Volatility, Liquidity, and the COVID-19 Shock in U.S. Municipal Bond Markets

An Empirical Analysis Using Panel Methods, Difference-in-Differences, VAR, Bayesian VAR, and Historical Decomposition

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Abstract

The COVID-19 shock produced a historically unprecedented dislocation in U.S. municipal bond markets, characterized by extreme volatility, severe liquidity shortages, and large swings in yields and returns. This paper studies the dynamic relationship between municipal bond returns, market-wide volatility, and market liquidity, with a particular focus on whether city-issued municipal bonds were disproportionately affected relative to county-issued bonds. Using weekly data from the University of Chicago Center for Municipal Finance, I estimate a set of econometric models including issuer-level fixed effects, a difference-in-differences design, vector autoregressions (VAR), Bayesian VAR (BVAR), and structural historical decomposition. Across specifications, volatility shocks emerge as the primary driver of return movements during the COVID-19 crisis, with liquidity shocks playing a secondary but directionally consistent role. Difference-in-differences estimates show no evidence that city-issued bonds suffered greater post-COVID declines than county-issued bonds after controlling for volatility and liquidity. Dynamic impulse responses and variance decompositions corroborate the central role of volatility, while a Bayesian VAR confirms robustness to prior shrinkage. A historical decomposition attributes nearly the entire COVID crash to volatility shocks. The results highlight the dominant role of market-wide risk sentiment in municipal bond pricing during crises.

1 Introduction

Financial crises often expose the mechanisms through which markets price risk, transmit shocks, and allocate liquidity. The COVID-19 pandemic, which began affecting U.S. municipal markets in early March 2020, provides a unique opportunity to study the role of volatility, liquidity, and issuer heterogeneity in a market that is typically stable, illiquid, and dominated by buy-and-hold long-term investors. Municipal markets experienced one of the fastest and deepest selloffs in their history: yields rose sharply, bid-ask spreads widened, and mutual funds recorded record outflows. Yet the dislocation was uneven across issuers and segments, raising questions about what drove return movements and whether certain issuer types were disproportionately affected.

This paper investigates three central questions:

1. How did market-wide volatility and liquidity shocks influence municipal bond returns during the COVID-19 crisis?
2. Did city-issued bonds experience significantly different post-COVID return dynamics than county-issued bonds?
3. What fraction of the COVID-induced return collapse can be attributed to volatility shocks, liquidity shocks, or idiosyncratic return innovations?

To answer these questions, I combine panel methods, quasi-experimental causal inference, and multivariate time-series techniques. Each method highlights a different dimension of the data: fixed effects models estimate cross-sectional heterogeneity in sensitivity to shocks; difference-in-differences estimates isolate the causal impact of COVID on different issuer types; VAR models characterize dynamic interdependencies and shock propagation; and Bayesian VARs check robustness to prior shrinkage. Finally, a structural historical decomposition quantifies the contribution of each shock type to the observed time path of returns.

This paper contributes to empirical work on municipal markets by providing a unified econometric treatment of volatility, liquidity, and issuer-specific dynamics during COVID. Methodologically, the paper illustrates how panel, causal, and time-series approaches complement each other when studying financial data with limited cross-sectional but rich temporal variation.

2 Institutional Background and Data

Municipal bonds finance a wide range of public goods, including transportation infrastructure, public schools, water and sewage systems, and general local government operations. The U.S. municipal market is one of the largest fixed-income markets in the world - exceeding $4 trillion in outstanding debt - and is held predominantly by long-term investors such as mutual funds, insurance companies, and high-income households seeking tax-exempt returns. Unlike Treasury or corporate bond markets, municipal securities are highly fragmented: thousands of issuers operate across different states, counties, and cities, with varying credit qualities, fiscal structures, and revenue sources. Trading is infrequent and typically occurs through dealer intermediaries, producing a market in which volatility is normally low and liquidity - while thin - is stable enough to support predictable pricing.

