A Supplemental Appendix for "The Option Value of Municipal Liquidity" Andrew Haughwout, Benjamin Hyman, and Or Shachar (2025)

A.1 Robustness and Sensitivity

A.1.1 Yields RD Specification Sensitivity

Table A.1: Estimate Sensitivity to Restrictions, Controls, Kernel, Bandwidth, Polynomial, and Clustering

Panel A. Two-Step Method

	(1)		(2)		(3)		(4)		(5)		(6)	
a. Pooled Post:												
Overall Yield	-12.56	(21.14)	-3.95	(17.68)	-9.73	(11.58)	**-18.87**	**(18.55)**	-19.22	(19.02)	-37.62	(27.00)
City Only	-29.18	(28.10)	-38.94	(28.23)	-6.96	(13.53)	**-27.06**	**(23.71)**	-28.03	(25.97)	-41.76	(32.98)
County Only	-17.02	(20.20)	-12.42	(30.68)	-18.92	(14.46)	**-15.67**	**(24.01)**	-15.69	(25.89)	-21.81	(45.16)
High-Rated	-0.48	(7.96)	1.72	(8.12)	-0.42	(5.83)	**-1.34**	**(7.32)**	-1.42	(8.06)	-3.31	(11.83)
Low-Rated	-83.27**	(38.12)	-81.79**	(38.73)	-68.54*	(36.53)	**-69.85****	**(32.34)**	-69.93**	(31.12)	-68.88	(45.30)
b. Pooled Pre:												
Overall Yield	-10.35	(11.23)	-8.11	(10.81)	-5.27	(6.72)	**-12.80**	**(11.96)**	-12.90	(11.84)	-21.63	(18.06)
City Only	-3.61	(10.99)	-8.19	(12.07)	-0.09	(7.11)	**-9.32**	**(12.15)**	-9.08	(11.96)	-13.90	(19.53)
County Only	-20.61	(13.14)	-21.58	(18.95)	-15.82	(12.07)	**-21.15**	**(18.90)**	-21.47	(18.50)	-23.49	(34.73)
High-Rated	-4.11	(5.46)	-6.43	(8.12)	-3.53	(5.06)	**-6.12**	**(7.66)**	-6.18	(7.61)	-6.95	(11.91)
Low-Rated	-38.44	(25.24)	-43.14	(33.77)	-21.46	(22.40)	**-24.14**	**(21.42)**	-23.76	(20.31)	-25.39	(26.72)
State FE	X		X		X		**X**		X		X	
Month FE	X		X		X		**X**		X		X	
Maturity FE												
Minimum State-Maturity Cell Size												
Estimator	Two-Step		Two-Step		Two-Step		**Two-Step**		Two-Step		Two-Step	
Bandwidth Method	IMSE		IMSE		Fixed		**IMSE**		IMSE		IMSE	
Kernel	Uniform		Uniform		Triangular		**Triangular**		Triangular		Triangular	
Polynomial Degree	1		2		1		1		1		2	
Bandwidth (Low-Rated Post)	[-130, 563]		[-227, 1426]		[-200, 500]		**[-208, 811]**		[-207, 798]		[-208, 811]	
Bandwidth (Low-Rated Placebo)	[-111, 643]		[-203, 1196]		[-200, 500]		**[-168, 863]**		[-169, 840]		[-168, 863]	
N (Low-Rated Post)	27,839		68,086		39,472		**43,823**		43,802		43,823	
N (Low-Rated Placebo)	8,006		17,262		12,735		**12,792**		10,495		12,792	
Clustering	Relative Pop		Relative Pop		Relative Pop		**Relative Pop**		Issuer		Relative Pop	

Panel B. CCFT Method

	(9)		(10)		(11)		(12)		(13)		(14)	
a. Pooled Post:												
Overall Yield	-20.91	(15.75)	-17.71	(17.80)	-8.88	(7.81)	**-18.32**	**(14.34)**	-18.22	(15.93)	-12.30	(14.56)
City Only	-26.64	(17.69)	-39.42*	(20.32)	-10.99	(10.36)	**-32.06****	**(16.13)**	-32.02	(21.38)	-31.53*	(18.63)
County Only	-16.00	(12.10)	-31.45	(23.57)	1.76	(6.39)	**-15.37**	**(12.63)**	-15.32	(13.74)	-25.60	(19.97)
High-Rated	-2.46	(6.04)	-4.08	(7.95)	0.13	(3.16)	**-2.22**	**(7.02)**	-1.81	(7.43)	-2.65	(7.95)
Low-Rated	-98.41***	(31.55)	-126.40***	(34.25)	-59.50**	(24.43)	**-77.51*****	**(26.09)**	-77.98***	(25.58)	-76.65**	(32.86)
b. Pooled Pre:												
Overall Yield	-9.91	(7.80)	-8.86	(10.19)	-5.97	(5.71)	**-9.25**	**(7.57)**	-9.48	(7.24)	-6.64	(7.68)
City Only	-9.86	(6.25)	-7.07	(8.21)	-9.39	(7.81)	**-7.22**	**(5.62)**	-7.50	(5.72)	-9.44	(7.24)
County Only	-27.91	(21.10)	-31.88*	(19.12)	4.03	(4.24)	**-24.67**	**(17.19)**	-22.99	(16.83)	-33.17	(25.27)
High-Rated	-9.65	(7.14)	-11.21	(10.86)	-1.16	(2.81)	**-9.50**	**(7.57)**	-9.60	(7.46)	-8.44	(8.51)
Low-Rated	-39.65**	(17.50)	-44.52*	(24.00)	-12.61	(14.90)	**-0.19**	**(17.84)**	0.18	(18.71)	-0.80	(21.12)
State FE	X		X		X		**X**		X		X	
Month FE												
Maturity FE	X		X		X		**X**		X		X	
Minimum State-Maturity Cell Size	X		X		X		**X**		X		X	
Estimator	CCFT		CCFT		CCFT		***CCFT***		CCFT		CCFT	
Bandwidth Method	IMSE		IMSE		Fixed		**IMSE**		IMSE		IMSE	
Kernel	Uniform		Uniform		Triangular		**Triangular**		Triangular		Triangular	
Polynomial Degree	1		2		1		**1**		1		2	
Bandwidth (Low-Rated Post)	[-149, 411]		[-228, 1101]		[-498, 4650]		**[-228, 676]**		[-227, 657]		[-465, 1275]	
Bandwidth (Low-Rated Placebo)	[-149, 591]		[-321, 1297]		[-498, 4650]		**[-250, 552]**		[-250, 563]		[-475, 1107]	
N (Low-Rated Post)	27,471		57,466		104,634		**46,040**		45,213		69,978	
N (Low-Rated Placebo)	7,559		19,044		33,912		**14,802**		14,802		19,827	
Clustering	Relative Pop		Relative Pop		Relative Pop		**Relative Pop**		Issuer		Relative Pop	

