70	1.57	2.57
OH	0.91	18.15	1.24	3.05	16.41	2.03	0.84	1.17	2.94	2.08	0.69	2.65
PA	0.59	14.99	1.56	2.20	15.33	2.46	0.90	0.98	3.38	2.09	1.46	1.91
SC	0.00	20.03	2.62	3.40	18.52	2.27	1.45	1.37	3.03	2.32	1.50	2.42
TX	-0.52	17.80	3.03	1.48	11.93	2.97	1.57	0.69	3.17	3.76	2.96	2.37
VA	1.72	21.33	2.24	1.98	13.15	2.32	1.27	0.81	3.31	2.56	0.92	1.20
WA	-0.12	17.81	2.73	3.01	16.66	1.62	1.53	1.30	3.45	3.58	2.81	2.40
WI	0.30	19.31	1.53	3.81	24.34	5.93	1.08	1.65	3.05	1.95	0.91	1.80
Range	3.22	7.90	2.65	4.55	20.85	16.26	1.01	1.45	1.15	1.81	3.08	2.93

Table 3: Predictive regressions

The table reports the results of estimating state-level predictive regressions that forecast one of six local macroeconomic variables at one of four forecast horizons. Here, the baseline predictive regression is

$$y_{i,t+h} = \alpha + \rho y_{i,t} + \boldsymbol{\beta X_t} + \gamma\varepsilon_{i,t}^{LTS} + u_{i,t+h},$$

where $y_{i,t}$ represents one of the unemployment rate (UR), coincident economic activity index (CI), conditional volatility of the coincident economic activity index (σ (CI)), leading economic activity index (LI), real personal income per capita (PI), or real gross state product (GSP) in state i at time t. The forecast horizons (h) are 3, 6, 9, or 12 months ahead, $\boldsymbol{X_t}$ is a matrix of variables related to aggregate asset prices, and $\varepsilon_{i,t}^{LTS}$ is the long-term slope of state i's municipal spread. The columns labeled "$\Delta\bar{R}^2$" report the changes in adjusted-R^2 obtained by including $\varepsilon_{i,t}^{LTS}$ in the predictive regressions. For each combination of macroeconomic variable and forecast horizon, $\Delta\bar{R}^2$ is calculated by estimating the predictive regression both with γ restricted to zero and with γ unrestricted, and then averaging the corresponding change in adjusted-R^2 across states. "Average $\Delta\bar{R}^2$" summarizes each column by reporting the mean value of $\Delta\bar{R}^2$ across the macroeconomic variables for a fixed forecast horizon. Finally, parentheses report the probability that each $\Delta\bar{R}^2$ statistic arises by chance, obtained via Monte Carlo simulations. The columns labeled "$\hat{\gamma}$" report the estimated value of γ obtained by pooling observations across states, and parentheses report the associated p-values. In Panel A, $\varepsilon_{i,t}^{LTS}$ is obtained by estimating equation (3) over the full sample period. In this case the standard errors associated with $\hat{\gamma}$ are calculated using a GMM procedure that takes the first-stage estimation error into account. In Panel B, $\varepsilon_{i,t}^{LTS}$ is defined as the differences between 20 year and 5 year municipal bond yields in excess of Treasury bond yields. The time period of this analysis ranges from January 2000 to December 2017.

	$\Delta\bar{R}^2$				$\hat{\gamma}$			
$h =$	3	6	9	12	3	6	9	12
Panel A: Estimated long-term slope								
UR	0.40	1.83	3.84	5.05	-0.51	-1.18	-1.78	-2.03
	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
CI	0.23	1.50	4.09	6.97	0.06	0.17	0.29	0.38
	(0.12)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
σ (CI)	0.16	1.15	2.86	3.38	-0.10	-0.22	-0.34	-0.37
	(0.83)	(0.14)	(0.00)	(0.00)	(0.02)	(0.01)	(0.00)	(0.00)
LI	1.64	4.21	5.71	4.12	0.08	0.12	0.14	0.12
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
PI	-0.06	1.23	1.57	1.32	-0.07	-0.15	-0.16	-0.14
	(0.80)	(0.09)	(0.13)	(0.19)	(0.01)	(0.00)	(0.00)	(0.01)
GSP	1.90	4.70	9.94	7.38	0.16	0.25	0.34	0.28
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Average $\Delta\bar{R}^2$	0.71	2.44	4.67	4.70	-	-	-	-
Panel B: Observable long-term slope								
UR	0.27	1.62	3.79	5.82	-1.65	-4.31	-6.69	-8.21
	(0.41)	(0.05)	(0.01)	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)
CI	0.19	1.56	4.46	8.20	0.20	0.66	1.15	1.58
	(0.64)	(0.02)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
σ (CI)	0.16	1.39	3.33	4.83	-0.34	-0.79	-1.08	-1.33
	(0.92)	(0.27)	(0.02)	(0.00)	(0.09)	(0.03)	(0.01)	(0.03)
LI	1.46	4.72	5.97	6.75	0.28	0.49	0.54	0.59
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
PI	-0.20	1.55	3.39	6.03	-0.14	-0.52	-0.71	-0.90
	(0.99)	(0.20)	(0.02)	(0.00)	(0.17)	(0.00)	(0.00)	(0.00)
GSP	0.93	3.88	9.14	11.68	0.45	0.87	1.33	1.49
	(0.07)	(0.03)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Average $\Delta\bar{R}^2$	0.47	2.45	5.01	7.22	-	-	-	-

Table 4: Predictive regressions: cross-sectional heterogeneity
The table reports the average difference in adjusted-R^2 ($\Delta\bar{R}^2$) obtained by estimating the following predictive regressions on a state-by-state basis:

$$y_{i,t+h} = \alpha + \rho y_{i,t} + \boldsymbol{\beta X_t} + \gamma\varepsilon_{i,t}^{LTS} + \delta\varepsilon_{j\neq i}^{LTS} + u_{i,t+h}$$

Here, $y_{i,t}$ represents the unemployment rate (UR), coincident economic activity index (CI), leading economic activity index (CI), real personal income (PI), or gross state product (GSP) observed in state i at time t. The forecast horizons (h) considered are 3, 6, 9, or 12 months, $\boldsymbol{X_t}$ is a matrix of variables related to aggregate asset prices, and $\varepsilon_{i,t}^{LTS}$ is the long-term slope of state i's municipal spread, obtained by estimating equation (3) over the full sample period. Finally, $\varepsilon_{j\neq i}^{LTS}$ refers to the long-term slope of the municipal spread from another state j that is either economically connected to, or disconnected from, state i. Panel A reports the results of setting δ to zero, and computing the difference in adjusted-R^2 obtained by estimating the predictive regressions with γ restricted to zero and with γ unrestricted. Specifically, for each combination of macroeconomic variable and forecast horizon, the panel reports the average value of $\Delta\bar{R}_i^2$ within the group of high and low tax privilege states. Here, the sample of states is split into two groups based on the median value of the state-level tax privilege from Babina *et al.* (2019). Panels B and C report the results of keeping γ unrestricted, and then estimating the predictive regressions with both δ restricted to zero and with δ unrestricted. In Panel B, the economic connectedness of states is measured using the value of freight shipped between pairs of states, whereas in Panel C the economic connectedness of states is proxied using the gravity measure of Tinbergen (1962). In both Panels B and C, the High (Low) entry corresponds to the average value of $\Delta\bar{R}_i^2$ across all 19 states when the predictive regression includes the long-term slope factor from the state j that is the most economically connected to (disconnected from) state i according to the given proxy for economic connectedness. Finally, the time period of this analysis ranges from January 2000 to December 2017.

		Panel A: Tax privilege				Panel B: Interstate shipping				Panel C: Gravity			
$h =$		3	6	9	12	3	6	9	12	3	6	9	12
	High (H)	0.54	2.32	4.56	5.50	0.08	0.33	1.04	2.14	0.09	0.40	1.26	2.96
UR	Low (L)	0.24	1.29	3.04	4.55	0.03	0.12	0.24	0.29	0.05	0.20	0.50	0.70
	Diff(H-L)	0.29	1.03	1.52	0.94	0.05	0.21	0.80	1.85	0.04	0.20	0.76	2.26
	High (H)	0.29	1.90	4.88	7.72	0.06	0.29	1.06	2.38	0.05	0.24	1.01	2.91
CI	Low (L)	0.16	1.05	3.22	6.14	0.08	0.24	0.46	0.62	0.10	0.34	0.75	1.11
	Diff(H-L)	0.12	0.85	1.65	1.58	-0.02	0.05	0.60	1.76	-0.05	-0.09	0.27	1.80
	High (H)	0.23	0.93	2.16	3.18	-0.06	0.89	0.98	1.66	0.18	0.80	0.54	2.11
σ (CI)	Low (L)	0.08	1.40	3.63	3.60	-0.06	0.33	0.34	0.48	0.10	0.25	0.40	0.64
	Diff(H-L)	0.16	-0.47	-1.47	-0.42	0.00	0.56	0.64	1.18	0.07	0.54	0.14	1.47
	High (H)	1.75	4.04	5.60	3.74	0.31	1.57	2.98	2.74	0.41	1.59	4.37	5.49
LI	Low (L)	1.52	4.40	5.84	4.53	0.11	0.32	0.60	0.44	0.36	0.51	0.81	0.64
	Diff(H-L)	0.23	-0.36	-0.25	-0.79	0.20	1.25	2.38	2.30	0.05	1.08	3.57	4.85
	High (H)	-0.09	1.70	2.17	1.66	-0.03	1.23	2.46	3.20	-0.18	0.41	1.67	1.91
PI	Low (L)	-0.02	0.71	0.90	0.95	0.02	0.78	1.33	2.45	-0.24	0.39	0.96	1.87
	Diff(H-L)	-0.06	0.99	1.28	0.71	-0.05	0.45	1.13	0.75	0.06	0.02	0.71	0.04
	High (H)	1.62	3.81	9.10	7.13	0.59	2.52	2.94	2.01	0.73	2.60	2.13	0.79
GSP	Low (L)	2.21	5.70	10.87	7.66	0.81	0.85	1.45	1.35	1.59	1.76	1.15	0.82
	Diff(H-L)	-0.59	-1.89	-1.77	-0.53	-0.22	1.66	1.49	0.66	-0.86	0.84	0.98	-0.03

Table 5: Spillover of local macroeconomic uncertainty
The table reports the results of predictive regression that assess whether changes in local macroeconomic uncertainty spill over to locally headquartered firms. Specifically, the following regression is estimated

$$\sigma_t\left(R_i\right)=\alpha+\beta\sigma_{t-h}\left(R_i\right)+\gamma\sigma_{t-h}\left(\mathrm{CI}_i\right)+\text{Time FE}+\text{State FE}+u_{i,t},$$

where $\sigma_t\left(R_i\right)$ denotes the realized volatility of firms located in state i in month t, $\sigma_{t-h}\left(\mathrm{CI}_i\right)$ refers to the measure of local macroeconomic uncertainty in state i at time t, and the forecast horizons (h) are 1, 3, and 12 months. The realized volatility of each state-level portfolio is defined as the value-weighted average realized volatility across all firms headquartered in the state, where firm-level realized volatility is measured as the standard deviation of the daily returns of each locally headquartered firm in month t. Local macroeconomic uncertainty is measured as the conditional volatility of each state's coincident economic activity index. Each regression includes time fixed effects, selected regressions include state fixed effects, and all standard errors are clustered at the state level. The sample period is from January 2000 to December 2017.