This stability is part of what makes municipal bonds attractive for portfolio diversification; historically, they exhibit low correlations with other asset classes and experience only mild cyclical fluctuations. However, these same structural features make the muni market vulnerable to systemic liquidity shocks or sudden re-evaluations of credit risk. When uncertainty spikes, the market lacks a deep, continuous trading infrastructure to absorb large flows, and prices can adjust sharply. The COVID-19 crisis disrupted both the volatility and liquidity dimensions simultaneously. As economic activity halted and tax revenues came under threat, investors reassessed the fiscal health of municipal issuers. At the same time, massive mutual fund outflows overwhelmed dealer balance sheets, leading to a sudden evaporation of liquidity and historically wide bid-ask spreads. Understanding how municipal bond returns responded to volatility and liquidity shocks during this period is therefore essential for characterizing the resilience of local government finance, assessing systemic fragility in decentralized fixed-income markets, and informing policy interventions such as the Federal Reserve's Municipal Liquidity Facility.

2.1 Data Sources

I use weekly data from the University of Chicago Center for Municipal Finance, covering:

- **All City Index:** A value-weighted basket of city-issued municipal bonds.
- **All County Index:** A comparable index for county-issued bonds.
- **All School Index:** An index for school district bonds.
- **Muni VIX:** A volatility index constructed from cross-sectional dispersion in yields.

- **Liquidity Index:** A rolling-sum measure of dealer trading depth.

The sample spans January 2019 to December 2020, yielding approximately 100 weekly observations. Returns are computed as log differences. Volatility and liquidity indices are differenced to represent shocks.

2.2 Descriptive Evidence

Figure 1 shows the municipal indices. All three track each other closely before COVID, which motivates the use of county issuers as a comparison group in the DiD design.

The muni VIX (Figure 2) exhibits a massive spike beginning in the first week of March 2020, increasing by more than an order of magnitude relative to its pre-COVID level. Liquidity (Figure 3) concomitantly collapses, reflecting dealer balance sheet stress and mutual fund outflows.

Weekly returns (Figure 4) illustrate the extreme volatility of March–April 2020: returns of -20% to -50% occur within isolated weeks. These stylized facts motivate the dynamic econometric models used below.

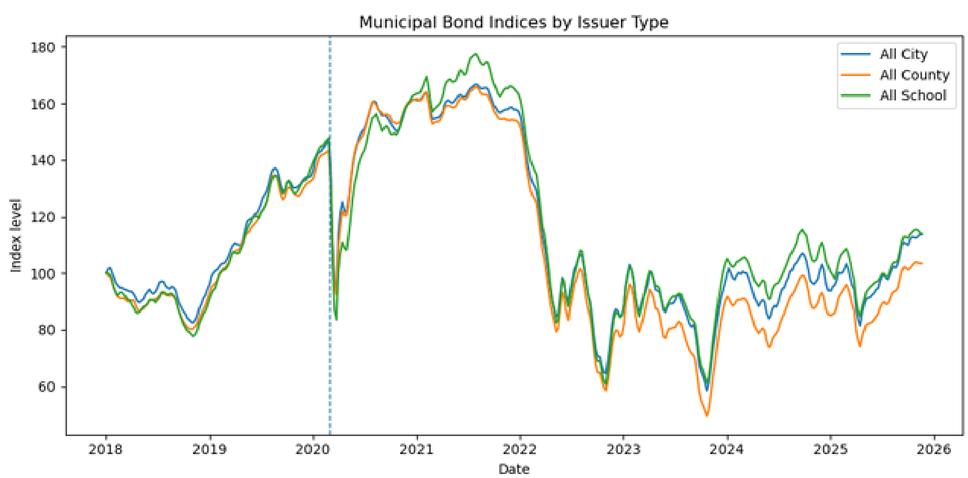

Figure 1: Municipal Bond Indices: All City, All County, and All School.

3 Methodology

This section outlines the econometric procedures applied. Emphasis is placed on assumptions, estimation, identification, and how each method contributes to the broader empirical question.