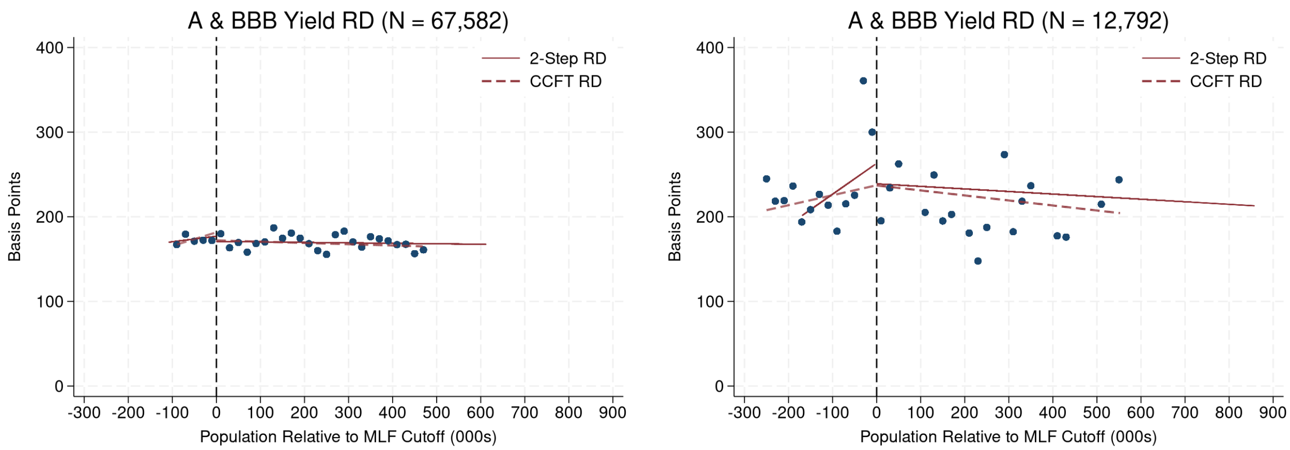
NOTES—Models (3), (4) and (12) feature in Table 2. Maturity FE bins are 0-1, 1-2, 2-3, 3-5, 57, 7-10, 10-20, 20-30, and 30-40 years. Minimum State-Maturity Cell Size requires 100 trades on each side of the cutoff within state-maturity cells to be included in regression. *** p≤0.01, ** p≤0.05, * p≤0.1.

A.1.2 Placebo RD Plots Prior to Crisis

In Figure A.1 and Figure A.2 we show yield and employment RD plots in the placebo using our two preferred models. These plots demonstrate relative smoothness across the cutoff prior to the pandemic.

Figure A.1: RD Placebo Plots of MLF Access Effect on Yields by Credit Worthiness

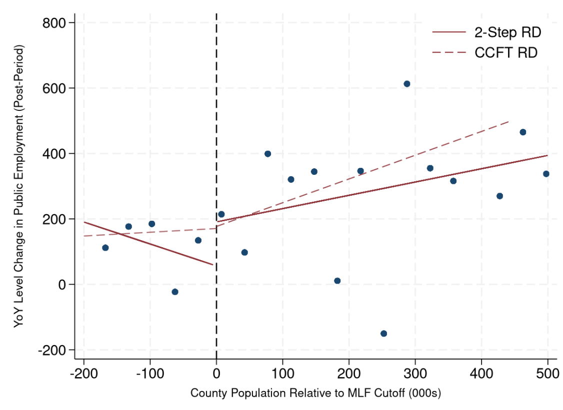
(a) High-Rated (b) Low-Rated



NOTES—Plots show regression slopes and intercepts from Equation 1 in the pre-period, overlaid on top of equally spaced pre-binned outcome data with a bin size of 20 (x-axis in thousands). Plots are shown over the optimal bandwidth selected using the IMSE-procedure, which produces asymmetric optimal bandwidth boundaries for each sample. 2-Step and CCFT estimates correspond to models (2) and (4) of Table 2 respectively. Binned data and observation counts correspond to covariate-adjustments from model (2) for exposition. Placebo period contains trades from January 1, 2020 to March 23, 2020.

Figure A.2: RD Placebo Plots of MLF Access Effect on Local Public Sector Employment

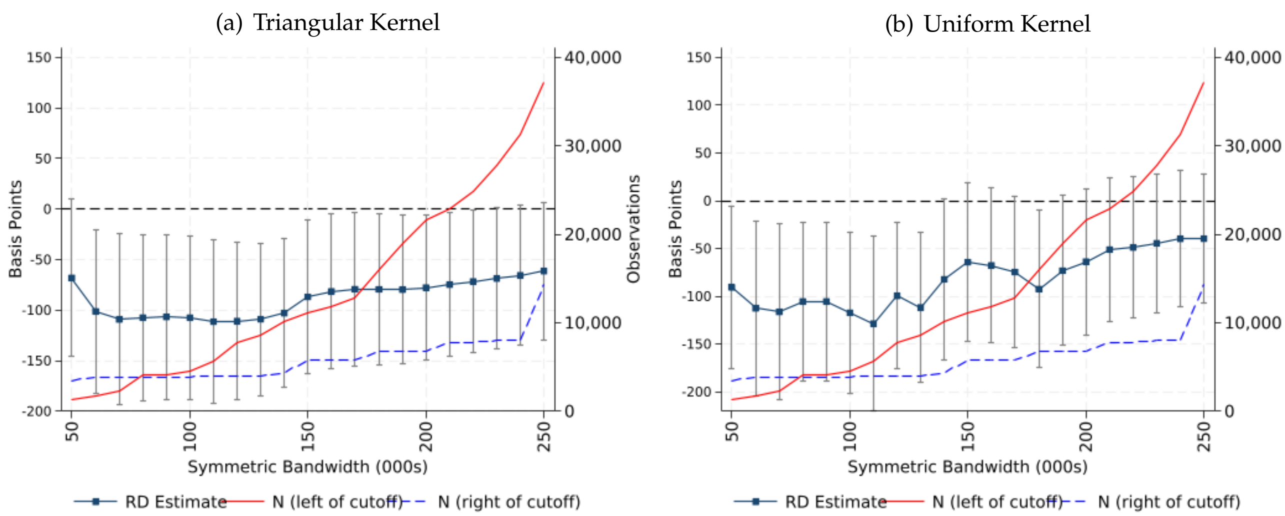
(a) Δ Employment, Pre-MLF (Placebo)



NOTES—Plot shows regression slopes and intercepts from Equation 1 for year-on-year differences in local public sector employment for the months of January and February, 2020, relative to January and February, 2019. Binned data and observation counts correspond to covariate-adjustments from model (1) of Table 3 for exposition.