	$h=1$ month			$h=3$ months			$h=12$ months		
$\sigma_{t-h}\left(R_i\right)$	0.81	0.81	0.68	0.76	0.75	0.60	0.58	0.57	0.36
	(24.14)	(23.74)	(11.97)	(22.06)	(21.24)	(10.88)	(15.51)	(15.02)	(7.74)
$\sigma_{t-h}\left(CI_i\right)$		0.04	0.04		0.05	0.04		0.07	0.03
		(2.05)	(3.65)		(1.97)	(3.24)		(2.20)	(1.62)
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State FE			Yes			Yes			Yes

Table 6: Long-term slope portfolios
The table reports the monthly returns of portfolios sorted on long-term slope of each state's municipal spread from month $t-1$, as well as the spread between the returns of the Flat (F) and Steep (S) slope portfolios. Here, the long-term slope of each state's municipal spread is obtained by estimating equation (3) over a recursive window. The portfolio formation procedure used to form these portfolios is described in Section 3.2. The average long-term slope of each portfolio is denoted by ε^{LTS}, while the mean and standard deviation of value-weighted portfolio returns are represented by $\mathbb{E}\left[R\right]$ and $\sigma\left(R\right)$, respectively. $\mathbb{E}\left[R_{EW}\right]$ 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 $\mathbb{E}\left[R-R_{\mathrm{IND}}\right]$ and $\mathbb{E}\left[R-R_{\mathrm{DGTW}}\right]$ 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 2002 to December 2017.

	ε^{LTS}	$\mathbb{E}\left[R\right]$	$\sigma\left(R\right)$	N(States)	N(Firms)	$\mathbb{E}\left[R_{EW}\right]$	$\mathbb{E}\left[R-R_{\mathrm{IND}}\right]$	$\mathbb{E}\left[R-R_{\mathrm{DGTW}}\right]$
Flat (F)	-1.10	1.02	4.83	2	354	1.36	0.17	0.16
Medium	0.14	0.85	4.14	14	1657	1.12	0.01	0.02
Steep (S)	1.35	0.60	4.70	2	313	1.07	-0.17	-0.14
Spread (F-S)		0.43	2.36			0.29	0.34	0.31
t(Spread)		(2.68)				(1.84)	(2.93)	(2.18)

Table 7: Characteristics of long-term slope portfolios

The table reports the formation-period characteristics of the portfolios sorted on the long-term slope of the municipal spread, the spread between the characteristics of the Flat (F) and Steep (S) slope portfolios (Spread (F-S)), and the Newey and West (1987) t-statistic associated with this difference (t(Spread)). Here, the long-term slope of each state's municipal spread is obtained by estimating equation (3) over a recursive window. In Panel A, the accounting and return-based 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. Panel B reports the equal-weighted average past local macroeconomic conditions associated with the states underlying each portfolio. Details on the construction of each variable are provided in Section OA.1 of the Online Appendix. The sample period ranges from January 2002 to December 2017.

	Flat (F)	Medium	Steep (S)	Spread (F-S)	t(Spread)
ME ($b)	64.73	59.70	60.90	3.83	0.92
BEME	-0.23	-0.24	-0.23	0.00	0.30
GP	0.00	0.00	0.00	-0.00	-0.22
ROA	0.02	0.02	0.02	0.00	0.17
ROE	0.04	0.04	0.05	-0.00	-0.43
Asset growth (%)	2.23	1.75	1.76	0.46	0.30
I/A (%)	-0.26	-0.33	-0.57	0.30	0.80
Accruals (%)	0.55	0.49	0.44	-0.10	-0.46
β	-0.00	-0.02	-0.03	0.03	1.81
Momentum (%)	2.62	1.47	1.17	1.45	1.38
Reversal (%)	0.38	0.15	-0.15	0.52	3.36
IVOL (%)	-1.08	-1.03	-1.04	-0.04	-1.94

Table 8: Controlling for idiosyncratic volatility and beta: double-sort analysis

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) is the industry-adjusted average IVOL (market beta) of firms located in each state, and the second-stage sorting variable is the long-term slope of a state's municipal spread. Here, the long-term slope of each state's municipal spread is obtained by estimating equation (3) over a recursive window. The sorts are conducted as follows. First, at the end of each month beginning in December 2001, the cross-section of states is sorted into three portfolios using the 20^{th} and 80^{th} percentiles of the cross-sectional distribution of the control variable. Next, within each of these characteristic-sorted portfolios, the cross-section of states is further sorted into three additional portfolios based on the 20^{th} and 80^{th} percentiles of the long-term slope factor at the same point in time. 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 Flat (F) and Steep (S) portfolio, 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 flat-minus-steep spread across all three characteristic-sorted portfolios is zero. The returns underlying this analysis span January 2002 to December 2017.

	Panel A: Controlling for IVOL			Panel B: Controlling for β		
	Low IVOL	Medium	High IVOL	Low β	Medium	High β
Flat (F)	0.73	1.19	1.13	0.92	0.89	0.90
Medium	0.66	0.88	0.74	0.76	0.88	0.94
Steep (S)	0.55	0.75	0.79	0.70	0.82	0.55
Spread(F-S)	0.18	0.45	0.34	0.22	0.07	0.35
p(Spread)	(0.46)	(0.01)	(0.16)	(0.36)	(0.65)	(0.21)
p(Joint)		(0.03)			(0.44)	

Table 9: Flat-minus-steep spread: Alternative explanations

The table reports the value-weighted monthly returns of portfolios sorted on the long-term slope of each state's municipal spread from month $t-1$, as well as the spread between the returns of the Flat (F) and Steep (S) long-term slope portfolios, after partitioning the sample based on one of three measures of firm visibility, and the cyclicality of state government expenditures. Here, the long-term slope of each state's municipal spread is obtained by estimating equation (3) over a recursive window, and the portfolio formation procedure follows that described in Section 3.2 with the following exceptions. In the columns labeled "Visibility," state-level portfolio returns are constructed after splitting the sample into groups of firms with high and low visibility, where group membership is determined by the median value of the firm-level visibility proxy proposed by Hong *et al.* (2008). Similarly, in the columns denoted "Analyst" ("Ownership"), state-level portfolio returns are constructed using the groups of firms with above and below median values of analyst following (institutional ownership). These variables are described in Section OA.1 of the Online Appendix. Lastly, the columns labeled "Cyclicality" splits the sample into the group of nine states that tend to implement more procyclical fiscal policies (High) and the group of nine states that tend to implement more countercyclical fiscal policies (Low). Here, the cyclicality of each state's fiscal policies is drawn from Table 1 of Da *et al.* (2018). Finally, parentheses report Newey and West (1987) t-statistics, and the sample period is from January 2002 to December 2017.

	Visibility		Analysts		Institutional		Cyclicality	
	High	Low	High	Low	High	Low	High	Low
Flat (F)	1.08	1.07	1.09	0.62	1.10	1.16	0.94	1.26
Medium	0.86	0.88	0.80	0.58	0.82	0.73	0.85	0.88
Steep (S)	0.55	0.63	0.62	0.68	0.58	0.58	0.34	0.59
Spread (F-S)	0.53	0.44	0.47	-0.07	0.52	0.58	0.61	0.67
t(Spread)	(2.58)	(2.30)	(2.66)	(-0.31)	(2.96)	(3.11)	(2.49)	(2.76)

Table 10: Future characteristics of long-term slope portfolios

The table reports the month $t+12$ accounting characteristics of the portfolios sorted on long-term slope of each state's municipal spread, the spread between the characteristics of the Flat (F) and Steep (S) slope portfolios (Spread (F-S)), and the Newey and West (1987) t-statistic associated with this spread (t(Spread)). Here, the long-term slope of each state's municipal spread is obtained by estimating equation (3) over a recursive window. 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-weighted average of these characteristics is computed across all firms in a given state, and the equal-weighted average of these characteristics is taken across all states assigned to each portfolio. Finally, the table reports the time-series average of each portfolio-level characteristics. Details on the construction of each variable is described in Section OA.1 of the Online Appendix, and the sample period ranges from January 2003 to December 2017.

	Flat (F)	Medium	Steep (S)	Spread (F-S)	t(Spread)
ME ($b)	65.19	60.47	61.30	3.89	0.83
BEME	-0.21	-0.23	-0.20	-0.01	-0.40
GP	0.00	-0.00	0.00	0.00	0.28
ROA	0.02	0.01	0.02	0.00	0.92
ROE	0.04	0.04	0.04	0.00	0.66
Asset growth (%)	2.33	1.24	1.61	0.72	0.37
I/A (%)	-0.16	-0.53	-0.25	0.08	0.23
Accruals (%)	0.53	0.37	0.56	0.02	0.07
SUE1 (%)	-0.08	0.12	-0.04	-0.04	-0.24
SUE2 (%)	-0.13	0.09	-0.05	-0.08	-0.67
SUE3 (%)	0.09	0.09	0.01	0.08	1.56

Table 11: Long-term slope portfolios: Excluding difficult to arbitrage stocks

The table reports the monthly value-weighted returns of portfolios sorted on the long-term slope of each state's municipal spread, as well as as the spread between the returns of the Flat (F) and Steep (S) long-term slope portfolios, after removing four groups of stocks that are considered different to arbitrage. Here, the long-term slope of each state's municipal spread is obtained by estimating equation (3) over a recursive window, and the portfolio formation procedure follows that described in Section 3.2 with the following exceptions. In the columns labeled "Large cap." or "High volume" ("Low IVOL"), state-level portfolio returns are constructed after excluding any firm whose market capitalization or trading volume (IVOL) is below (above) the 30^{th} (70^{th}) percentile of the cross-sectional distribution of the relevant variable in months $t-1$. The column labeled "High priced" constructs the state-level portfolio returns after removing all firms whose share price is below \$5 in month $t-1$. Finally, parentheses report Newey and West (1987) t-statistics, and the sample period is from January 2002 to December 2017.

	Large cap.	High priced	Low IVOL	High volume
Flat (F)	1.07	1.08	1.03	1.03
Medium	0.80	0.85	0.83	0.86
Steep (S)	0.64	0.68	0.72	0.60
Spread (F-S)	0.43	0.40	0.32	0.43
t(Spread)	(2.60)	(2.34)	(1.92)	(2.66)

Table 12: Long-term slope portfolios: alternative measurements

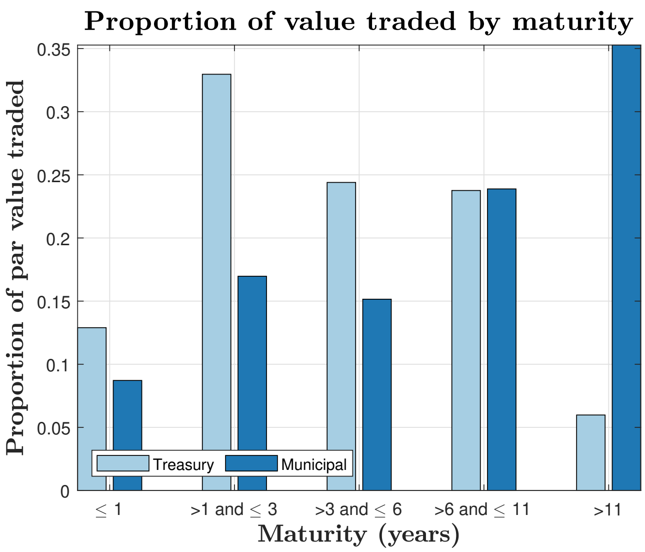
The table reports the value-weighted monthly returns of portfolios sorted on alternative definitions of the long-term slope of each state's municipal spread, as well as the spread between the returns of the Flat (F) and Steep (S) long-term slope portfolios. States are sorted following the portfolio formation procedure described in Section 3.2, with long-term slope of each state's municipal spread measured in one of the five following ways. First, the baseline procedure is repeated, except that the municipal yields underlying the analysis are not adjusted for differences in taxes across states. Second, the spread is constructed by estimating equation (3) over the full sample period, instead of estimating this equation over an expanding window. Third, equation (3) is restricted so that the state-level DNS curvature factor is projected on the national DNS curvature factor only. Fourth, equation (3) is extended to include the square of each national DNS factor as additional regressors. Finally, equation (1) is directly applied to the tax-adjusted municipal-Treasury spread, and portfolios are sorted on the basis of the third factor from this regression. These five cases are denoted "No tax," "Full sample," "Single," "Squared," and "Spread," respectively. Newey and West (1987) t-statistics are reported in parentheses, and the sample period is from January 2002 to December 2017.