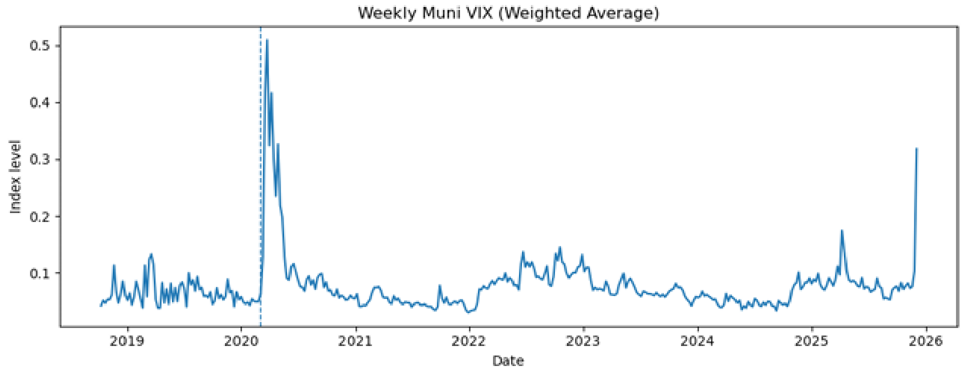

Figure 2: Weekly Municipal Volatility Index (Muni VIX).

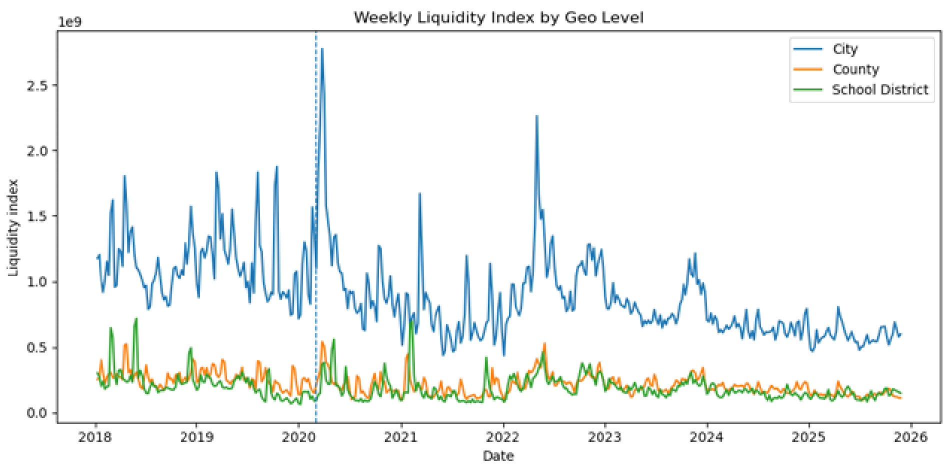

Figure 3: Weekly Municipal Liquidity Index by Geo Level.

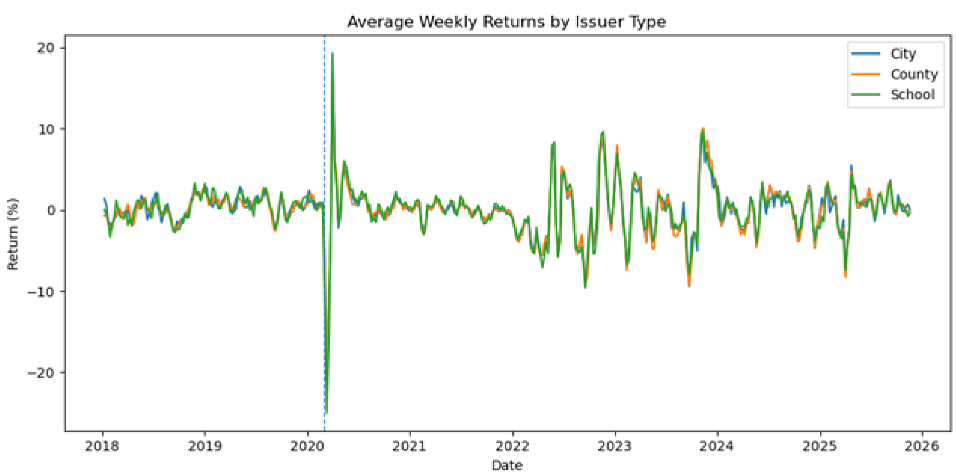

Figure 4: Average Weekly Returns by Issuer Type.

