Inflation Surprises and Municipal Bond Pricing: Evidence from Green and Conventional Municipal Bond Indices

Chaitanya Venkateswaran

Geneva Graduate Institute

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Prof. Marko Mlikota

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Abstract

This paper examines whether green municipal bonds differ from conventional municipals in their exposure to inflation risk. Using monthly U.S. municipal bond index data from 2015 to 2025, I estimate local projection impulse responses of the green–minus–vanilla return spread to inflation surprises constructed from realized CPI inflation and survey-based inflation expectations. Frequentist local projections reveal modest and delayed relative underperformance of green municipals following positive inflation surprises. To improve precision in a small-sample setting, I implement a Bayesian local projection with a conjugate Gaussian (ridge) prior, yielding smoother and more stable dynamic responses while preserving the qualitative pattern. An extension controlling for changes in long-term Treasury yields shows that discount-rate movements only partially mediate the response, indicating the presence of residual green-specific repricing channels. Overall, the results suggest that green municipals exhibit modest but economically meaningful differential exposure to inflation news.

1 Introduction

Green bonds have become an increasingly important instrument for financing climate-related public investment by U.S. state and local governments. As municipal issuers expand their use of green labels to fund renewable energy, transportation, and climate-resilient infrastructure, a natural question is whether green municipal securities differ from conventional municipals in their exposure to macroeconomic risks, particularly inflation.

Existing evidence on green-bond pricing is mixed. Professors from our institute in Panizza et al. (2025) recently found modest pricing differences for green sovereign bonds, while Partridge and Medda (2018) documents a green premium in U.S. municipal bond markets. Martell (2024) emphasizes that inflation and interest rate movements can affect local government fiscal conditions and municipal bond pricing, suggesting that inflation forecast errors may have meaningful implications for relative municipal bond performance.

Building on this, this paper asks:

1. Do green municipal bonds respond differently than conventional municipals to unexpected inflation?

2. How does the relative performance of green and conventional municipal bonds evolve following an inflation forecast error?

3. How does Bayesian shrinkage affect inference and estimated dynamics in a small sample?

To answer these questions, I estimate monthly local projections of green–minus–vanilla municipal bond return spreads on inflation forecast errors. Focusing on the return spread isolates differential pricing associated with green labeling, abstracting from movements common to the municipal market. I complement frequentist inference with Bayesian local projections using a Gaussian (ridge) prior to improve precision in a short time series. As an extension, I implement a reduced-form decomposition controlling for long-term Treasury yield changes to assess the role of discount-rate versus residual green-specific repricing channels.

Economic Interpretation. Differences in inflation exposure between green and conventional municipal bonds may reflect differences in cash-flow duration, investor clientele, regulatory uncertainty, or liquidity premia. The reduced-form analysis does not isolate

these channels individually but provides evidence on their combined effect on relative pricing.

2 Data and Construction of Key Variables

2.1 Bond Indices and Returns

I use the *S&P U.S. Municipal Green Bond Index* and the *S&P U.S. Municipal Bond Index* from 2016 to 2025. Daily index levels are converted to month-end levels by selecting the last available trading day in each calendar month. Monthly log returns are then computed as

$$r_t = \Delta \log(P_t) = \log(P_t) - \log(P_{t-1}).$$

I define the return spread as

$$r_t^{\text{spread}} = r_t^{\text{green}} - r_t^{\text{muni}}$$

2.2 Inflation and Inflation Expectations

Inflation is measured using the CPIAUCSL from the Federal Reserve Bank of St. Louis (FRED) database. Monthly year-over-year inflation is constructed as

$$\pi_t^{\text{yoy}} = 100 \times \left(\log(\text{CPI}_t) - \log(\text{CPI}_{t-12}) \right).$$

Inflation expectations are proxied by the *University of Michigan Survey of Consumers inflation expectations series (MICH)*, also obtained from FRED. Expectations are shifted by twelve months so that $\mathbb{E}_t[\pi_t^{\text{yoy}}]$ reflects information available to agents at time t about inflation realized over the subsequent twelve months. Hence, the inflation forecast error is defined as

$$s_t = \pi_t^{\text{yoy}} - \mathbb{E}_{t-12}[\pi_t^{\text{yoy}}],$$

2.3 Interest-Rate Control

For the decomposition extension, I use the monthly change in the 10-year Treasury yield (DGS10) also from FRED, denoted Δy_t^{10}, measured in basis points.