	No tax	Full sample	Single	Squared	Spread
Flat (F)	0.97	1.08	1.05	1.14	1.01
Medium	0.87	0.83	0.84	0.84	0.85
Steep (S)	0.53	0.71	0.67	0.58	0.64
Spread (F-S)	0.45	0.38	0.37	0.56	0.37
t(Spread)	(2.68)	(2.05)	(2.00)	(3.54)	(2.22)

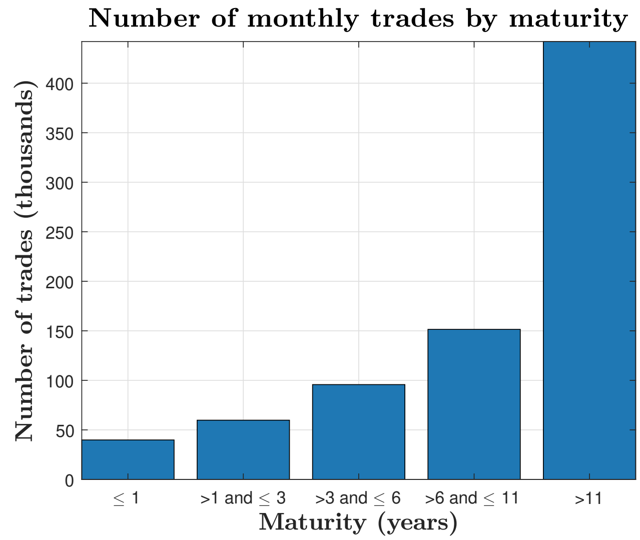
Table 13: Long-term slope portfolios: heterogeneity in firm localization

The table reports the monthly returns of portfolios sorted on long-term slope of each state's municipal spread from month $t-1$, as well as the spread between the returns of the Flat (F) and Steep (S) slope portfolios. Here, the long-term slope of each state's municipal spread is obtained by estimating equation (3) over a recursive window. The analysis follows the portfolio formation procedure described in Section 3.2 with the following exceptions. The results reported in the column labeled "$\leq$ 5" ("$\geq$ 6") are obtained using state-level stock returns that are computed as the equal-weighted average across all firms headquartered in a particular state that name five or fewer (six or more) state names in their 10-K filings in the previous calendar year. State-name counts for each firm-year are obtained by crawling EDGAR following the method outlined by García and Norli (2012). the mean and standard deviation of value-weighted portfolio returns are represented by $\mathbb{E}[R]$ and $\sigma(R)$, respectively. Finally, Newey and West (1987) t-statistics are reported in parentheses. The sample period is from January 2002 to December 2017.

	$\leq$ 5 states		$\geq$ 6 states	
	$\mathbb{E}[R]$	$\sigma(R)$	$\mathbb{E}[R]$	$\sigma(R)$
Flat (F)	1.72	6.26	1.24	6.47
Medium	1.25	5.78	1.15	6.07
Steep (S)	1.25	6.10	1.12	6.41
Spread (F-S)	0.46	2.77	0.12	2.57
t(Spread)	(2.13)		(0.64)	



(a) **Par value traded monthly**



(b) **Number of monthly trades**

Figure 1: Trading activity in the secondary market for municipal debt
The figure reports measures of trading activity in the secondary market for municipal debt. Subfigure (a) displays the proportion of par value traded in the municipal debt market by five maturity groups, and compares this to the proportion of par value traded in the United States Treasury debt market by the same maturity groups. Here, data on the monthly par value traded in the municipal debt space is obtained from the Municipal Securities Rulemaking Board (MSRB), and data on the monthly par value traded in the U.S. Treasury market is obtained from the Federal Reserve Bank of New York's Primary Dealer Statistics. Subfigure (b) displays the mean number of trades per month by maturity in the secondary market for municipal debt as recorded by the MSRB. The data underlying this figure ranges from January 2005 to December 2017.

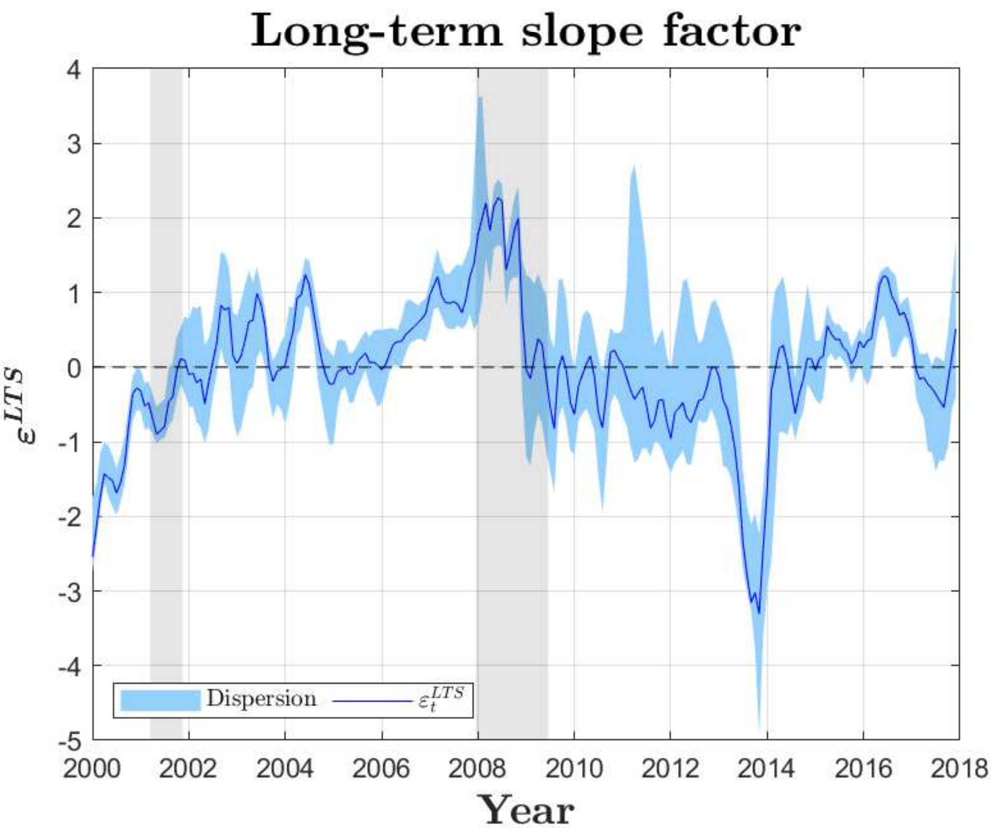


Figure 2: Time-series of the long-term slope factor
The figure reports the monthly time series of the long-term slope of the municipal spread, obtained by estimating equation (3). Equation (3) is estimated on a state-by-state basis, and the average long-term slope factor is obtained weighted by factor associated with each state by the gross state product (GSP) of the state. This GSP-weighted factor is represented by the solid blue line, and the cross-sectional dispersion of the factor is represented by the blue shaded region. The time period for this analysis is January 2000 to December 2017.

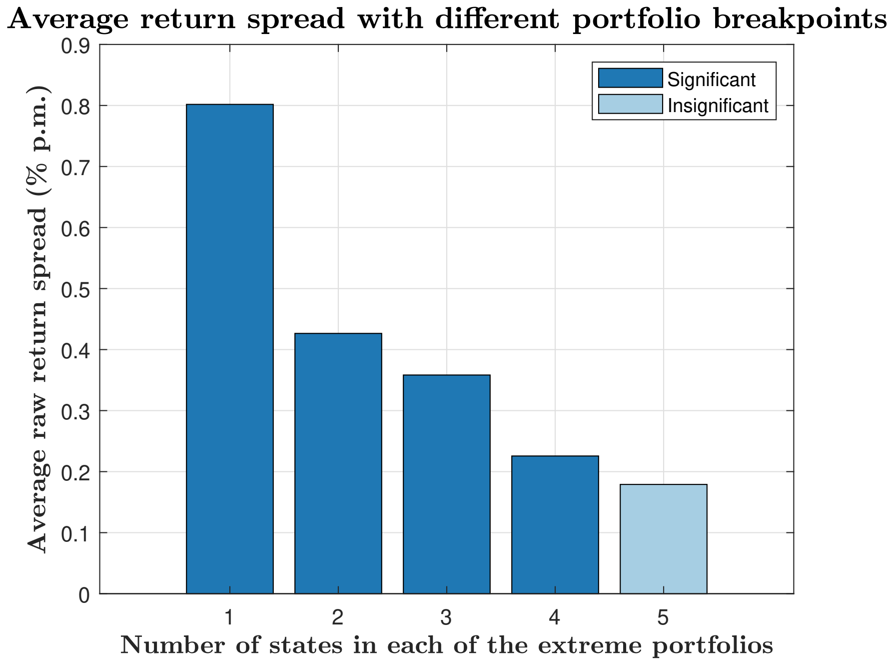


Figure 3: Average returns to the FMS spread: alternative breakpoints.
The figure reports the average monthly return of the flat-minus-steep (FMS) spread as the number of states included in each of the extreme slope portfolios is altered. Specifically, portfolio sorts similar to those described in Section 3.2 are implemented, but the breakpoints used to determine portfolio membership are set so that between 1 and 5 states enter each of the extreme portfolios. Bars shaded dark (light) blue correspond to average returns that are statistically significant (insignificant) at the 10% level using Newey and West (1987) standard errors. Finally, the returns underlying these analyses span January 2002 to December 2017.

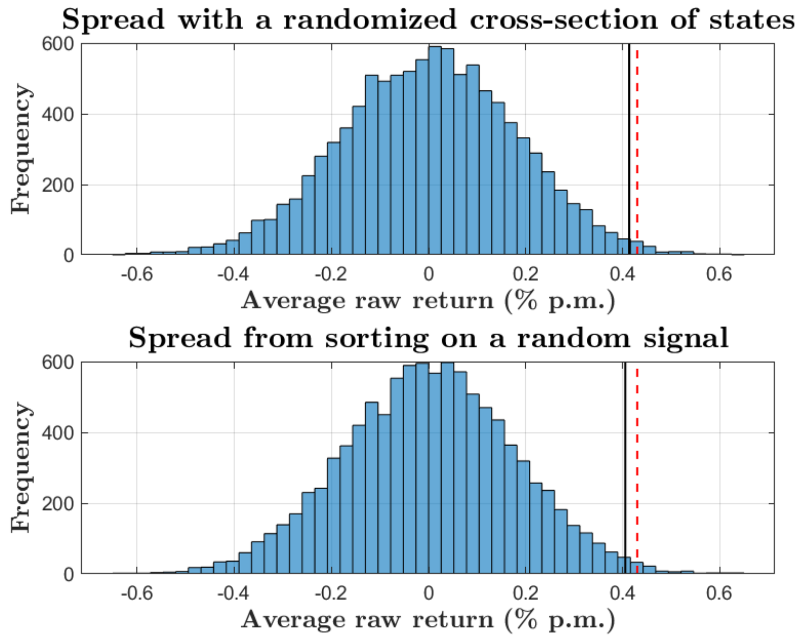


Figure 4: Placebo tests: FMS spread across 10,000 simulations.
The figure displays the distributions of the flat-minus-steep (FMS) long-term slope spreads across 10,000 simulations. In each set of simulations the FMS spread is constructed following the procedure described in Section 3.2 with the following modifications. In the top panel, the cross-section of stock returns associated with each simulation is randomized. In the bottom panel, each set of portfolio sorts is based on randomly generated variables that mimic the temporal properties of the long-term slope factor. In each panel, the dashed red line corresponds to the magnitude of the FMS spread in the data, while the solid black line corresponds to the 99^{th} percentile of the spread across the $10,000$ simulations.