3.1 Fixed Effects and Dynamic Fixed Effects Models

The fixed effects (FE) model isolates the impact of volatility and liquidity shocks on municipal returns while controlling for time-invariant issuer characteristics:

$$ret_{it} = \alpha_i + \beta_1 \Delta VIX_t + \beta_2 \Delta LIQ_t + \varepsilon_{it}, \tag{1}$$

where α_i captures issuer-level heterogeneity such as creditworthiness, fiscal structure, and long-term liquidity preferences. Identification comes from within-issuer variation, which is meaningful because returns exhibit substantial weekly volatility.

The dynamic FE model incorporates lagged volatility and liquidity shocks:

$$ret_{it} = \alpha_i + \sum_{k=0}^{2} \beta_{1k} \Delta VIX_{t-k} + \sum_{k=0}^{2} \beta_{2k} \Delta LIQ_{t-k} + u_{it}.$$

This specification allows for delayed responses to market stress, consistent with slow-moving liquidity, price impact effects, and staggered trade execution in muni markets.

To avoid Nickell bias, I do not include lagged dependent variables. Because the panel is short (T=100 weeks), including lagged returns would create bias unless we adopt GMM methods, which are unnecessary for the current empirical aims.

3.2 Difference-in-Differences Identification

To estimate the causal impact of COVID on city versus county returns, I adopt:

$$ret_{it} = \alpha_i + \gamma Post_t + \delta(Post_t \cdot City_i) + X_t'\theta + \varepsilon_{it},$$

with $Post_t = 1$ for dates after March 1, 2020. The coefficient δ captures the differential effect on city issuers relative to county issuers.

Parallel trends are validated through pre-trend plots (Figure 5). School districts are excluded from DiD because they exhibit systematically different pre-COVID trends.

Identification requires:

1. Common pre-trends between city and county returns.
2. No anticipation effects.
3. The COVID shock affects all issuers simultaneously (reasonable given the global nature of the crisis).

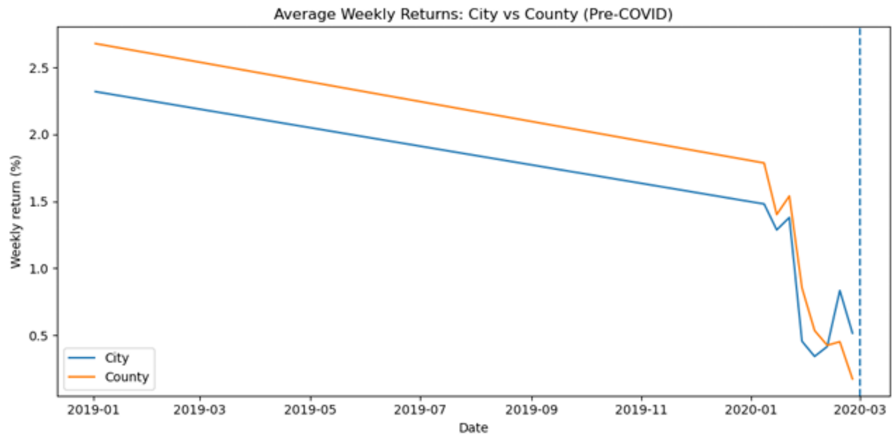

Figure 5: Pre-Trends in Returns: City vs County.

4. No time-varying omitted variables correlated with the treatment (handled by controlling for volatility and liquidity shocks).