A.1.3 Permutation Tests

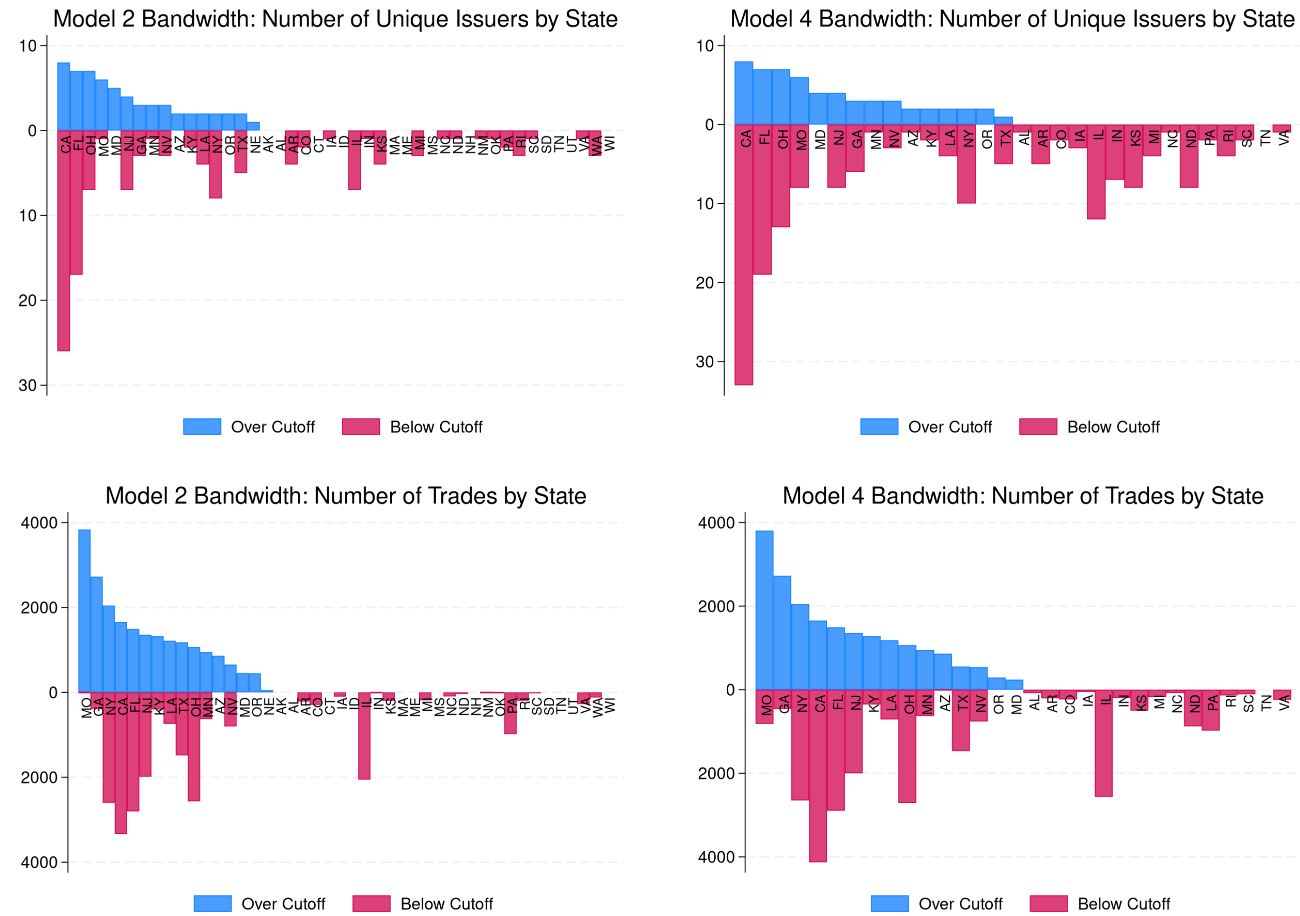
Figure A.3: Robustness of A/BBB Yield RD Estimates to Bandwidth Size Around Cutoff



NOTES—Figures show the sensitivity of A/BBB yield RD estimates to using increasing symmetric bandwidths. While the preferred specification uses a data-driven IMSE-optimal asymmetric bandwidth in which the econometrician cannot choose the bandwidth, here we show results for a symmetric bandwidth in population relative to the cutoff using our preferred first-order polynomial, by increasing the bandwidth by 10,000 in population in each iteration. We start at 50,000 in population to ensure at least 1,000 observations on each side of the cutoff. Panel (a) shows results using a triangular kernel while panel (b) shows results using a uniform kernel, both of which use the 2-step model for covariate adjustment given the manual setting of bandwidth boundaries in each iteration in this simulation.

A.1.4 Overlap in Number of Issuers and Trades by State in A/BBB RD Regressions

Figure A.4: Number of Issuers and Trades by State, Post-MLF Sample



NOTES—Figure shows number of unique issuers and trades by state of the issuer contributing to each of our preferred post-MLF estimation samples from Table 2 models (2) and (4).

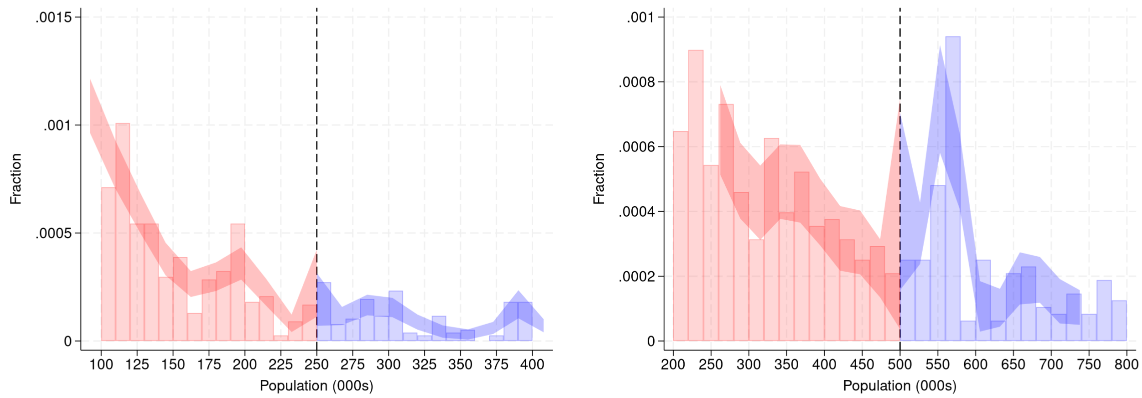
A.1.5 Manipulation Tests

In Figure A.5, we show formal McCrary (2008) running variable manipulation tests, using the Cattaneo et al. (2018) method of local polynomial density estimation with robust standard errors, where bandwidths for density tests are data-driven and thus do not span the whole support of the histogram.

Consistent with cutoffs being chosen using round-number heuristics and the MLF's regulatory population eligibility lists being lagged by 1 to 2 years (2018 and 2019), we find no evidence of cutoff manipulation by policymakers, nor cutoff-targeting based on the underlying distribution of of issuers. We also provide p-values from a density manipulation test associated with a discrete running variable (Frandsen, 2017), should lumpy population observations be interpreted as discrete rather than continuous. The Frandsen (2017) test of equality of projected intercepts at the cutoff produces to a p-value of 0.967 for counties, and 0.388 for cities, significantly away from conventional p-values that would reject equality.

Figure A.5: Manipulation Test for City and County Population Running Variables

(a) Density Test for City Populations: (b) Density Test for County Populations:



NOTES—Figure separately plots histograms of unique cities and counties on either side of their respective MLF population cutoffs, and estimates 95% confidence intervals from local polynomial fits on each side of cutoff using the Cattaneo et al. (2018) method. Significant overlap in confidence intervals signifies a passing test. City manipulation density test is overlaid on top of a histogram with binwidths of 10,000 while county manipulation density test is overlaid on top of histograms with binwidths of 25,000 (due to there being fewer counties than cities). Fractions are small because majority of cities and counties fall below 100,000 and 200,000 in population respectively.

A.1.6 Yields Sensitivity to CARES Act Notch in CRF Aid Formula

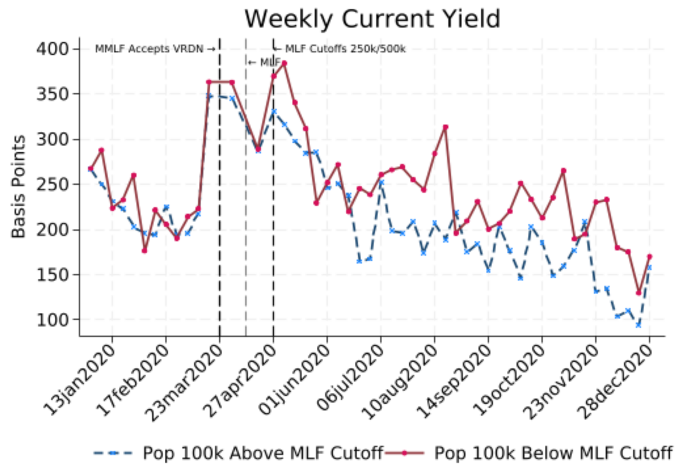
As discussed in the context of employment effects, we identify one potential confounding policy with the MLF: the March 27 CARES act included a Coronavirus Relief Fund (CRF) provision that "local governments serving a population of at least 500,000, as measured in the most recent census data, may elect to receive assistance directly from Treasury. Such direct local assistance allocations reduce the allocation that is made to the state government (keeping the state allocation constant)."[33] In other words, localities over 500,000 in population may have had quicker or more direct access to CRF aid, relative to localities just under that cutoff that had to rely on downstreaming from their underlying state allocation cap.[34] Since allocation caps were fixed to the right of this cutoff, but unrestricted to the left, the amounts received may have been differentially higher or lower to the right of the cutoff.