A Online Appendix

OA.1 Variable description and construction

OA.1.1 State-level macroeconomic variables

Unemployment rate (UR). The monthly unemployment rate associated with each state is constructed by the U.S. Bureau of Labor Statistics and is released monthly as part of the Current Employment Statistics (CES) program. Additional details are available at the following URL: `https://www.bls.gov/sae/`.

Coincident economic activity index (CI). The monthly coincident economic activity index for each state is constructed by The Federal Reserve Bank of Philadelphia by estimating a latent dynamic single-factor model that builds on the model described by Crone and Clayton-Matthews (2005). This latent factor model isolates the common variation in state-level nonfarm payroll employment, average hours worked in manufacturing by production workers, the unemployment rate, and wage and salary disbursements deflated by the consumer price index, and summarizes the current economic conditions using a single variable. The trend of this variable is constrained to equal growth rate of the state's gross state product (GSP), so that the long-term growth in the coincident economic activity index is consistent with the long-term growth rate of each state's GSP. Additional details are available at the following URL: `https://www.phil.frb.org/research-and-data/regional-economy/indexes/coincident/`.

Leading economic activity index (LI). The monthly leading economic activity indexes for each state are constructed by The Federal Reserve Bank of Philadelphia and are used to predict the six-month growth rate of the state's coincident economic activity index. Future values of the coincident economic activity index are predicted using the current and past values of the coincident economic activity index, as well as a number of variables that lead the business cycle. These leading variables include state-level housing permits (1 to 4 units), state initial unemployment insurance claims, delivery times from the Institute of supply Management manufacturing survey, and the spread between the 10-year Treasury bond and the 3-month Treasury bill. Additional details regarding this variable are available at the following URL: `https://www.philadelphiafed.org/research-and-data/regional-economy/indexes/leading/`.

Real gross state product (GSP). Real gross state product for each state is produced by the U.S. Bureau of Economic Analysis (BEA) on a quarterly basis. The data is computed as sum of the value added from all industries operating in a given state. The data is reported in millions of chained 2012 dollars. Additional details regarding this variable are available at the following URL: `https://www.bea.gov/data/gdp/gdp-state`.

Real personal income (PI). Real personal income for each state is computed by first deflating quarterly total personal income, which produced by the U.S. BEA, by the consumer price index from the BLS to account for changes in the price level over time. The resulting series is then standardized by the resident population of each state as determined by the U.S. Census Bureau.

Volatility of coincident economic activity ($\boldsymbol{\sigma(CI)}$). The volatility of the coincident economic activity index is calculated by fitting an AR(1)-GARCH(1,1) model to the time series of monthly growth rates of the state-level coincident economic activity index.

OA.1.2 Firm-level accounting and return characteristics

Accruals (ACC). In line with Sloan (1996) total accruals are measured as the annual change in noncash working capital (NCWC) minus the firm's depreciation and amortization expense (Compustat Annual item DP) for the most recent reporting year. Total accruals are scaled by each firm's average total assets (Compustat item AT) reported for the previous two fiscal years. Noncash working capital is the change in current assets (Compustat Annual item ACT) minus the change in cash and short-term investments (Compustat Annual item CHE), minus the change in current liabilities (Compustat Annual item LCT), plus the change in debt included in current liabilities (Compustat Annual item DLC), plus the change in income taxes payable (Compustat Annual item TXP). If either Compustat item DLC or Compustat item TXP is missing, then its value is set to zero.

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). The book value of assets in each year is deflated by the GDP deflator and expressed in terms of 2009 dollars.

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).

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

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

[20] This research note and the code for implementing the procedure is available at the following URL:

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 $t-1$.

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).

Market beta (Beta). The market beta of each firm at the end of month t is computed by regressing the daily excess returns of the firm on the excess market return, provided that there are at least 15 valid daily returns in the month of interest.

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.

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).

Return on equity (ROE). Return on equity is defined as net income (Compustat Quarterly item NIQ) divided by the lagged book equity. Here, book equity is computed on a quarterly basis by following the procedure outlined by Daniel and Titman (2006) (see the definition of book equity used in the construction of the book-to-market ratio, above).

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 CSHPRQ, 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).

`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.

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.1.3 National business cycle predictors

Default spread. The default spread is computed by taking the difference in yields between Moody's seasoned BAA corporate bond yield minus Moody's seasoned AAA corporate bond yield. Data related to each variable are obtained from FRED.

Price-to-dividend ratio. The aggregate monthly price-dividend ratio is computed following Boudoukh, Michaely, Richardson and Roberts (2007) such that the measure of total dividends includes both cash dividends and share buybacks. As in Van Binsbergen and Koijen (2010) cash dividends are restricted to all cash ordinary dividends (those with CRSP item DISTCD beginning with one) and liquidation dividends (those with CRSP item DISTCD beginning with two and either ending in two or ending in eight). Annual share buybacks are calculated as expenditures on the purchase of common and preferred stock (Compustat Annual item PRSTKC) plus reductions in the value of net outstanding preferred stock (Compustat Annual item PSTKRV). To convert annual repurchases to the monthly frequency the annual repurchases are evenly divided over the 12 months of the fiscal year. Finally, the aggregate price-dividend ratio in month t is computed as the sum of the product of shares outstanding (CRSP item SHROUT) and share price (CRSP item PRC) across all firms. This quantity is then divided by the sum of the product of shares outstanding and monthly total dividends over the previous 12 months across all firms. The purpose of taking the trailing sum of total dividends over the previous 12 months is to mitigate seasonal effects in the payout series.

Term spread. The term spread is calculated by taking the difference between the 10 year constant maturity Treasury yield and the 2 year constant maturity Treasury yield. Data related to each yield are obtained from FRED.

OA.2 Out-of-sample analysis

Section 2.1 shows that the long-term slope of a state's municipal spread helps explain variation in six local macroeconomic variables, including a state's gross state product, unemployment rate, and degree of macroeconomic uncertainty. These results are establish by estimating a series of in-sample predictive regressions. The results of these analyses, reported in Table 3 of the main text, show that adding the long-term slope of each state's municipal spread to equation (4) boosts the adjusted-R^2 of this model by an average of 4.70% when forecasting the 12-month ahead values of these variables.

Although the results of the predictive regressions are easy to interpret, there are two potential issues with these results. Each of these issues may overstate the usefulness of the long-term slope of the municipal spread for predicting local macroeconomic outcomes. First, the main measure of the long-term slope of the municipal spread that is added to equation (4) is obtained by estimating equation (3) over the full sample period. This means that the factor loadings underlying equation (3), and consequently the residuals that emerge from this equation, is estimated by using data that is unavailable to market participants in real time. Second, and similarly, the macroeconomic data underlying the regressions in Section 2.1 are from FRED. This means that these data reflect the final revised values of each variable, and neglect the fact that economic figures are revised often. Since the information contained in future data revisions are unavailable to forecasters standing at a given point in time, this use of revised data can overstate the degree of predictability documented in Table 3 (e.g., Ghysels, Horan and Moench (2017)).

A pseudo out-of-sample forecasting exercise is implemented to address both of these issues. This exercise ensures that only information that is available to market participants standing at time t is used to predict local macroeconomic outcomes at time $t+h$. The out-of-sample forecasts are implemented as follows. For the macroeconomic variables available at the monthly (quarterly) frequency, the first out-of-sample prediction is obtained by estimating each forecasting model – described below – over an in-sample estimation period that ranges from January 2000 to December 2002 (December 2003).[21][22] The resulting parameter estimates are then used to predict the macroeconomic outcome corresponding to January 2003 (January 2004). The estimation period is then increased by either one or three months, depending on whether the macroeconomic outcome is recorded monthly or quarterly, respectively, and all models are then re-estimated to produce the out-of-sample prediction for the next period. This recursion continues until the last forecast of each variable is produced for December 2017. Finally, all h-period ahead forecasts are direct rather than indirect forecasts.

For the purpose of completeness, the results reported below consider the usefulness of both the long-term slope of the municipal spread, and the level and the short-term slope of the municipal spread, for forecasting local macroeconomic outcomes. The estimated level (denoted $\varepsilon_{i,t}^{L}$) and short-term slope (denoted $\varepsilon_{i,t}^{STS}$) of each state's municipal spread are obtained analogously to the estimated long-term slope of the municipal spread. That is, the following two equations, which mimic equation (3) in the main text, are estimated:

$$l_{i,t} = \alpha_i^l + \beta_i^{l,l} L_t + \beta_i^{l,s} S_t + \beta_i^{l,c} C_t + \varepsilon_{i,t}^{L} \tag{A1}$$

$$s_{i,t} = \alpha_i^s + \beta_i^{s,l} L_t + \beta_i^{s,s} S_t + \beta_i^{s,c} C_t + \varepsilon_{i,t}^{STS}. \tag{A2}$$

Here, $l_{i,t}$ and $s_{i,t}$ are obtained by estimating equation (1) in the main text.

The out-of-sample forecasts of the five state-level macroeconomic outcomes are obtained using the following two single-equation time-series forecasting models.

Model 1. The first model, which serves as the benchmark model, predicts the future value of each macroeconomic variable based on (i) the current value of the variable of interest, and (ii) the first principal component (PC hereafter) of the aggregate price-to-dividend ratio, Treasury term spread, and corporate default spread. This PC, which accounts for approximately 73% of the common variation in these three price-based variables over the full sample period, is denoted by F_t. F_t is extracted from the panel of financial market variables in each period using data that is available up to time t. By including only the first PC of these variables in the model, rather than adding each

[21] Since the BEA only reports quarterly estimates of real GSP beginning in 2005, the time period for which GSP data is available is truncated compared to the other measures of economic activity considered. Consequently, the first-in sample estimation period spans January 2006 to December 2011, and the first one-quarter ahead forecast corresponds to the quarter ending in March 2006. The forecasts are then recursively updated, as described above, until the final forecast related to December 2017 has been produced.

[22] For computational simplicity, I do not consider out-of-sample forecasts of the conditional volatility of each state's coincident economic activity index (denoted σ (CI)). Since σ (CI) is obtained by fitting an AR(1)-GARCH(1,1) model to the monthly growth rate of each state's coincident economic activity index, this avoids the need to estimate, and forecast, σ (CI) on a recursive basis.

national asset-pricing variable to the benchmark model separately, the model incorporates aggregate financial market data in a parsimonious way. This benchmark model can be written as

$$y_{i,t+h} = \alpha + \rho y_{i,t} + \beta F_t + u_{i,t+h}, \tag{A3}$$

where all variables besides F_t follow the definitions provided in Section 2.1.