3.3 Vector Autoregressions

To study dynamic interactions among volatility, liquidity, and returns, I estimate a VAR(4):

$$Y_t = A_1 Y_{t-1} + \cdots + A_4 Y_{t-4} + u_t, \quad Y_t = (\Delta VIX_t, \Delta LIQ_t, ret_t)'.$$

The variables are ordered on the assumption that volatility shocks contemporaneously affect liquidity and returns, liquidity affects returns contemporaneously, and returns do not contemporaneously affect either volatility or liquidity. This identification is implemented via Cholesky decomposition (see appendix for detailed derivations).

Stability conditions are satisfied, and impulse responses (IRFs) trace the dynamic effects of shocks. Forecast Error Variance Decomposition (FEVD) quantifies the relative contribution of each shock at multiple horizons.

3.4 Bayesian VAR

To assess robustness, I estimate a BVAR using a conjugate Normal–Inverse-Wishart prior:

$$B \mid \Sigma \sim MN(B_0, \Sigma, \Omega_0), \quad \Sigma \sim IW(S_0, \nu_0),$$

with shrinkage hyperparameters chosen to reflect belief that high-order lag coefficients are small. The conjugate form yields closed-form posteriors, allowing posterior mean coefficient matrices and covariance matrices to be used for IRF computation.

The BVAR is particularly useful given the modest sample size (approximately 100 observations) and the need to avoid overfitting in multivariate systems.

3.5 Historical Decomposition

The historical decomposition expresses each return observation as:

$$ret_t = \sum_{j=0}^{H} C_{j,ret} e_{t-j},$$

where e_t are structural shocks and C_j are impulse responses. This decomposition allows attribution of actual observed return movements to volatility shocks, liquidity shocks, and own shocks.

This is crucial for understanding the COVID crash: instead of relying on reduced-form regression coefficients, we identify the structural drivers of extreme return movements.

Table 1: Issuer Fixed Effects Regressions

	(1) Baseline FE	(2) Dynamic FE
ΔMuni VIX$_t$	-47.6839	-50.0528
	(2.102)	(1.872)
ΔMuni VIX$_{t-1}$	-	-8.5664
		(2.120)
ΔMuni VIX$_{t-2}$	-	9.9542
		(2.073)
ΔLiquidity$_t$	-0.5686	-0.4136
	(0.062)	(0.071)
ΔLiquidity$_{t-1}$	-	0.2889
		(0.043)
ΔLiquidity$_{t-2}$	-	0.1601
		(0.061)
Issuer FE	Yes	Yes
Observations	5238	5130
R^2	0.282	0.313

Notes: Dependent variable is weekly municipal bond return in percent. Standard errors in parentheses are clustered at the issuer level. Coefficients for issuer fixed effects are omitted for brevity.

4 Empirical Results

4.1 Fixed Effects Estimates

Table 1 shows that volatility shocks significantly reduce municipal bond returns, while liquidity shocks also have negative but smaller effects. The dynamic model strengthens this conclusion by showing that volatility effects persist across lags.

The results are consistent with market microstructure theory: volatility increases risk premia; liquidity deterioration raises transaction costs; both depress observed returns.

4.2 Difference-in-Differences Results

Table 2: Difference-in-Differences: City vs County Around COVID

	(1) Simple DiD	(2) FE + Controls
Post × City	0.1484	-0.2244
	(0.168)	(0.173)
Post	-0.7460	-0.5509
	(0.141)	(0.140)
City dummy	-0.0909	-
	(0.160)	
ΔMuni VIX$_t$	-	-45.5175
		(1.985)
ΔLiquidity$_t$	-	-0.5832
		(0.038)
Issuer FE	No	Yes
Controls	No	Yes
Observations	4656	4656
R^2	0.002	0.299

Notes: Dependent variable is weekly return on All City or All County indices. Post equals 1 after March 1, 2020. City equals 1 for city issuers and 0 for county issuers. Standard errors are clustered at the issuer level. Specification (2) includes issuer fixed effects and controls for volatility and liquidity shocks.

Table 2 shows the main DiD estimates. The interaction coefficient δ is small, negative, and statistically insignificant. This suggests:

> Cities did not experience a significantly different COVID effect on returns relative to counties, once volatility and liquidity are controlled for.