As discussed, this poses a potential problem for counties in our analysis, which are subject to the April 27 MLF population cutoff (also using 500,000 as an eligibility threshold). In the context of yields, we are served by two additional tests to help us tease apart CARES from MLF effects, which were not available in our employment analysis. We first note that visually, we have substantial variation in the month that elapsed between the CARES and MLF revision announcement. During this inter-announcement interval, yields appeared to trend almost identically (shown in Figure 4), whereas they diverged earlier among employment outcomes. Second, only one of the two cutoffs (counties) were aligned exactly at 500,000, whereas the other cutoff (cities) was not. We thus show in Figure A.6 the variation underlying our main results for low-rated (A & BBB) yields, excluding counties from the analysis and thus only focusing on the 250,000 *city* population cutoff which is unimpaired by CARES aid—or at least, only affected far away from the cutoff in a way in which the RD polynomial can fully control for.

[33] `https://crsreports.congress.gov/product/pdf/R/R46298`.

[34] CRF aid allocation caps for localities greater than 500,000 in population are calculated as the product of the total state allocation (based on population) weighted by locality population share.

Figure A.6: Mean Yields within 100k of MLF Population Cutoff, Low-Rated (A & BBB) Cities Only



NOTES—Figure shows mean weekly yields (pooled over buyer and seller prices) for low-rated city eligible issuers with cutoff-relative populations between 0 and 100,000 inclusively (blue dashed series), and issuers with cutoff-relative populations greater than or equal to -100,000 and less than 0 (red solid series). Trades between announcements are pooled into a single period beginning on the announcement day. See text for sample restrictions and definitions. *Source:* MSRB, S&P, Moody's, Fitch

This additional test shows a very similar pattern to our main results including counties, and our yield RD estimates for low-rated cities are similarly robust and statistically significant. While the results for employment are less conclusive, we can more confidently conclude that investors seem not to have responded to CARES act aid, whereas they did respond to an MLF emergency liquidity option.

A.1.7 Selection on Transacted Trades

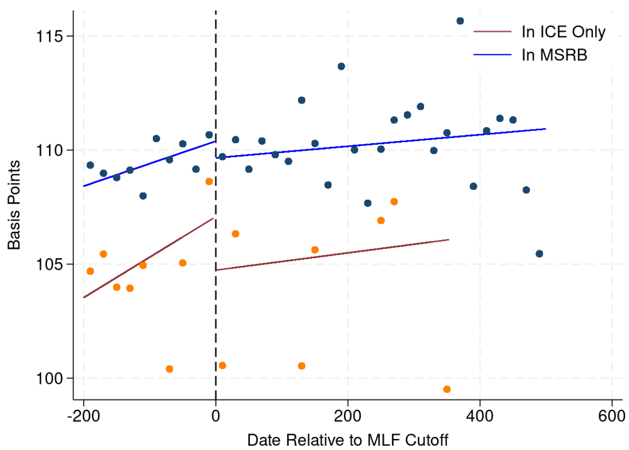
To assess the potential bias of measuring liquidity of traded bonds (that might be more liquid than the broader universe of outstanding bonds), we use quoted prices and yields from the Intercontinental Exchange (ICE). The dataset includes daily quotes for bonds whether they are traded or not. Quotes are based on independent daily evaluations for fixed income securities, including hard-to-value, thinly traded issuance. According to Kelly et al. (2023), pages 1976-1977: "ICE, through its acquisition of Interactive Data Corporation, is considered the gold standard for corporate bond data and is the standard source used by banks, asset managers, and hedge funds." So far, the data has been used primarily in the corporate bond literature (e.g., Kelly et al., 2023, Schaefer and Strebulaev, 2008, Israel et al., 2017, and Boyarchenko and Elias, 2024).

Figure A.7 uses our preferred CCFT model and specification from Table 2, column (4). We reproduce our main RD effects on prices and yields (MSRB-based sample), and compare them to quoted prices and yields for bonds in the ICE data. While prices of transacted bonds are indeed higher overall, yields are also higher due to transaction selection on higher coupon rates. Reassuringly, panel (b) shows that the magnitude of the A/BBB RD is invariant to using transacted or quoted yields.

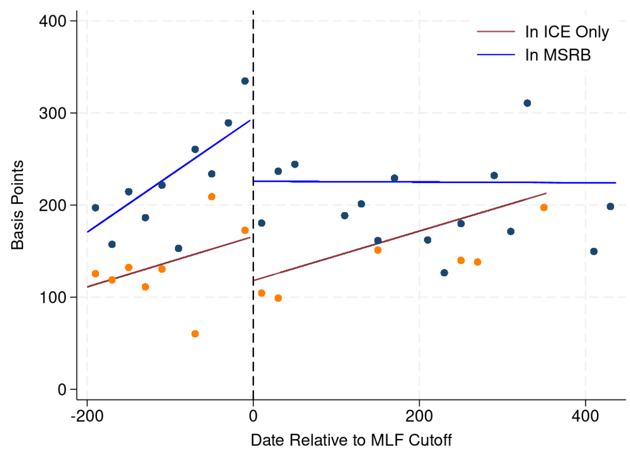
The potential bias of using traded yields of bonds that might be more liquid than bonds that are not traded, and therefore their yields are unobservable, might also affect the yields decomposition analysis in Section Section 7. If we were to attribute all the yield differential (from 150 bps on average for ICE to 200 bps on average for MSRB) in Figure A.7 panel (b) to the liquidity risk component, it would translate to a 33% overstatement of the liquidity risk component. Then, as a back-of-the-envelope calculation, we can apply that wedge to the range of originally reported liquidity components of our liquidity-credit decomposition, of about 21.5% to 28.0% in the pre-crisis period (100% - 78.5% and 100% - 72.0%), that increases our liquidity premia range to 28.7% to 37.3%, still leaving a very significant residual role for credit risk.

Figure A.7: RD Plots of Price and Yield: Transacted (MSRB) versus non-Transacted (ICE Only)

(a) A/BBB Transacted vs. Quoted Price



(b) A/BBB Transacted vs. Quoted Yield



NOTES—Figure shows transcated versus quoted price (denominator of yields) in panel (a), and yields in panel (b). MSRB series correspond to main A/BBB results, while "ICE Only" series shows results for quoted trades that never ultimately transacted.