2.4 Summary Statistics

Table 1 reports summary statistics for monthly returns and inflation forecast errors.

Table 1: Descriptive Statistics (Monthly)

Variable	Mean	Std. Dev.	Min	Max
r_t^{green}	0.001615	0.018587	-0.056948	0.062985
r_t^{muni}	0.001807	0.014554	-0.036969	0.057344
r_t^{spread}	-0.000192	0.004909	-0.021701	0.012165
s_t (inflation surprise)	0.027506	1.739809	-2.701995	5.095577

Notes: Returns are monthly log returns computed from month-end index levels. Inflation surprise is realized year-over-year CPI inflation minus Michigan inflation expectations.

3 Methodology

3.1 Frequentist Local Projections

For horizons $h = 0, 1, \ldots, H$, I estimate the local projection regression

$$r_{t+h}^{\text{spread}} = \alpha_h + \beta_h s_t + \sum_{\ell=1}^{L} \phi_{h,\ell} r_{t-\ell}^{\text{spread}} + \sum_{\ell=1}^{L} \psi_{h,\ell} s_{t-\ell} + u_{t+h},$$

where r_{t+h}^{spread} denotes the green–minus–vanilla municipal bond return spread h months ahead and s_t is the inflation surprise. The coefficient β_h is the impulse response at horizon h. Lags of the spread control for persistence in relative bond performance, while lagged surprises account for serial correlation and delayed responses to inflation news.

Identification relies on the assumption that inflation surprises are conditionally exogenous with respect to future innovations in return spreads, conditional on lagged spreads and lagged shocks. Formally, identification requires

$$\mathbb{E}\left[u_{t+h} \mid s_t, \{r_{t-\ell}^{\text{spread}}\}_{\ell=1}^{L}, \{s_{t-\ell}\}_{\ell=1}^{L}\right] = 0 \qquad \text{for all } h.$$

Under this conditional moment restriction, ordinary least squares consistently estimates

β_h as the linear projection of r_{t+h}^{spread} onto the innovation s_t and lagged controls, with each horizon estimated separately.

Because monthly returns exhibit serial correlation, heteroskedasticity, and overlapping observations across horizons, inference is based on Newey–West heteroskedasticity- and autocorrelation-consistent (HAC) standard errors with horizon-dependent bandwidths. Results are robust to alternative Newey–West bandwidth choices (see Appendix).

Applicability and Alternatives:

Local projections (LPs) are particularly well suited when shocks are observed directly and are plausibly exogenous, as with inflation forecast surprises. They allow for flexible, horizon-specific dynamics without imposing the tight dynamic restrictions of vector autoregressive (VAR) models, which hrequire correct specification of joint system dynamics, invertibility of the moving-average representation, and normalization or ordering assumptions for shock identification. LPs provide direct reduced-form impulse responses with minimal identifying assumptions - along with transparency in small samples.

LPs estimate linear conditional mean responses and therefore capture best linear approximations to potentially nonlinear underlying dynamics. The results should thus be interpreted as reduced-form linear effects rather than structural nonlinear responses.

The analysis is carried out on a relatively small monthly sample (2016–2025, 108 observations) which cannot be expanded much further since the very first green muni bond in the US was only issued in 2013 in Massachusetts. A key limitation is that horizon-by-horizon estimation can be noisy at longer horizons with a smaller sample size, motivating the Bayesian shrinkage approach introduced below.