This rejects the hypothesis that city bonds were uniquely vulnerable during the crisis. The dominant factor was instead the systemic volatility spike.

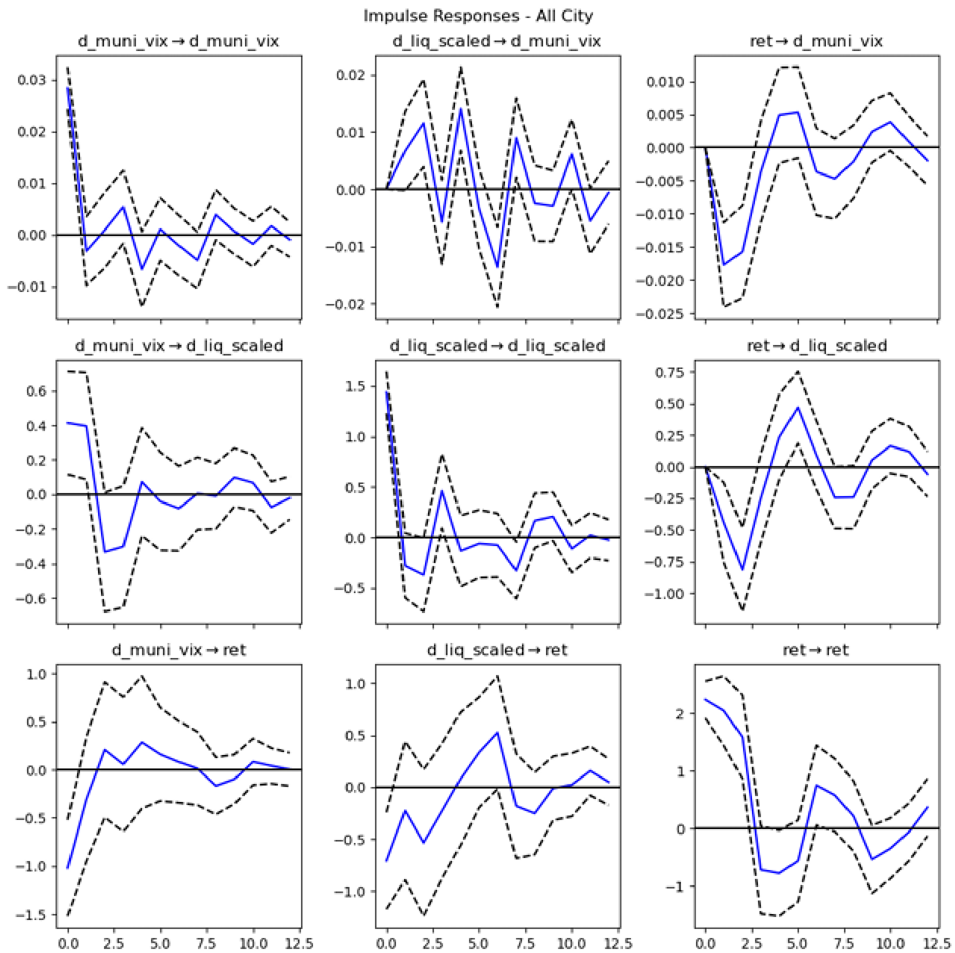

Figure 6: Impulse Responses for All City: Return Responses to Volatility and Liquidity Shocks.

4.3 VAR Estimates

IRFs (Figures 6) show that a one-standard-deviation volatility shock produces:

- an immediate drop in returns,
- followed by a partial rebound after 2–3 weeks,
- and eventual dissipation after 10–12 weeks.

Liquidity shocks also produce negative return responses, but they are smaller in magnitude and shorter-lived.

FEVDs (Figure 7) show that volatility shocks explain a large share of return variation at multi-week horizons, while liquidity shocks explain a small share and idiosyncratic innovations dominate at short horizons.