Model 2. The second model, which serves as the alternative model, is written as

$$y_{i,t+h} = \alpha + \rho y_{i,t} + \beta F_t + \gamma \varepsilon^x_{i,t} + u_{i,t+h}. \tag{A4}$$

Here, Model 2 extends Model 1 by adding one of the yield factors obtained from each state's term structure of municipal spreads: $\varepsilon^x_{i,t}$ for $x \in \{L, STS, LTS\}$. Thus, Model 2 predicts each macroeconomic outcome by combining variation related to the current value of the macroeconomic variable, national financial market data, and a municipal yield factor.

Comparing the accuracy of the forecasts produced by equation (A3) to accuracy of those produced by equation (A4) provides a simple way to evaluate whether including any of the three municipal yield factors in Model 2 result in more accurate real-time predictions of local business conditions. The forecast performance of Model 2 is compared to that of Model 1 using two different metrics: root mean squared forecast errors (RMSFEs) and a panel version of the Diebold and Mariano (1995) test proposed by Pesaran, Schuermann and Smith (2009). These two metrics are described below.

Root mean squared forecast errors. The predictive accuracy of Model 2 is first evaluated by computing the model's RMSFE over the pseudo out-of-sample period for each combination of state, macroeconomic outcome variable, forecast horizon, and municipal yield factor. To aid in the interpretation of the results, the RMSFEs produced by Model 2 are scaled by those generated by Model 1 to report relative RMSFEs. Relative RMSFEs that are less (greater) than one indicate that Model 2 produces more (less) accurate forecasts than Model 1 within a given state. Then, to assess the relative predictive accuracy of Model 2 across all 19 states, the empirical distribution of these relative RMSFEs is examined. If Model 2 produces a median relative RMSFE that is less than one across the 19 states, then Model 2, which also includes a municipal yield factor, typically produces more accurate forecasts than Model 1, which does not include any municipal yield data.

Panel Diebold and Mariano (1995) tests. While relative RMSFEs are easy to interpret, they do not formally test whether the forecasts produced by Model 2 are more accurate than those produced by Model 1. Thus, the panel version of the Diebold and Mariano (1995) test developed by Pesaran *et al.* (2009) is used to determine whether the predictive ability of Model 2 significantly exceeds that of Model 1 over the pseudo out-of-sample period.

This test is implemented by defining the forecast loss differential associated with forecasting macroeconomic variable y in state i at time t using Model 2 relative to Model 1 as $z_{y,i,t}(h) = \left[e^{(2)}_{y,i,t}(h)\right]^2 - \left[e^{(1)}_{y,i,t}(h)\right]^2$. Here, $e^{(X)}_{y,i,t}(h)$ represents the h-year ahead forecast error from predicting macroeconomic variable y in state i at time t using Model $X \in \{1, 2\}$. Fixing y and h, the test statistic, denoted DM, is obtained by considering $z_{i,t} = \alpha_i + \varepsilon_{i,t}$, and testing whether $\alpha_i < 0$ for any state. Under the null hypothesis that $\alpha_i = 0$ for all states, and assuming that $\varepsilon_{i,t} \overset{iid}{\sim} (0, \sigma^i_i)$, the test statistic is $DM = \bar{z}/\left[\sqrt{V(\bar{z})}\right] \sim \mathcal{N}(0, 1)$. The definition $\bar{z} = \frac{1}{I}\sum_{i=1}^{I} \bar{z}_i$, where $\bar{z}_i = \frac{1}{T}\sum_{t=1}^{T} z_{i,t}$, is from Pesaran *et al.* (2009), and $V(\bar{z})$ is computed following Newey and West (1987) to account for the serial correlation in $\bar{z}$ from multi-period ahead forecasts.

Since negative values of DM suggest that $z_{y,i,t}(h)$ is typically negative, or that the squared forecast errors from Model 1 tend to be larger than those from Model 2, negative values of DM indicate that Model 2 *outperforms* Model 1. Additionally, since this test is one-sided and the DM statistic follows an asymptotically standard normal distribution, the appropriate 1%, 5%, and 10% critical values are -2.326, -1.645, and -1.282 respectively.

Table A1 reports the results of the pseudo out-of-sample forecasting exercise described above. The table shows the median relative RMSFE across the 19 states in the sample, as well as the panel DM test statistic and its associated p-value, for each combination of macroeconomic variable, forecast horizon, and yield factor. Each forecast evaluation metric is setup so that lower values of the metric reflect the case in which Model 2 produces more accurate forecasts than Model 1.

Consistent with the conclusions from Section 2 of the main text, adding the long-term slope of the municipal spread to Model 2 produces numerous (statistically significant) forecast gains. For instance, the median relative RMSFEs obtained by adding this factor to Model 1 are less than one in value in 17 out of the 20 cases considered. The magnitudes of these relative RMSFEs indicate that the forecasts produces by Model 2 are often between 1% to 5% more accurate than those produced by Model 1. Furthermore, the panel DB test statistics show that these forecast gains are statistically significant in 15 out of the 20 cases considered. In contrast, the level and short-term slope of each state's municipal yield spread is typically uninformative about future local economic conditions (also see Table A8 of the Online Appendix).

It is worth noting that the forecast gains reported in Table A1 are likely to provide a lower bound on those achievable in practice. For instance, since Timmermann (2006) argues that averaging forecasts across numerous models provides a simple way hedge against model uncertainty, more accurate forecasts of state-level business conditions may be obtained by computing forecast combinations. Likewise, since the out-of-sample forecast exercise implemented above does not leverage the fact that the factors related to the term structure of a state's municipal spread are available at higher frequencies (e.g., daily), the mixed-data sampling (MIDAS) models developed by Ghysels, Santa-Clara and Valkanov (2005, 2006) are not considered. Since MIDAS models that predict low-frequency macroeconomic outcomes using high-frequency financial data often produce forecast gains over the traditional (low-frequency) models considered above (e.g., Andreou, Ghysels and Kourtellos (2013)), more accurate forecasts of local business conditions may also be obtained by expanding the set of forecasting models considered.

Table A1: Out-of-sample forecast performance

The table reports the results of pseudo out-of-sample forecast analyses that predict the h-month ahead state-level unemployment rate (Panel A), coincident economic activity index (Panel B), leading economic activity index (Panel C), real personal income per capita (Panel D), and real gross state product (Panel E), where $h \in \{3, 6, 9, 12\}$ months. Rows labeled RRMSFE report the median value of the root mean squared forecast error (RMSFE) of Model 2 including either the level, short-term slope, or long-term slope factor relative to the RMSFE of Model 1. Rows labeled DM compare the forecast performance of Model 2 to that of Model 1 model using the panel Diebold and Mariano (1995) test proposed by Pesaran *et al.* (2009), with rows labeled p(DM) reporting the p-value associated with this test in parentheses. All models and forecast evaluation metrics are described in Section OA.2. Finally, the time period underlying this analysis ranges from January 2000 to December 2017.

	Level (ε^L)				Short-term slope (ε^{STS})				Long-term slope (ε^{LTS})			
$h =$	3	6	9	12	3	6	9	12	3	6	9	12
Panel A: Unemployment rate												
RRMSFE	1.026	1.058	1.041	1.015	1.033	1.039	1.021	0.997	0.989	0.982	0.980	0.966
DM	5.982	9.189	5.176	1.175	10.144	8.768	3.189	-1.247	-4.551	-5.655	-6.606	-8.203
p(DM)	(1.00)	(1.00)	(1.00)	(0.88)	(1.00)	(1.00)	(1.00)	(0.11)	(0.00)	(0.00)	(0.00)	(0.00)
Panel B: Coincident index												
RRMSFE	1.018	1.037	1.031	1.018	1.010	1.027	1.021	1.008	0.981	0.982	0.972	0.962
DM	0.761	1.517	2.852	4.063	1.754	5.333	5.483	4.112	-5.424	-5.457	-8.413	-9.113
p(DM)	(0.78)	(0.94)	(1.00)	(1.00)	(0.96)	(1.00)	(1.00)	(1.00)	(0.00)	(0.00)	(0.00)	(0.00)
Panel C: Leading index												
RRMSFE	1.043	1.088	1.112	1.049	1.012	1.025	1.006	0.960	0.974	0.950	0.964	0.959
DM	6.399	6.974	8.791	3.863	5.116	6.946	-0.253	-7.952	-6.374	-7.773	-10.202	-9.201
p(DM)	(1.00)	(1.00)	(1.00)	(1.00)	(1.00)	(1.00)	(0.40)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Panel D: Real personal income												
RRMSFE	1.009	1.038	1.059	1.069	1.031	1.066	1.050	1.034	1.010	0.987	0.988	0.983
DM	0.889	2.797	3.830	4.437	4.069	5.720	5.026	4.234	2.472	-1.148	-2.000	-1.564
p(DM)	(0.81)	(1.00)	(1.00)	(1.00)	(1.00)	(1.00)	(1.00)	(1.00)	(0.99)	(0.13)	(0.02)	(0.06)
Panel E: Real gross state product												
RRMSFE	0.979	1.185	1.158	1.079	1.030	1.012	1.047	1.028	1.032	1.037	0.942	0.997
DM	-0.562	3.218	3.435	0.249	1.508	1.471	2.021	1.015	2.365	0.701	-2.476	-1.029
p(DM)	(0.29)	(1.00)	(1.00)	(0.60)	(0.93)	(0.93)	(0.98)	(0.84)	(0.99)	(0.76)	(0.01)	(0.15)

OA.3 Supplemental tables and figures

OA.3.1 Factor loadings underlying the dynamic Nelson-Siegel model

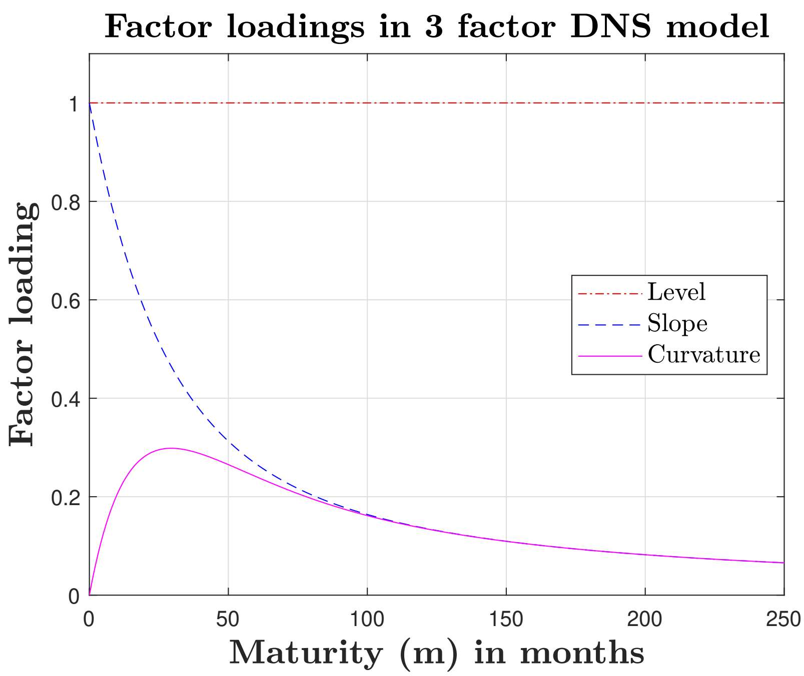


Figure A1: Factor loadings underlying dynamic Nelson-Siegel model
The figure displays the factor loadings underlying the dynamic Nelson-Siegel model proposed by Diebold and Li (2006) when the shape parameter (i.e. λ in equation (1) of the main text, or Λ in equation (2) of the main text) is set to 0.0609. In this figure the level, slope, and curvature factor loadings refer to the coefficients of either l, s, and c in equation (1) of the main text or L, S, and C in equation (2) of the main text, respectively.