A.1.8 List of A and BBB Issuers within 100k of Cutoff

Table A.2: Low-Rated (A and BBB) Issuers within 100k of MLF Cutoff

BaseCUSIP	Issuer Name	State	Issuer Type	Number of Cusips	Number of Trades	Above/Below Cutoff
119677	Buffalo	NY	Local Government	110	8083	1
650367	Newark	NJ	Local Government	100	14337	1
889278	Toledo	OH	Local Government	90	6611	1
86607C	Summit County	OH	County Government	87	2132	1
46360R	Irvine	CA	Local Government	75	5062	1
660393	North Las Vegas	NV	Local Government	54	15270	0
46360T	Irvine	CA	Local Government	48	4210	1
85233S	St Louis	MO	Local Government	40	5030	1
825434	Shreveport	LA	Local Government	32	4676	0
743787	Providence	RI	Local Government	32	4295	0
549310	Lucas County	OH	County Government	30	12260	0
463805	Irving	TX	Local Government	29	3317	0
79307T	St Paul	MN	Local Government	29	986	1
759861	Reno	NV	Local Government	28	2027	1
555542	Macon Bibb County	GA	Local Government	28	1531	0
70643U	Pembroke Pines	FL	Local Government	27	3302	0
010047	Akron	OH	Local Government	27	2820	0
79488C	Salinas	CA	Local Government	24	2147	0
396068	Greenville County	SC	County Government	20	378	1
270764	East Baton Rouge Parish	LA	County Government	20	1917	0
759829	Reno	NV	Local Government	19	3336	1
86607D	Summit County	OH	County Government	16	1506	1
133402	Cameron County	TX	County Government	15	456	0
66041H	North Las Vegas	NV	Local Government	11	313	0
537374	Little Rock	AR	Local Government	11	1886	0
43615F	Hollywood	FL	Local Government	10	699	0
650366	Newark	NJ	Local Government	10	4389	1
534310	Lincoln	NE	Local Government	9	1203	1
29634D	Escondido	CA	Local Government	9	254	0
613549	Montgomery County	OH	County Government	8	2756	1
55553N	Macon Bibb County	GA	Local Government	8	569	0
690278	Overland Park	KS	Local Government	7	155	0
79164T	St Louis	MO	Local Government	6	3521	1
743940	Providence	RI	Local Government	5	364	0
702521	Pasco County	FL	County Government	5	772	1
873477	Tacoma	WA	Local Government	3	255	0
759830	Reno	NV	Local Government	2	119	1
928844	Volusia County	FL	County Government	2	326	1
344610	Fontana	CA	Local Government	2	926	0
607715	Modesto	CA	Local Government	2	369	0
035895	Anne Arundel County	MD	County Government	1	41	1
051672	Aurora	IL	Local Government	1	44	0
696712	Palmdale	CA	Local Government	1	41	0
768861	Riverside	CA	Local Government	1	809	1

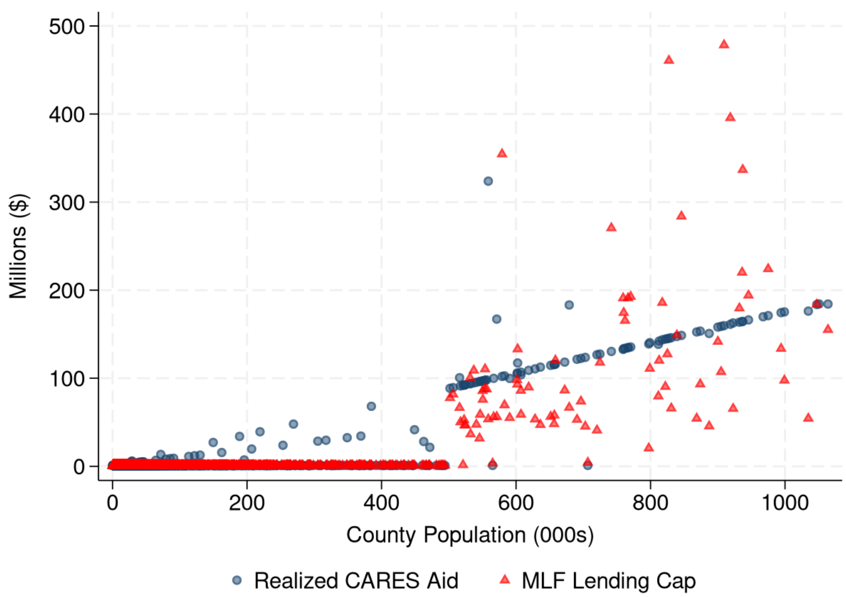
NOTES—Data contain 43 unique issuers with 831 unique outstanding bonds or notes. Each bond contributes additional variation to RD estimates, however inference only leverages differences between issuers (standard errors clustered by relative population). 20 issuers are above the MLF cutoff, while 23 are below. Irvine, Newark, North Las Vegas, Reno, and St. Louis are listed twice, but these reflect different issuers within those cities (for example, economic development corporations may issue their own independent debt).

A.2 Additional Results

A.2.1 MLF and CARES Variation in Lending and Aid

To illustrate the difficulty in decomposing total employment effects into those emanating from CARES versus MLF, in Appendix Figure A.8, we compare variation in MLF lending caps, calculated as 20% of each government's 2017 "own-source general and utility revenue" (OSGUR) as per MLF regulations,[35] and the amount of aid either apportioned directly to each local government through the CARES Act based on the CRF population formula (right of the cutoff), or received as indirect downstreamed aid to county governments, hand-assembled by the National Association of Counties (NACO Aid). We unfortunately are unable to locate any data on downstreamed aid to cities, which are therefore omitted from the plot. According to the CARES Act CRF Allocation Formula, no population can be double-covered by both its underlying city and county for aid, however, each entity above the cutoff can independently claim direct aid on behalf of its constituents. We use direct CARES aid data received by either cities or counties from USASpending.gov (the US Treasury's official tracker of fiscal expenditures). Nevertheless, this analysis requires total county aid, which is comprised of direct county aid in addition to direct aid paid to a county's underlying cities. To this end, we split the direct city aid across counties based on the county CRF cap were it to have accessed the aid directly. Because aid received is calculated with the "latest" population vintage, we estimate the county-level allocation with minor error.

Figure A.8: Variation in MLF Lending Caps and direct CARES Aid Allocations



NOTES—Data shows MLF lending caps (based on 2017 OSGUR) and realized direct aid allocations calculated from the CRF population formula (see footnote) plus $1, combined with incomplete data on downstreamed aid from states to counties on the left of the cutoff. Two values greater than $500m are suppressed for exposition. Data are shown over the county population running variable, the unit of analysis for all employment results.

Of note, counties at the 500,000 cutoff were eligible for about the same amount of potential lending as direct aid, making comparisons difficult. Downstreamed data is largely incomplete on the right, and there is nothing precluding downstreamed aid to fully close the gap to the left of the cutoff were full data available. In fact, it can be seen by extending the slope to the left of the cutoff, that some states followed

[35]See April 9, 2020, MLF Term Sheet for further details on MLF lending cap calculation.

the same formula for smaller localities even though this was not legally binding.[36, 37]

A.3 Additional Background and Data Construction Details

A.3.1 Expanded Primer on the Municipal Bond Market

The $3.8 trillion municipal bond market contains more than 50,000 issuers and 1 million individual bonds, making it approximately half the size of the corporate bond market with 10 times as many issuers. Roughly 90% of this market is exempt from federal income tax,[38] and more than 80% is rated investment grade. Consequently, municipal bond default rates have historically been low (Appleson et al., 2012). As of May 2020, 26% of outstanding debt was issued directly by state, city, county, and other local governments, 41% by utilities, service, and transit issuers, 21% by school districts, and 8% by public hospitals. Unlike treasury and corporate bond markets, 70% of municipal debt is held by retail investors (a third of which is in mutual funds and ETFs) seeking tax advantages associated with municipal bond returns.[39] Unlike the corporate sector, municipal debt is also commonly issued in deals containing many different tenors as independent bonds, facilitating more predictable budget smoothing.