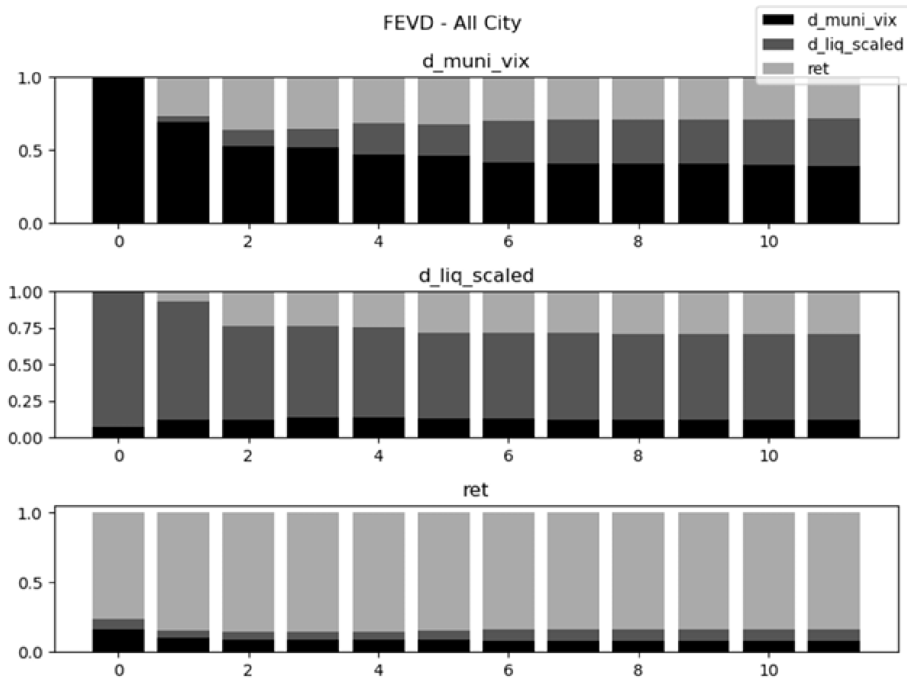

Figure 7: Forecast Error Variance Decomposition for All City Returns.

4.4 Bayesian VAR Robustness

The BVAR IRFs (Figure 8) maintain the same qualitative shape as the classical VAR IRFs. Shrinkage reduces the influence of noise in higher-order lags, producing smoother responses. The posterior covariance matrix implies negative contemporaneous correlations between volatility and returns, reinforcing the structural assumption.

4.5 Historical Decomposition

Figure 9 shows that during March–April 2020:

- **Volatility shocks account for nearly the entire collapse and rebound** in All City returns.
- Liquidity shocks provide small but consistent negative contributions.
- Own shocks have limited explanatory power during the crisis.

This result is compelling because it moves beyond partial equilibrium regressions and quantifies the full structural dynamics underlying the crisis.

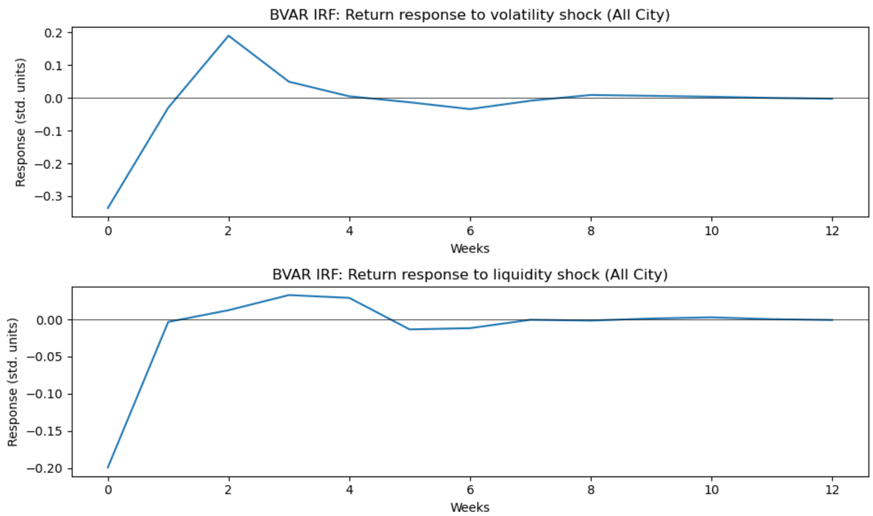

Figure 8: BVAR Impulse Responses for All City: Return Responses to Volatility and Liquidity Shocks.