3.2   Bayesian Local Projections with Gaussian (Ridge) Prior

To mitigate small-sample noise and overfitting in the local-projection framework, I estimate a Bayesian analogue of the baseline model using a conjugate Gaussian regression prior. For each horizon h, the model is

$$r_{t+h}^{\text{spread}} = X_t \theta_h + u_{t+h}, \qquad u_{t+h} \sim \mathcal{N}(0, \sigma_h^2),$$

where X_t collects the constant, the inflation surprise, and lagged controls. Conditional on σ_h^2, coefficients are assigned a Gaussian prior:

$$\theta_h \mid \sigma_h^2 \sim \mathcal{N}(0, \sigma_h^2 \lambda^{-1} I),$$

with a noninformative Jeffreys prior on σ_h^2. This conjugate structure implies that the posterior mean of θ_h coincides with a ridge-regularized estimator.

The ridge prior shrinks coefficients toward zero, reflecting the belief that large dynamic responses are unlikely absent strong evidence. The shrinkage parameter λ governs the bias–variance tradeoff: larger values induce stronger shrinkage, reducing estimation variance and producing smoother impulse response functions at the cost of some bias. Credible intervals are obtained from the marginal Student-t posterior distribution of the coefficients.

The Bayesian specification assumes that regression coefficients are a priori centered at zero with finite variance, reflecting the belief that large dynamic responses are unlikely absent strong evidence in the data. This specification is particularly suitable in settings with limited time-series length and multiple lagged regressors, where frequentist estimates may be unstable. Its main advantage is improved precision and interpretability of impulse responses through regularization, while its main limitation is sensitivity to the choice of λ and the introduction of shrinkage bias. Sensitivity analyses are therefore reported for alternative values of the shrinkage parameter.

3.3 Economic Decomposition Extension: Discount-Rate vs. Residual Channels

To assess whether the baseline spread response primarily reflects discount-rate exposure, I augment the local projection specification by controlling for changes in the long-term risk-free yield. For each horizon h, I estimate

$$r_{t+h}^{\text{spread}} = \alpha_h + \beta_h^{(r)} s_t + \delta_h \Delta y_t^{10} + (\text{lags of } r^{\text{spread}}, s, \Delta y^{10}) + u_{t+h},$$

where Δy_t^{10} denotes the monthly change in the 10-year Treasury yield.

This specification isolates the component of the inflation surprise transmitted through movements in discount rates. The decomposition assumes that, conditional on contemporaneous and lagged changes in the long-term Treasury yield, the remaining variation in inflation surprises captures non–discount-rate channels affecting relative municipal bond pricing.

If inclusion of Δy_t^{10} substantially attenuates the estimated response to s_t, the baseline effect is interpreted as being driven primarily by duration or discount-rate exposure. If the response remains similar, the results are consistent with residual green-specific repricing, such as changes in risk premia, liquidity, or valuation associated with green labeling.

This exercise should be interpreted as a reduced-form mediation test rather than a fully structural decomposition.

4 Empirical Results

4.1 Baseline Impulse Responses

Figure 1 plots impulse responses of the green–minus–vanilla municipal bond return spread to an inflation surprise, estimated using frequentist and Bayesian local projections. Shaded areas denote 95% HAC confidence intervals for the frequentist LP and 95% marginal posterior credible intervals for the Bayesian LP. Conditional on an inflation surprise at time t, responses are close to zero at short horizons, become modestly negative at intermediate horizons, and gradually return toward zero thereafter. Given the relatively small monthly sample (108 observations), we emphasize qualitative patterns.
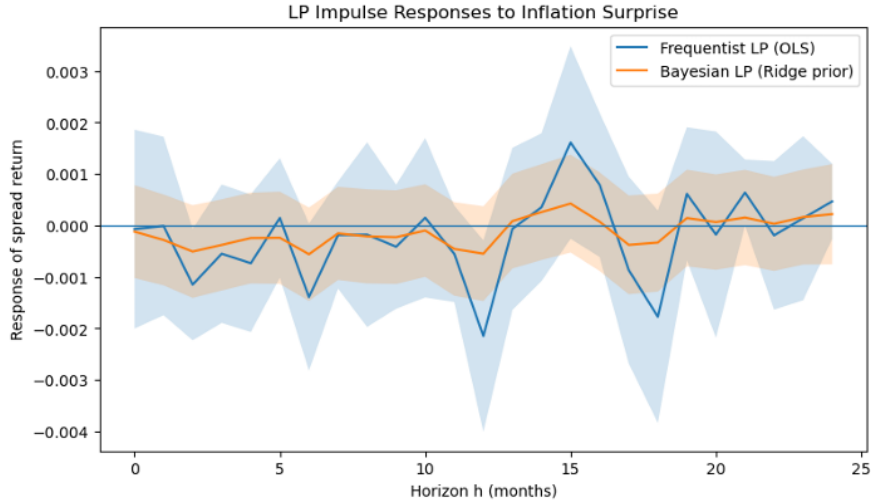