Government issuers in this market are often required to balance their operating budgets, and can usually only borrow long term in order to finance infrastructure investments. In 2015, 48 of 50 US states had some form of balanced budget requirement (BBR), while 39 of 50 had strong constitutional or statutory requirements (Brookings Tax Policy Center, 2015), limiting deficit spending across fiscal cycles.[40] GO bonds, which constitute approximately 30% of the long-term municipal market, are not secured by a specific revenue source but are instead backed by the "full faith and credit of the taxing authority" and typically finance capital projects like bridges and schools. The large remainder of the long term market (60%) is dominated by Revenue bonds issued by public enterprises and secured by defined revenue sources (such as transit revenue, airport feels, bridge tolls, etc.).[41]

Less well known but central to this paper, state and local governments also frequently leverage the $440 billion short-term municipal note market to bridge cash flow gaps within fiscal years. As localities depend on revenues that are only received at specific intervals, budget officers seek to smooth spending in anticipation of such receipts, and can do so by issuing tax anticipation notes (TANs), revenue anticipation notes (RANs), and bond anticipation notes BANs. Other notes include tax and revenue anticipation notes (TRANs), tender option bonds (TOBs), and Variable Rate Demand Notes (VRDNs), the latter of which comprises roughly half of the short-term market. Short-term notes are typically secured by the revenues expected to be received later in the fiscal year, and are paid off when said revenues arrive. A classic example is the proceeds from final settlements of state income tax returns due April 15 (the federal tax filing deadline), which can include taxable unearned income and capital gains (typically not withheld). Other examples include quarterly property tax receipts, or expected surges in airport fees during the holiday season.

[36] Within states, any jurisdiction with population greater than 500,000 received *direct* US Treasury access to the population share of the state allocation * 45%, whereas the remaining 55% of was controlled by the state. By contrast, localities with populations *under* 500,000 had to rely on downstreaming from their underlying states (who in this case controlled 100% of the local allocation), leaving aid to smaller localities potentially more politicized, less certain, or slower to materialize.

[37] While the kinked nature of the CARES population formula appears at first to provide a potential test in which a regression kink design (RKD) may help discern between these two policies, the underlying kink is in fact a flat schedule in the variation of interest—aid per person. That is, when both the outcome variable and treatment variable are highly correlated with the running variable (as it is here), there is in fact no kink in the denominator since the aid allocation formula is based on population itself, and therefore no meaningful variation in aid to leverage.

[38] Some bonds are "double-exempt" for local residents, applicable to tax liabilities at both Federal and State levels (e.g. CA state bonds for CA residents), whereas others are "triple-exempt" at the local level as well (e.g. New York City bonds).

[39] Outstanding debt by sector calculated from Bloomberg, as of 5/19/2020. Retail share calculated from the Board of Governors, "Financial Accounts of the United States, Z.1, as of 1Q2020." Retail holdings calculated from MSRB.

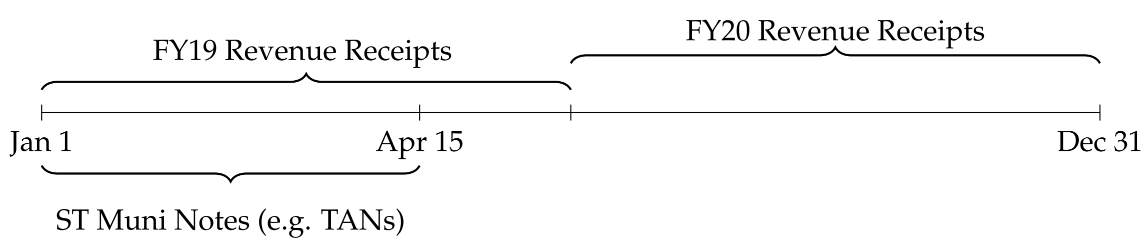
[40] Some states further prohibit or limit GO bond issues, including Arizona, Colorado, Idaho, Indiana, Iowa, Kansas, Kentucky, Nebraska, North Dakota, South Dakota, and Wyoming.

[41] MSRB, Bloomberg, calculated as of 5/21/2020.

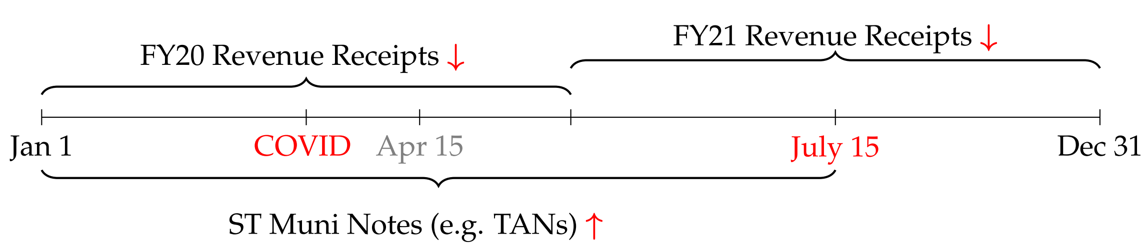
While many of these features of the municipal market have remained relatively constant for several decades, one notable change in recent years has been the increasing share of muni holdings in mutual funds, which nearly doubled to $800 billion since 2010 (from 10% to 20% of the market) and by some measures now reflect one third of overall muni holdings (WSJ, Oct 2019). Importantly, municipal holdings by mutual funds have also become more concentrated, with over 70% of muni mutual funds held by the 10 largest fund families (investment banks).[42] This trend played a key role in the municipal liquidity crisis when the COVID-19 shock hit financial markets.

A.3.2 Pass-Through of Market Distress to Budgets and the Real Economy

In a normal expansionary year, such as 2019, state and local governments incur expenses such as payroll, debt service, etc., but only receive expected revenue at distinct intervals, as shown in the timeline below. One prominent example of such a revenue source is the proceeds from final settlements of state income tax returns, typically due April 15 (the federal tax filing deadline), which can include taxable unearned income (typically not withheld).[43] When governments are short of revenue yet have guaranteed sources of future receipts, they can issue short-term anticipation notes on municipal bond markets to help smooth out the temporary shortfall. Take for example, the state of New York, whose tax base includes large amounts of capital gains realized in the prior calendar year. Taxes on these amounts are typically received on April 15. New York may issue a 4-month TAN in anticipation of this revenue on Jan 1, 2019, maturing April 30th, 2019 (one month after its fiscal cycle closes). This would generate bond proceeds to smooth out cash flow, and would be secured by revenue incoming on April 15, enabling the government to start spending part of the expected settlement amount in the interim.



However, when an economy experiences a major income shock accompanied by a bond market liquidity crisis, as was the case with the COVID-19 pandemic and the muni market, there are three distinct ways in which this enters fiscal budgeting, shown in red in the timeline that follows.



First, income receipts decline in both the current and upcoming fiscal cycles. While tax assessments may be revised downwards, 2021 budgets were for the most part already set when the COVID pandemic took hold. This led to a decline in the revenue that would normally cover these planned expenditures. Second, as a matter of fiscal policy, the IRS extended the 2020 federal tax deadline from April to July 15th, increasing the quantity of short-term notes governments desired to issue on the market to plug the additional cash flow gap. Third, while the temporary misalignment of expenditures and revenue needs (even if unexpectedly large in a specific year) are normally able to be remedied through the bond