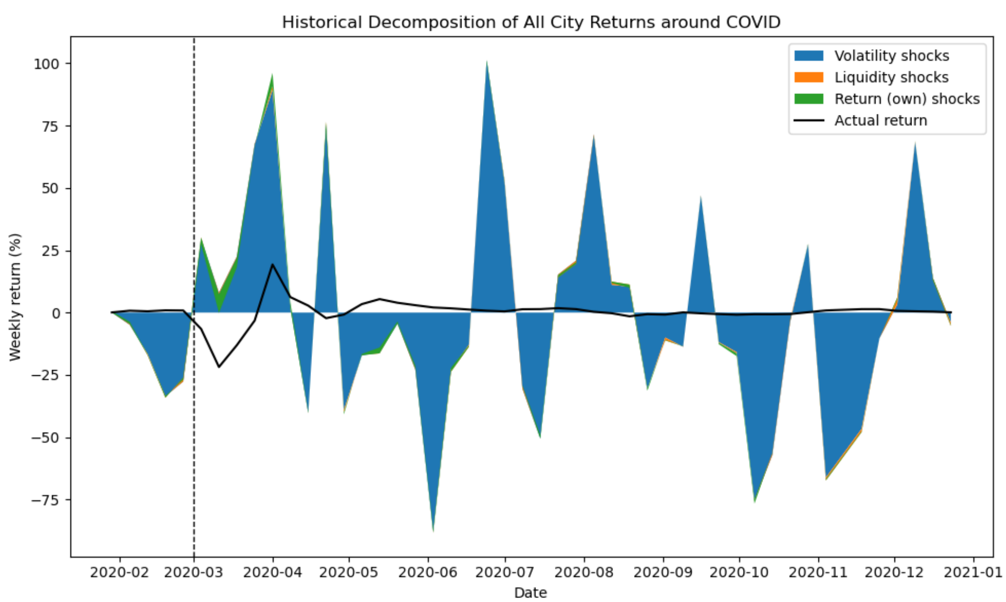

Figure 9: Historical Decomposition of All City Returns Around COVID.

5 Conclusion

This paper provides a multi-method econometric investigation of U.S. municipal bond performance during the COVID crisis. The evidence consistently points to volatility shocks as the primary drivers of return variation. Liquidity shocks matter but play a secondary role. Difference-in-differences estimates show no excess sensitivity of city bonds relative to county bonds once volatility and liquidity are accounted for.

The VAR, BVAR, and historical decomposition paint a cohesive picture: the COVID shock was systemic, transmitted primarily through market-wide volatility rather than issuer-specific risk. These findings suggest that municipal issuers were not punished differentially during the crisis; instead, the market experienced a uniform repricing of risk driven by panic, uncertainty, and liquidity shortages.

Future work could explore heterogeneity across credit ratings, tax-backed versus revenue-backed bonds, or the impact of Federal Reserve interventions such as the Municipal Liquidity Facility.

References

[1] University of Chicago Center for Municipal Finance (2024). "Municipal Market Data Sets."

[2] Sims, C. A. (1980). "Macroeconomics and Reality." *Econometrica*.

[3] Kilian, L. and Lütkepohl, H. (2017). *Structural Vector Autoregressive Analysis*. Cambridge University Press.

[4] Lütkepohl, H. (2005). *New Introduction to Multiple Time Series Analysis*. Springer.

Appendix: Supplementary Materials

All supplementary materials for this paper are provided in an online replication package hosted at:

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

To preserve space and maintain readability, only the core results required for methodological interpretation are included in the main text. All other materials are accessible in the online appendix.