OA.3.2 National and state dynamic Nelson-Siegel factors

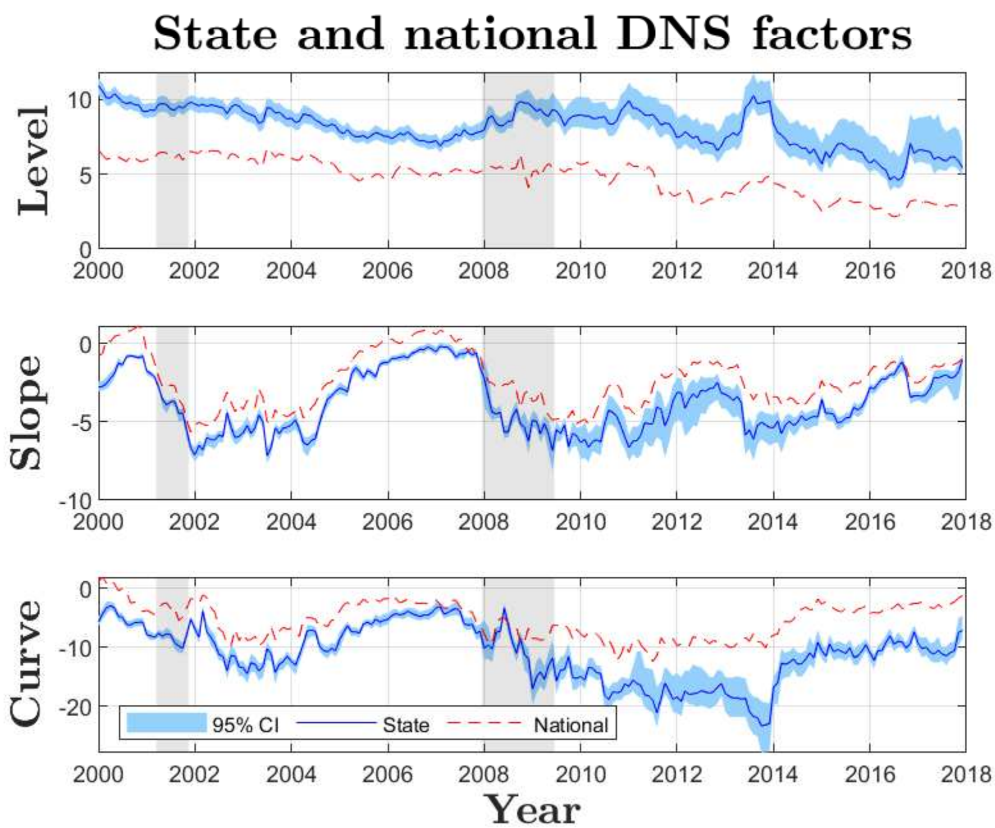


Figure A2: Time series of state and national dynamic Nelson-Siegel factors
The figure reports the monthly time series of the state and the national dynamic Nelson-Siegel (DNS) level, slope, and curvature factors in the top, middle, and bottom subfigures, respectively. The national DNS factors are represented by dashed red lines, whereas the average GSP-weighted state DNS factors are displayed by the solid blue lines. The 95% confidence interval associated with the state DNS factors is represented by the blue shaded region. The state-level DNS factors are obtained by estimating equation (1) of the main text, while the national DNS factors are obtained by estimating equation (2) of the main text. The time span for the analysis is January 2000 to December 2017.

Table A2: State and national DNS yield factors: summary statistics
The table reports the summary statistics associated with the state-level dynamic Nelson-Siegel (DNS) factors, obtained by estimating equation (1) within each state, in Panel A, and the national DNS factors, obtained by estimating (2), in Panel B. The summary statistics reported for each factor are the time-series mean, standard deviation (SD(TS)), minimum, and maximum, as well as the mean cross-sectional dispersion of each factor across states (SD(CS)). The table also reports the one, 12, and 30 month autocorrelation of each factor, along with an augmented Dickey-Fuller (ADF) unit root test statistic and its associated p-value. Summary statistics for the state-level factors in Panel A are obtained by GSP-weighting each variable across states. Finally, the sample period is from January 2000 to December 2017.

Factor	Mean	SD(TS)	SD(CS)	Min.	Max.	$\hat{\rho}(1)$	$\hat{\rho}(12)$	$\hat{\rho}(30)$	ADF	p(ADF)
Panel A: State DNS factors										
l	8.102	1.323	0.488	4.580	10.887	0.946	0.500	0.162	-1.387	0.154
s	-3.792	1.898	0.337	-7.160	-0.181	0.948	0.392	-0.377	-1.092	0.251
c	-11.072	4.828	0.922	-23.307	-2.934	0.948	0.649	0.143	-0.871	0.332
Panel B: National DNS factors										
L	4.808	1.219	-	2.144	6.727	0.961	0.719	0.442	-1.288	0.182
S	-2.347	1.733	-	-5.674	1.124	0.965	0.345	-0.429	-1.087	0.253
C	-5.424	3.093	-	-12.404	1.897	0.933	0.501	-0.068	-1.169	0.223

OA.3.3 Constructing the local yield factors

Table A3: State-level exposures to national level, slope, and curvature factors
The table reports the results of estimating equations (A1) and (A2) of the Online Appendix, and equation (3) of the main text, on a state-by-state basis. Specifically, the table reports the the factor exposures (β) associated with projecting the state-level DNS factors on the set of national DNS factors over the full sample period. The table also reports the adjusted-R^2 from each of these time-series regressions. The sample period ranges from January 2000 to December 2017.

	Panel A: Level (ε^L)				Panel B: Short-term slope (ε^{STS})				Panel C: Long-term slope (ε^{LTS})			
State	$\beta^{l,l}$	$\beta^{l,s}$	$\beta^{l,c}$	$\bar{R}^2$	$\beta^{s,l}$	$\beta^{s,s}$	$\beta^{s,c}$	$\bar{R}^2$	$\beta^{c,l}$	$\beta^{c,s}$	$\beta^{c,c}$	$\bar{R}^2$
CA	0.86	-0.05	-0.21	72.26	0.00	0.98	0.15	86.29	1.93	0.43	1.30	72.55
CT	0.72	-0.09	-0.01	70.58	0.04	1.01	0.02	91.14	1.40	0.68	1.11	82.56
FL	0.90	0.02	-0.11	76.68	-0.11	0.94	0.08	90.95	1.40	0.35	1.15	77.96
GA	1.06	0.02	-0.05	81.82	-0.12	0.99	0.01	90.95	1.08	0.48	1.26	83.29
IL	0.13	-0.23	-0.02	26.43	0.25	0.89	0.18	79.40	0.79	0.79	0.92	76.68
MA	0.94	-0.01	-0.05	78.20	-0.06	0.99	0.02	90.30	1.37	0.58	1.14	81.97
MD	1.22	0.04	-0.04	84.47	-0.18	1.03	0.01	90.53	1.00	0.52	1.29	84.33
MI	0.87	-0.05	-0.12	74.24	0.01	0.98	0.12	89.54	1.39	0.72	0.95	81.76
MN	1.00	-0.02	-0.03	80.43	-0.07	1.03	-0.03	91.36	1.31	0.57	1.23	82.77
NC	1.07	0.04	-0.07	83.18	-0.13	1.03	0.03	91.73	1.16	0.31	1.30	81.82
NJ	0.61	-0.13	0.01	57.68	0.09	1.02	0.03	89.89	1.26	0.74	1.05	79.81
NY	1.17	0.01	-0.07	86.01	-0.17	0.98	0.06	90.70	1.18	0.70	1.10	79.43
OH	1.01	-0.01	-0.08	80.49	-0.07	0.99	0.04	89.80	1.23	0.63	1.26	82.39
PA	0.74	-0.05	-0.08	60.42	0.04	1.01	0.04	88.67	1.36	0.52	1.27	78.20
SC	1.04	0.02	-0.05	80.50	-0.11	1.02	0.01	91.20	1.23	0.40	1.28	81.39
TX	0.96	-0.00	-0.08	79.52	-0.07	0.90	0.06	90.03	1.22	0.54	1.18	81.08
VA	1.06	0.03	-0.06	81.88	-0.15	1.01	0.01	90.94	1.16	0.37	1.31	81.34
WA	0.88	-0.03	-0.06	78.45	-0.06	0.91	0.02	90.33	1.40	0.63	1.19	82.19
WI	1.02	-0.04	-0.07	82.33	-0.07	0.99	0.02	91.01	1.25	0.69	1.23	82.00

OA.3.4 Forecasting state-level macroeconomic outcomes

Table A4: In-sample predictive regressions: median across states

The table reports the median difference in the adjusted-R^2 ($\Delta\bar{R}^2$) obtained by estimating the following predictive regression on a state-by-state basis when γ is restricted to zero and when γ is unrestricted:

$$y_{i,t+h} = \alpha + \rho y_{i,t} + \boldsymbol{\beta X_t} + \gamma \varepsilon_{i,t}^{LTS} + u_{i,t+h}$$

Here, $y_{i,t}$ represents one of the unemployment rate (UR), coincident economic activity index (CI), conditional volatility of the coincident economic activity index (σ (CI)), leading economic activity index (CI), real personal income per capita (PI), or real gross state product (GSP) observed in state i at time t. The forecast horizons (h) considered are 3, 6, 9, or 12 months ahead, $\boldsymbol{X_t}$ is a matrix of variables related to aggregate asset prices. Finally, $\varepsilon_{i,t}^{LTS}$ denotes the long-term slope of a state's municipal spread. In Panel A, this variable is obtained by estimating equation (3) over the full sample period. In Panel B, this variable is obtained by computing the difference between 20 year and 5 year municipal yields in excess of Treasury yields. For each combination of macroeconomic variable and forecast horizon, the table reports the median change in adjusted-R^2 across all 19 states. The time period ranges from January 2000 to December 2017.

	Panel A: Estimated (ε^{LTS})				Panel B: Observable			
$h =$	3	6	9	12	3	6	9	12
UR	0.26	1.24	3.02	4.64	0.11	1.11	2.96	5.64
CI	0.13	0.89	3.13	6.86	0.16	1.41	4.07	7.56
σ (CI)	0.29	0.29	0.47	0.48	0.74	0.70	0.50	0.22
LI	1.33	3.86	4.72	3.61	1.15	4.43	5.20	6.66
PI	-0.24	0.79	1.07	0.89	-0.27	0.97	3.43	6.25
GSP	1.54	4.36	11.20	6.15	0.36	2.75	7.27	11.25
Average $\Delta\bar{R}^2$	0.55	1.90	3.93	3.77	0.37	1.90	3.91	6.26

Table A5: Predictive regressions: baseline adjusted-R^2

The table reports the average adjusted-R^2 obtained by estimating the following predictive regression on a state-by-state basis:

$$y_{i,t+h} = \alpha + \rho y_{i,t} + \boldsymbol{\beta X_t} + u_{i,t+h}$$

Here, $y_{i,t}$ represents either the unemployment rate (UR), coincident economic activity index (CI), conditional volatility of the coincident economic activity index (σ (CI)), leading economic activity index (LI), real personal income per capita (PI), or real gross state product (GSP) observed in state i at time t. The forecast horizons (h) considered are 3, 6, 9, or 12 months ahead, and $\boldsymbol{X_t}$ is a matrix of variables related to aggregate asset prices. For each combination of macroeconomic variable and forecast horizon, the table reports the average adjusted-R^2 across all 19 states. The final row summarizes each column by reporting the average adjusted-R^2 across macroeconomic variables, while keeping the forecast horizon fixed. The time period of this analysis ranges from January 2000 to December 2017.