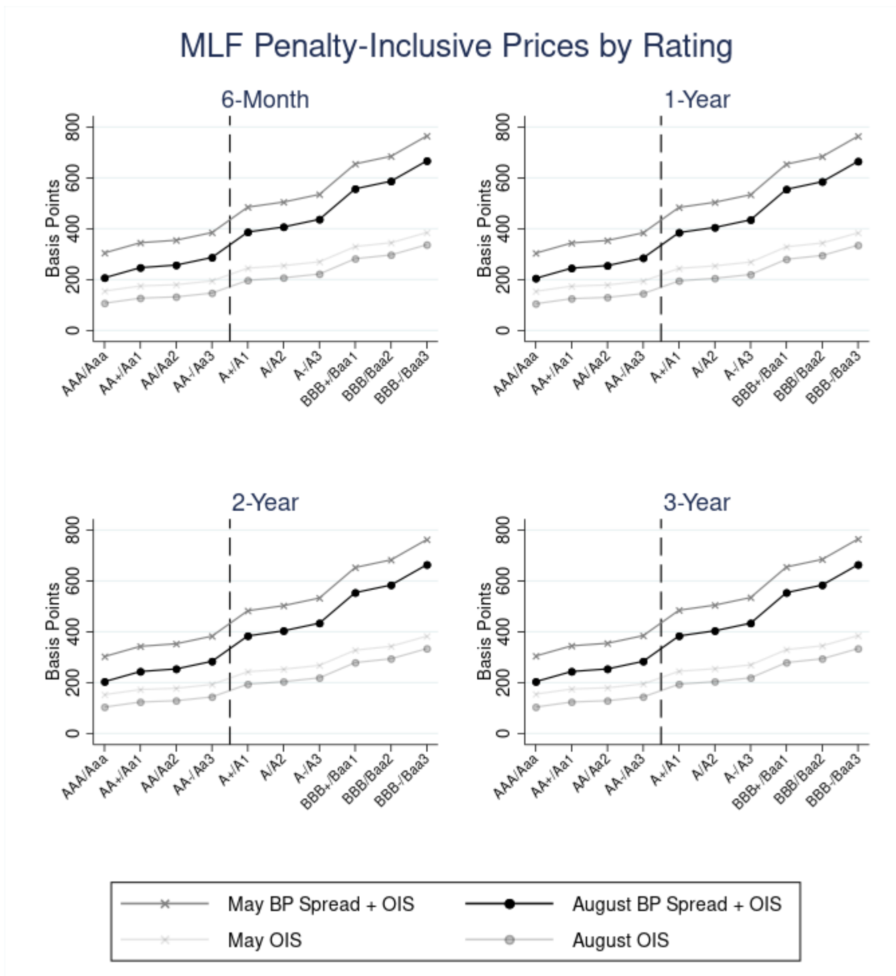
[42] Calculations from "Financial Accounts of the United States, Z.1, as of 1Q2020".

[43] Other examples include quarterly property tax receipts, or expected surges in airport fees during the holiday season.

market, the simultaneous large financial sell off of fixed income assets effectively drove investor demand for munis toward zero, leaving governments unable to borrow. This was the challenge faced by the US economy in mid-March of 2020; local governments could not borrow on private municipal markets despite their increasing need to do so because of demand conditions, potentially constraining payroll obligations.

A.3.3 MLF Pricing Grid

Figure A.9: MLF Pricing Grid



NOTES—Figure shows penalty pricing grid by issuer ratings when it was announced on May 11, 2020, and revised on August 11, 2020, for different loan term lengths. OIS = overnight index swap rate, meant to represent prevailing private market interest rates, here pulled on May 27, 2020, and August 12, 2020, respectively. Dotted line indicates distinction between "high" and "low" rated issuers as defined in the paper. Pricing schedules are similar with slight variations for different tenors. See MLF Pricing Term Sheet for further details.

A.3.4 Matching MSRB Issuer Names to Census Populations

Our goal is to assign a single Census population to any city, county, or state municipal bond issuer that has traded on the secondary market at any point since Jan. 1, 2019, including all MLF eligible and ineligible issuers. We start with the term-sheet referenced U.S. Census Bureau datasets that include

2018 city populations greater than 50,000, and 2019 county populations greater than 50,000.[44] This provides populations for larger issuers, however we also desire to match populations to smaller issuers so that they may contribute to the RD running variable further away from the cutoff. To this end, we complement our analysis with the full population Census file "sub-est2019_all.csv", a place-level dataset with both 2019 and 2018 populations for localities of *all* populations.[45] This file contains a place description such as the city or county's name (which is always followed by the type suffix, such as "CITY" or "COUNTY"), state, census place code, and geographic code level (*sumlev*), allowing us to isolate the administrative name and its geographic level.

We desire the dataset be uniquely identified by city (county) name and city (county) state, so reshape wide the 2018 (2019) populations by *sumlev*, which produces a maximum of 6 potential population measures for each geographic code, corresponding to the number of unique values *sumlev* can take:

1. Minor Civil Divisions (MCDs)[46]
2. MCD "parts"
3. County place parts
4. Incorporated places (cities, towns, boroughs, villages)
5. Consolidated cities
6. Consolidated city parts

The data separately document localities whose "part" or "balance" spills over into another locality, which we subsequently drop (i.e. we drop (2) and (6)).[47] We then designate a rule to choose among these candidate populations. Most places have one or two population measures, but they will not have all six. If all non-missing populations are the same, or if there is only one population, we use that population. If any of the populations are different (0.1% of localities (27 observations; 3 of which ultimately do not merge to MSRB-Bloomberg)), we flag and omit them the analysis.

Finally, we go through a multi-step process to merge MSRB issuer names (from their security descriptions) to Census place names. This involves flagging duplicate MSRB place names within state which arise erroneously from our cleaning algorithm, and remapping them based on their original security description to their appropriate population. For example, "SPRINGFIELD TOWNSHIP, NJ" in the Census may correspond to "SPRINGFIELD, NJ" in MSRB trade data; by removing the township suffix, we can match these. But doing this universally risks false positives in other cases: for example, the Census might contain "HEMPSTEAD VILLAGE, NY", "HEMPSTEAD TOWN, NY", and "HEMPSTEAD CITY, NY" (all separate localities), while MSRB may only contain one HEMPSTEAD, NY. Removing suffixes here would lead to duplicate matches. We thus only remove such suffixes when the resulting merge is one-to-one, causing a loss rate of 4% of unmatched trades.

We also consider special treatment for matching fully consolidated cities (e.g. City and County of San Francisco) which have only one set of issuers at either the city or county level, and partially consolidated city-counties (e.g. Miami City vs. Dade County) which may have different revenue sources. We follow

[44] U.S. Census Bureau, "Annual Estimates of the Resident Population: April 1, 2010 to July 1, 2018" for cities, as of April 6, 2020; and U.S. Census Bureau, "Population, Population Change, and Estimated Components of Population Change: April 1, 2010 to July 1, 2019" for counties, as of April 6, 2020.

[45] The sub-est2019_all.csv file can be found here: `https://www2.census.gov/programs-surveys/popest/datasets/2010-2019/cities/totals/`.

[46] States in New England, New York, and Wisconsin, all classify towns as MCDs.

[47] A "balance" is a consolidated city minus the semi-independent incorporated places located within the consolidated city (overlapping service populations which would be double counted if we did not drop them). Incorporated places can cross both county and Minor Civil Division (MCD) boundaries. In such cases a separate record indicates the population estimates for the part of a place in each of its parent counties or MCDs. For such records, the place name is sometimes followed by the designation "pt" (which stands for part), allowing us to isolate these cases.

the MLF term sheet in assigning these cases to city and/or county eligibility lists based on the revenue sources of underlying issuers. Lastly, we manually flag potential counties that issue on behalf of cities ("downstreamers") based on their detailed issuer and security description. Among issuers with a reliable MSRB issuer name and actively trading post-2019, our final cleaning procedure results in 6,143 city (1,880 county) BaseCUSIPs (unique at the issuer level) that match a population to MSRB data, and 361 city (41 county) issuers that do not retrieve a match.

MSRB Data Cleaning

Since January 1998, MSRB has required registered dealers to report all municipal bond transactions. The trade record includes information about CUSIP, date and time of the trade, price and yield, maturity, coupon, and a flag whether the dealer bought from a customer, sold to a customer, or whether it is an interdealer trade. In January 2015, MSRB started to publicly disseminate those transactions with up to a 15 minutes delay.