Figure 1: Impulse Responses of Green–Vanilla Spread Returns to Inflation Surprises

The frequentist estimates exhibit substantial horizon-to-horizon variability, while the Bayesian ridge-regularized estimates yield smoother and more attenuated responses, reflecting shrinkage toward zero. At horizon $h = 2$, the frequentist estimate is negative and statistically different from zero, while Bayesian credible intervals generally include zero at most horizons, indicating modest but imprecisely estimated relative underperformance of green municipals following inflation surprises.

In economic terms: At its peak, the frequentist estimate implies approximately 10 basis points of relative underperformance of green municipals in a single month, corresponding to about $100,000 for a $100 million portfolio.

4.2 Cumulative Responses

Figure 2 reports cumulative responses defined as

$$\mathbb{E}\left[\sum_{j=1}^{h} r_{t+j}^{\text{spread}} \,\middle|\, s_t = 1\right],$$

estimated directly via cumulative local projections. Cumulative responses are negative over most horizons and grow in magnitude over the first year, indicating gradual cumulative underperformance of green municipals following inflation forecast errors. Bayesian cumulative responses are smaller in magnitude but follow the same qualitative pattern.
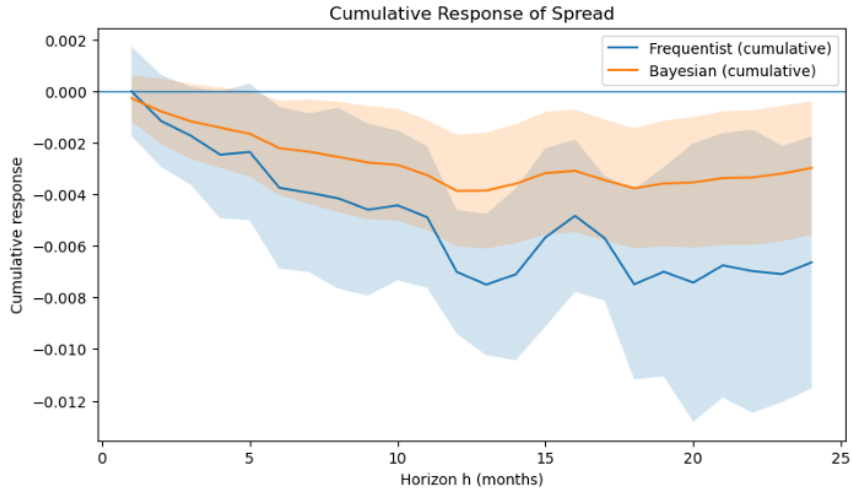

Figure 2: Cumulative Response of Green–Vanilla Spread Returns

4.3 Sensitivity to Regularization

Figure 3 illustrates sensitivity of the Bayesian impulse responses to alternative values of the shrinkage parameter. In simple terms, this graph helps us understand: *Is our Bayesian regularization creating the shape of the result, or is the result already in the data?*.
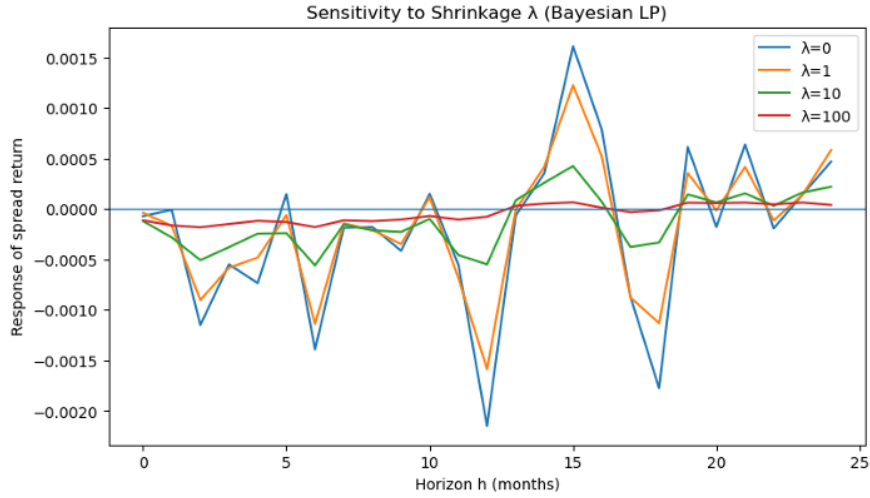