	Baseline adjusted-R^2			
$h =$	3	6	9	12
UR	88.54	66.77	46.81	34.66
CI	91.38	73.46	53.46	36.27
σ (CI)	36.20	22.84	15.24	11.87
LI	55.99	33.55	29.09	27.22
PI	61.74	36.34	15.14	6.81
GSP	61.01	31.95	16.97	18.03
Average $\bar{R}^2$	71.73	48.41	32.29	24.60

Table A6: Predictive regressions: longer horizon predictions

The table reports the average difference in the adjusted-R^2 ($\Delta\bar{R}^2$) obtained by estimating the following predictive regression on a state-by-state basis both when γ is restricted to zero and when γ is unrestricted:

$$y_{i,t+h} = \alpha + \rho y_{i,t} + \boldsymbol{\beta X_t} + \gamma \varepsilon^{x}_{i,t} + u_{i,t+h}$$

Here, $y_{i,t}$ represents either the unemployment rate (UR), coincident economic activity index (CI), conditional volatility of the coincident economic activity index (σ (CI)), leading economic activity index (CI), real personal income per capita (PI), or real gross state product (GSP) observed in state i at time t. The forecast horizons (h) considered are $h \in \{15, 18, 21, 24, 27, 30, 33, 36, 39, 42, 45, 48\}$ months ahead, and $\boldsymbol{X_t}$ is a matrix of variables related to aggregate asset prices. Finally, $\varepsilon^{LTS}_{i,t}$ denotes the long-term slope of a state's municipal spread. In Panel A, this variable is obtained by estimating equation (3) over the full sample period. In Panel B, this variable is obtained by computing the difference between 20 year and 5 year municipal yields in excess of Treasury yields. For each combination of macroeconomic variable and forecast horizon, the table reports the average change in adjusted-R^2 across all 19 states. Finally, parentheses report the results of a simulation exercise that computes the probability that the observed $\Delta\bar{R}^2$ arises by chance. The time period of this analysis ranges from January 2000 to December 2017.

$h =$	15	18	21	24	27	30	33	36	39	42	45	48
Panel A: Estimated long-term slope (ε^{LTS})												
UR	5.06	4.18	3.01	2.41	2.27	1.96	1.48	0.99	0.85	1.15	2.09	3.12
	(0.00)	(0.00)	(0.01)	(0.04)	(0.04)	(0.12)	(0.46)	(0.88)	(0.96)	(0.94)	(0.74)	(0.45)
CI	8.58	7.91	6.15	4.50	3.41	2.43	1.57	0.78	0.40	0.44	0.73	1.14
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.30)	(0.93)	(1.00)	(1.00)	(0.99)	(0.98)
σ (CI)	2.44	1.87	2.47	3.05	2.95	1.91	1.52	1.31	1.13	1.24	0.94	1.56
	(0.02)	(0.11)	(0.02)	(0.00)	(0.00)	(0.08)	(0.22)	(0.37)	(0.53)	(0.50)	(0.76)	(0.44)
LI	2.03	1.11	1.68	3.33	2.31	1.05	0.53	0.67	1.13	1.86	2.37	2.48
	(0.06)	(0.41)	(0.09)	(0.00)	(0.04)	(0.76)	(0.99)	(0.98)	(0.93)	(0.75)	(0.56)	(0.50)
PI	-0.10	8.40	12.81	16.93	6.50	1.69	-0.66	-0.68	-0.68	1.79	1.86	2.71
	(0.97)	(0.00)	(0.00)	(0.00)	(0.00)	(0.43)	(1.00)	(1.00)	(1.00)	(0.21)	(0.16)	(0.13)
GSP	2.10	1.27	-0.42	0.47	-0.24	1.35	-0.01	-0.90	0.19	-0.38	1.14	2.63
	(0.35)	(0.59)	(0.98)	(0.85)	(0.97)	(0.65)	(0.96)	(1.00)	(0.90)	(0.94)	(0.53)	(0.14)
Panel B: Observable long-term slope												
UR	3.91	3.97	3.79	3.96	4.18	3.93	3.09	1.87	1.31	1.56	2.60	3.63
	(0.27)	(0.24)	(0.19)	(0.07)	(0.02)	(0.05)	(0.33)	(0.92)	(0.99)	(0.96)	(0.61)	(0.12)
CI	6.69	7.34	7.20	6.75	5.87	4.70	3.38	1.75	0.87	0.76	1.03	1.39
	(0.01)	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)	(0.11)	(0.89)	(1.00)	(1.00)	(1.00)	(0.97)
σ (CI)	2.56	2.43	3.31	4.32	5.18	3.86	2.81	2.51	1.75	1.50	1.38	1.99
	(0.26)	(0.31)	(0.06)	(0.01)	(0.00)	(0.01)	(0.12)	(0.22)	(0.62)	(0.74)	(0.77)	(0.45)
LI	3.53	2.10	3.43	6.21	3.79	1.92	1.26	1.06	1.44	2.72	2.99	2.35
	(0.03)	(0.27)	(0.01)	(0.00)	(0.04)	(0.79)	(0.99)	(1.00)	(0.80)	(0.07)	(0.04)	(0.30)
PI	-0.14	5.74	9.16	14.71	5.54	2.74	0.10	-1.04	-1.14	0.09	0.39	1.43
	(1.00)	(0.00)	(0.00)	(0.00)	(0.05)	(0.67)	(1.00)	(1.00)	(1.00)	(0.99)	(0.97)	(0.84)
GSP	6.00	4.35	0.40	-0.20	0.17	1.38	1.55	1.03	2.83	2.34	2.53	0.56
	(0.07)	(0.19)	(0.97)	(0.99)	(0.99)	(0.92)	(0.94)	(0.96)	(0.66)	(0.68)	(0.53)	(0.96)

Table A7: $\Delta\bar{R}^2$ from predictive regressions: without tax-adjusted municipal yields
The table reports the results of estimating state-level predictive regressions that forecast one of six local macroeconomic variables at one of four forecast horizons. Here, the municipal yield data is not adjusted for differences in incomes taxes across states, and the baseline predictive regression is

$$y_{i,t+h} = \alpha + \rho y_{i,t} + \boldsymbol{\beta X_t} + \gamma \varepsilon_{i,t}^{LTS} + u_{i,t+h},$$

where $y_{i,t}$ represents one of the unemployment rate (UR), coincident economic activity index (CI), conditional volatility of the coincident economic activity index (σ (CI)), leading economic activity index (LI), real personal income per capita (PI), or real gross state product (GSP) in state i at time t. The forecast horizons (h) are 3, 6, 9, or 12 months ahead, $\boldsymbol{X_t}$ is a matrix of variables related to aggregate asset prices, and $\varepsilon_{i,t}^{LTS}$ is the long-term slope of state i's municipal spread. The columns labeled "$\Delta\bar{R}^2$" report the changes in adjusted-R^2 obtained by including $\varepsilon_{i,t}^{LTS}$ in the predictive regressions. For each combination of macroeconomic variable and forecast horizon, $\Delta\bar{R}^2$ is calculated by estimating the predictive regression both with γ restricted to zero and with γ unrestricted, and then averaging the corresponding change in adjusted-R^2 across states. "Average $\Delta\bar{R}^2$" summarizes each column by reporting the mean value of $\Delta\bar{R}^2$ across the macroeconomic variables for a fixed forecast horizon. Finally, parentheses report the probability that each $\Delta\bar{R}^2$ statistic arises by chance, obtained via Monte Carlo simulations. The columns labeled "$\hat{\gamma}$" report the estimated value of γ obtained by pooling observations across states, and parentheses report the associated p-values. In Panel A, $\varepsilon_{i,t}^{LTS}$ is obtained by estimating equation (3) over the full sample period. In this case the standard errors associated with $\hat{\gamma}$ are calculated using a GMM procedure that takes the first-stage estimation error into account. In Panel B, $\varepsilon_{i,t}^{LTS}$ is defined as the differences between 20 year and 5 year municipal bond yields in excess of Treasury bond yields. The time period of this analysis ranges from January 2000 to December 2017.

	$\Delta\bar{R}^2$				$\hat{\gamma}$			
$h =$	3	6	9	12	3	6	9	12
Panel A: Estimated long-term slope								
UR	0.50	2.29	4.72	5.92	-1.01	-2.31	-3.41	-3.83
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
CI	0.33	2.01	5.23	8.44	0.12	0.34	0.56	0.72
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
σ (CI)	0.21	1.24	2.97	3.54	-0.20	-0.39	-0.60	-0.66
	(0.71)	(0.07)	(0.00)	(0.00)	(0.01)	(0.01)	(0.00)	(0.00)
LI	2.04	4.90	6.09	4.00	0.15	0.23	0.25	0.21
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
PI	-0.16	0.80	1.05	0.62	-0.09	-0.23	-0.24	-0.18
	(0.92)	(0.25)	(0.27)	(0.51)	(0.03)	(0.00)	(0.00)	(0.04)
GSP	1.98	4.96	9.34	6.54	0.28	0.44	0.57	0.44
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Average $\Delta\bar{R}^2$	0.82	2.70	4.90	4.84	-	-	-	-
Panel B: Observable long-term slope								
UR	0.35	1.92	4.38	5.77	-3.22	-8.05	-12.38	-14.13
	(0.09)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
CI	0.21	1.60	4.60	7.74	0.40	1.20	2.09	2.72
	(0.36)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
σ (CI)	0.12	1.20	3.08	4.97	-0.59	-1.36	-1.97	-2.66
	(0.92)	(0.23)	(0.00)	(0.00)	(0.06)	(0.02)	(0.01)	(0.01)
LI	1.25	4.11	5.59	4.41	0.45	0.80	0.92	0.85
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
PI	-0.36	-0.32	-0.27	0.18	0.16	-0.21	-0.01	0.29
	(1.00)	(1.00)	(1.00)	(0.96)	(0.33)	(0.34)	(0.96)	(0.31)
GSP	0.66	5.57	7.94	6.86	0.97	2.23	2.75	2.61
	(0.17)	(0.00)	(0.00)	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)
Average $\Delta\bar{R}^2$	0.37	2.35	4.22	4.99	-	-	-	-

Table A8: Predictive regressions: alternative yield factors

The table reports the average difference in the adjusted-R^2 ($\Delta\bar{R}^2$) obtained by estimating the following predictive regression on a state-by-state basis both when γ is restricted to zero and when γ is unrestricted:

$$y_{i,t+h} = \alpha + \rho y_{i,t} + \boldsymbol{\beta X_t} + \gamma \varepsilon^x_{i,t} + u_{i,t+h}$$

Here, $y_{i,t}$ represents either the unemployment rate (UR), coincident economic activity index (CI), conditional volatility of the coincident economic activity index (σ (CI)), leading economic activity index (CI), real personal income per capita (PI), or real gross state product (GSP) observed in state i at time t. The forecast horizons (h) considered are 3, 6, 9, or 12 months ahead, and $\boldsymbol{X_t}$ is a matrix of variables related to aggregate asset prices, and $\varepsilon^x_{i,t}$ for $x \in$ {L,STS} is a yield factor related to a state's municipal spread. In Panel A (Panel B) the level (short-term slope) of the municipal spread, denoted $\varepsilon^L_{i,t}$ ($\varepsilon^{STS}_{i,t}$) is obtained by estimating equation (3) with $l_{i,t}$ ($s_{i,t}$) from equation (1) on the left-hand side. For each combination of macroeconomic variable, forecast horizon, and municipal yield factor, the table reports the average value of the adjusted-R^2 across all 19 states. Finally, parentheses report the results of a simulation exercise that computes the probability that the observed $\Delta\bar{R}^2$ arises by chance. The time period of this analysis ranges from January 2000 to December 2017.

	Level (ε^L)				Short-term slope (ε^{STS})			
$h =$	3	6	9	12	3	6	9	12
UR	0.09	0.25	0.45	0.54	0.11	0.25	0.35	0.34
	(0.96)	(0.99)	(0.99)	(1.00)	(0.59)	(0.81)	(0.89)	(0.95)
CI	0.09	0.19	0.25	0.31	0.11	0.24	0.28	0.26
	(0.93)	(0.99)	(1.00)	(1.00)	(0.39)	(0.72)	(0.92)	(0.98)
σ (CI)	0.32	0.18	0.30	0.53	0.27	0.51	0.38	0.54
	(0.65)	(0.99)	(0.99)	(0.96)	(0.47)	(0.44)	(0.76)	(0.64)
LI	-0.06	0.01	0.34	0.17	0.03	0.19	0.22	1.16
	(1.00)	(1.00)	(0.99)	(1.00)	(0.97)	(0.95)	(0.97)	(0.18)
PI	-0.34	0.84	1.97	3.17	-0.13	-0.32	0.80	2.02
	(1.00)	(0.47)	(0.15)	(0.01)	(0.83)	(0.98)	(0.19)	(0.00)
GSP	0.89	2.31	5.23	6.03	0.42	0.02	0.30	4.62
	(0.08)	(0.19)	(0.03)	(0.02)	(0.17)	(0.77)	(0.69)	(0.00)
Average $\Delta\bar{R}^2$	0.17	0.63	1.42	1.79	0.39	0.88	1.45	1.44

Table A9: Predictive regressions: baseline adjusted-R^2 with the long-term slope
The table reports the average adjusted-R^2 obtained by estimating the following predictive regression on a state-by-state basis:

$$y_{i,t+h} = \alpha + \rho y_{i,t} + \boldsymbol{\beta X_t} + \gamma \varepsilon_{i,t}^{LTS} + u_{i,t+h}$$

Here, $y_{i,t}$ represents either the unemployment rate (UR), coincident economic activity index (CI), conditional volatility of the coincident economic activity index (σ (CI)), leading economic activity index (LI), real personal income per capita (PI), or real gross state product (GSP) observed in state i at time t. The forecast horizons (h) considered are 3, 6, 9, or 12 months ahead, and $\boldsymbol{X_t}$ is a matrix of variables related to aggregate asset prices. Finally, $\varepsilon_{i,t}^{LTS}$ represents the long-term slope of each state's municipal spread, obtained by estimating equation (3) over the full sample period. For each combination of macroeconomic variable and forecast horizon, the table reports the average adjusted-R^2 across all states. The final row summarizes each column by reporting the average adjusted-R^2 across macroeconomic variables, while keeping the forecast horizon fixed. The time period of this analysis ranges from January 2000 to December 2017.

	Baseline $\bar{R}^2$			
$h =$	3	6	9	12
UR	88.94	68.60	50.65	39.71
CI	91.61	74.96	57.55	43.24
σ (CI)	36.36	23.99	18.10	15.25
LI	57.63	37.76	34.80	31.33
PI	61.69	37.57	16.71	8.13
GSP	62.91	36.66	26.92	25.41
Average $\bar{R}^2$	72.55	51.11	37.33	29.56

OA.3.5 Municipal yields and stock returns

Table A10: Transition matrix of constituents between slope-sorted portfolios
The table shows the probability of a state sorted into portfolio $i \in$ {Flat, Medium, Steep} in month t, where i is the row index, being sorted into portfolio $j \in$ {Flat, Medium, Steep} 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 3.2. The sample period ranges from January 2002 to December 2017.

Portfolio in	Portfolio in month $t+1$		
month t	Flat	Medium	Steep
Flat	0.503	0.474	0.024
Medium	0.070	0.861	0.069
Steep	0.008	0.497	0.495

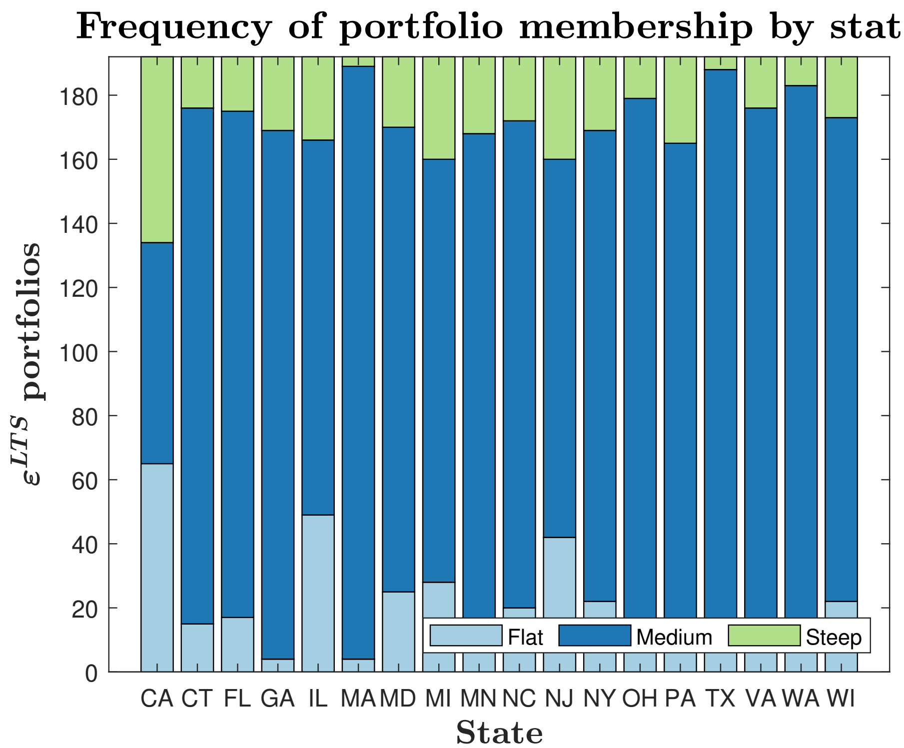


Figure A3: Frequency of portfolio membership by state
The figure reports the number of months each state is sorted into the flat, medium, and steep long-term slope portfolio. States are sorted into portfolios at the end of each month following the portfolio formation procedure described in Section 3.2. The sample period ranges from January 2002 to December 2017.

Table A11: Long-term slope portfolios: alternative factors and unconditional sorts
The table reports the monthly returns of portfolios sorted on (i) the level, (ii) the short-term slope, and (iii) the unconditional long-term slope of each state's municipal spread, as well as the spread between the returns of the Flat (F) and Steep (S) portfolios. The portfolio formation procedure follows that described in Section 3.2 with the following exception. In the columns labeled "ε^L" ("ε^{STS}") the level (short-term slope) of the municipal spread is obtained by estimating equation (3) with $l_{i,t}$ ($s_{i,t}$) from equation (1) on the left-hand side. In the column labeled "ε^{LTS} (unconditional)," portfolios are sorted on the long-term slope of each state's municipal spread, obtained by estimating equation (3), but each state is permanently assigned to a portfolio depending on the value of this long-term slope factor in December 2001. The average and standard deviation of 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 is from January 2002 to December 2017.

	ε^L		ε^{STS}		ε^{LTS} (unconditional)	
	$\mathbb{E}[R]$	$\sigma(R)$	$\mathbb{E}[R]$	$\sigma(R)$	$\mathbb{E}[R]$	$\sigma(R)$
Flat (F)	0.79	4.69	0.87	4.64	0.97	5.18
Medium	0.87	4.12	0.82	4.17	0.82	4.18
Steep (S)	0.70	5.03	1.01	4.73	0.88	4.06
Spread (F-S)	0.09	2.51	-0.14	2.22	0.09	2.76
t(Spread)	(0.51)		(-0.82)		(0.50)	

Table A12: Long-term slope portfolios: sorting on the observable long-term slope
The table reports the monthly returns of portfolios sorted on long-term slope of each state's municipal spread from month $t-1$, as well as the spread between the returns of the Flat (F) and Steep (S) slope portfolios. Here, the long-term slope of each state's municipal spread is defined as the difference between 20 year and 5 year municipal yields in excess of Treasury yields. The portfolio formation procedure used to form these portfolios is described in Section 3.2. The average long-term slope of each portfolio is denoted by LTS, while the mean and standard deviation of 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 2002 to December 2017.

	LTS	$\mathbb{E}[R]$	$\sigma(R)$	N(States)	N(Firms)	$\mathbb{E}\left[R^{EW}\right]$	$\mathbb{E}[R-R_{\text{IND}}]$	$\mathbb{E}[R-R_{\text{DGTW}}]$
Flat (F)	1.16	1.02	4.86	2	282	1.25	0.09	0.08
Medium	1.46	0.85	4.16	14	1594	1.15	0.01	0.04
Steep (S)	1.85	0.60	4.57	2	448	0.96	-0.14	-0.21
Spread (F-S)		0.43	2.51			0.28	0.24	0.29
t(Spread)		(2.33)				(2.15)	(1.87)	(2.04)

Table A13: Long-term slope portfolios: excluding groups of states
The table reports the monthly returns of portfolios sorted on the long-term slope of each state's municipal spread, as well as the spread between the returns of the Flat (F) and Steep (S) long-term slope portfolios. Here, the long-term slope of each state's municipal spread is obtained by estimating equation (3) over a recursive window. The average and the standard deviation of the value-weighted portfolio returns are denoted by $\mathbb{E}[R]$ and $\sigma(R)$, respectively. The portfolio formation procedure follows that described in Section 3.2 with the following two exceptions. First, in the columns labeled "Excluding large" the three largest states in the sample are excluded from the sample. Second, in the columns labeled "Excluding distressed" four states whose municipal debt markets have been tested by municipal defaults or severe fiscal distress are excluded from the sample. Finally, parentheses report Newey and West (1987) t-statistics. The sample is from January 2002 to December 2017.

	Excluding large: CA,NY,TX		Excluding "distressed:" CA,IL,MI,PA	
	$\mathbb{E}[R]$	$\sigma(R)$	$\mathbb{E}[R]$	$\sigma(R)$
Flat (F)	1.11	5.04	0.79	5.01
Medium	0.89	4.19	0.90	4.02
Steep (S)	0.60	4.62	0.31	5.01
Spread (F-S)	0.51	2.93	0.48	3.00
t(Spread)	(2.78)		(2.20)	

Table A14: Value-weighted flat-minus-steep spread and unconditional factor models The table reports the results of time-series regressions of the value-weighted flat-minus-steep spread (the portfolio that buys firms located in states where the long-term slope of the municipal spread is flat and shorts firms located in states where the long-term slope of the municipal spread is steep) on a number of common risk 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 returns span January 2002 to December 2017.

	CAPM	FF3F	FF4F	FF5F	q
MKTRF	0.03	0.05	0.03	-0.01	-0.01
	(0.50)	(0.91)	(0.55)	(-0.19)	(-0.18)
SMB		-0.01	-0.01	-0.07	-0.09
		(-0.20)	(-0.09)	(-0.98)	(-1.11)
HML		-0.15	-0.16	-0.13	
		(-2.25)	(-2.43)	(0.48)	
UMD			-0.04		
			(-0.78)		
Profit.				-0.25	-0.17
				(-2.23)	(-1.34)
Invest.				0.04	-0.12
				(0.34)	(-1.05)
α	0.41	0.41	0.43	0.53	0.51
	(2.54)	(2.66)	(2.66)	(3.20)	(2.91)

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