Figure 3: Bayesian Impulse Responses to λ Sensitivity

As λ increases, impulse response magnitudes are monotonically compressed and profiles become smoother, while the timing and qualitative shape of the responses are preserved. This pattern indicates that the dynamic structure of the response is present in the data, while the Ridge Prior primarily controls sampling variability rather than driving the results.

4.4 Discount-Rate Decomposition

Figure 4 compares baseline impulse responses to those obtained when controlling for contemporaneous and lagged changes in the 10-year Treasury yield. At several horizons, controlling for long-term yield changes modestly attenuates the magnitude of the response, while at others the response remains similar and confidence bands overlap substantially. This pattern indicates partial mediation of the inflation-surprise effect through discount-rate movements, but does not support a purely mechanical duration-based explanation.
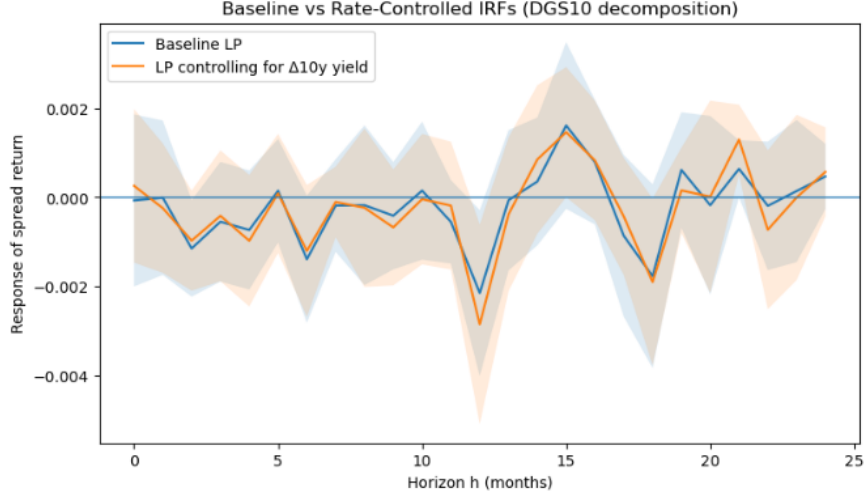
Figure 4: Baseline vs. Rate-Controlled IRFs

The persistence of negative cumulative responses is consistent with the presence of residual green-specific repricing channels, such as risk premia, liquidity, or valuation effects. The Appendix reports placebo IRFs with different HAC bands.

5   Conclusion

Using local projections of the green–minus–vanilla municipal bond return spread on inflation forecast errors, this paper finds modest but persistent relative underperformance of green municipals following higher-than-expected inflation. Although monthly effects are small, they accumulate over intermediate horizons to economically meaningful magnitudes.

Bayesian local projections with a Gaussian (ridge) prior yield smoother and more stable impulse responses than frequentist estimates, highlighting the value of regularization in small samples with multiple lagged controls. Controlling for long-term Treasury yield changes partially attenuates the response, indicating that inflation affects green municipal pricing not only through discount-rate movements but also through residual green-specific repricing channels.

The analysis is conducted at the index level within the U.S. municipal bond market; heterogeneity across bond types and international markets is beyond the scope of this study - but can be potential extensions to this work.

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Data Sources

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Appendix: Supplementary Materials

https://github.com/chaitanyavenkateswaran/municipal-bond