We first keep unique observations at the CUSIP—trade_date—RTRS_Control_Number level, using the RTRS_PUBLISH_DATE and RTRS_PUBLISH_TIME variables to ensure that duplicates are not arising from missing data. Then, in addition to the sampling restrictions applied to our RD analysis, for the yield decomposition sample, we further apply the following conditions:

1. Delete CUSIPs with:
   (a) missing coupon and maturity information for all trades
   (b) a listed coupon greater than 20%
   (c) a listed maturity over 100 years
   (d) fewer than 10 trades in the entire sample
2. Delete transactions where:
   (a) the price is less than 50 (i.e., 50% of face value)
   (b) the price is greater than 150 with a short time to maturity
   (c) trade date is after the maturity date of the bond

Mergent Data Cleaning

The key characteristics from Mergent that we use include CUSIP, issuer name, offering amount, source of funds and use of proceeds, bond credit rating as rated by S&P, Moody's, and/or Fitch, coupon type (fixed, variable, or zero), the tax status of the coupon payments, callability and first call date, insurance status and the identity of the insurer, and pre-refunding status and timing. The Mergent data ratings provide a longer time series of ratings data relative to the Bloomberg ratings data used in the RD analysis. A few of the variables require some adjustments. Specifically:

Coupon Type: Mergent's variable *coupon_code* indicates the coupon type. However, for fixed-rate bonds issued at a discount or at a premium, it only indicates OID and OIP respectively. Most of these bonds are fixed-rate, nevertheless for these bonds we also use the VARRATE table to determine the coupon type.

Ratings: There are also duplicate observations at the CUSIP—rating_type—rating_date level, sometimes with different ratings values. Rating agencies submit revisions of ratings that are then posted in the Mergent database as a new rating instead of a revision to a current rating. The data provider is in the process of correcting that in its database, so for such observations we use ratings data from Bloomberg.

A.3.5 NRSRO Ratings Concordance and Plurality Ratings

Each of S&P, Moody's, and Fitch, maintain separate ratings systems for long and short-term bonds. S&P and Moody's also use separate systems for short-term municipal note ratings. We map of each these to 8 aggregate ratings bins that are guided by S&P's convention: AAA, AA, A, BBB, BB, B, C, D. To do so, we use the following concordances, which were developed manually in consultation with a number of sources.[48] The resulting columns ending in *_agg* form the basis of our plurality ratings, calculated as the plurality across long-term, short-term, and muni-note bonds based on their "aggregate" ratings.

[48]These include S&P reference, Moody's reference, and Fitch reference. Some disaggregated ratings are identified from MSRB trades rather than the NRSRO's themselves, however have natural mappings.

Figure A.10: Ratings Concordances to Aggregated Credit Rating Bins

Fitch, Long-Term Ratings

rank	*fitch_rating_lt*	*fitch_rating_lt_agg*	*fitch_rating_desc*
1	AAA+	AAA	Prime
2	AAAe	AAA	Prime
3	AAApre	AAA	Prime
4	AAA	AAA	Prime
5	AAA-	AAA	Prime
6	AA+e	AA	High Grade
7	AA+	AA	High Grade
7	AAe	AA	High Grade
8	AA	AA	High Grade
9	AA-e	AA	High Grade
10	AA-	AA	High Grade
11	A+e	A	Upper Medium Grade
12	A+	A	Upper Medium Grade
12	Ae	A	Upper Medium Grade
13	A	A	Upper Medium Grade
14	A-	A	Upper Medium Grade
15	BBB+	BBB	Lower Medium Grade
16	BBB	BBB	Lower Medium Grade
17	BBB-	BBB	Lower Medium Grade
18	BB+	BB	Non-Investment Grade Speculative
19	BB	BB	Non-Investment Grade Speculative
20	BB-	BB	Non-Investment Grade Speculative
21	B+	B	Highly Speculative
22	B	B	Highly Speculative
23	B-	B	Highly Speculative
24	CCC	C	Extermeley Speculative
25	DDD	D	In Default
26	DD	D	In Default
27	D	D	In Default

Fitch, Short-Term Ratings

rank	*fitch_rating_st*	*fitch_rating_st_agg*
1	F1+e	AA
2	F1+	AA
3	F1	A
4	F2	BBB
5	F3	BBB
6	B	B
7	C	C
8	D	D
9	/	D

Moody's, Long-Term Ratings

rank	*moody_rating*	*moody_rating_lt_agg*	*moody_rating_desc*
1	#Aaa	AAA	Prime
2	Aaa	AAA	High grade
3	Aa1	AA	High grade
4	Aa2	AA	High grade
5	Aa3e	AA	High grade
6	Aa3	AA	High grade
7	A1	A	Upper medium grade
8	A2	A	Upper medium grade
9	A3	A	Upper medium grade
10	Baa1	BBB	Lower medium grade
11	Baa2	BBB	Lower medium grade
12	Baa3	BBB	Lower medium grade
13	Ba1	BB	Non-investment grade speculative
14	Ba2	BB	Non-investment grade speculative
15	Ba3	BB	Non-investment grade speculative
16	B1	B	Highly speculative
17	B2	B	Highly speculative
18	B3	B	Highly speculative
19	Caa1	CCC	Substantial risks
20	Caa2	CCC	Extremely speculative
21	Caa3	CCC	Default imminent with little prospect for recovery
22	Ca	C	Default imminent with little prospect for recovery
23	C	D	In default
24	/	D	In default

Moody's, Short-Term Ratings

rank	*moody_rating_st*	*moody_rating_st_agg*
1	P-1	A
2	P-2	BBB
3	P-3	BBB

Moody's, Muni-Note Ratings

rank	*moody_rating_muninotes*	*moody_rating_muninotes_agg*
1	MIG1	A
2	VMIG1	A
3	MIG2	A
4	VMIG2	A
5	VMIG3	BBB
6	MIG3	BBB
7	SG	D

S&P, Long-Term Ratings

rank	*sp_rating_lt*	*sp_rating_lt_agg*	*sp_rating_desc*
1	AAA+	AAA	Prime
2	AAA	AAA	Prime
3	AAA-	AAA	Prime
4	AA+	AA	High Grade
5	AA	AA	High Grade
6	AA-	AA	High Grade
7	A+	A	Upper Medium Grade
8	A	A	Upper Medium Grade
9	A-	A	Upper Medium Grade
10	BBB+	BBB	Lower Medium Grade
11	BBB	BBB	Lower Medium Grade
12	BBB-	BBB	Lower Medium Grade
13	BB+	BB	Non-Investment Grade Speculative
14	BB	BB	Non-Investment Grade Speculative
15	BB-	BB	Non-Investment Grade Speculative
16	B+	B	Highly Speculative
17	B	B	Highly Speculative
18	B-	B	Highly Speculative
19	CCC+	CCC	Substantial Risks
20	CCC	CCC	Extermeley Speculative
21	CCC-	CCC	Default Imminent with little prospect for recovery
22	CC+	CC	Default Imminent with little prospect for recovery
23	CC	CC	Default Imminent with little prospect for recovery
24	C-	C	Default Imminent with little prospect for recovery
25	SD	D	In Default
26	D	D	In Default

S&P, Short-Term Ratings

rank	*sp_rating_st*	*sp_rating_st_agg*
1	A-1+	A
2	A-1	A
3	A-2	BBB
4	A-3	BBB
5	B	B
6	C	C
7	/	D
8	D	D

S&P, Muni-Note Ratings

rank	*sp_rating_muninotes*	*sp_rating_muninotes_agg*
1	SP-1+	A
2	SP-1	A
3	SP-2	BBB
4	SP-3	BB
5	D	D

A.3.6 Liquidity-Credit Risk Decomposition Details

In this section we discuss the various liquidity measures that enter our yields decomposition. As with our main cities and counties sample, we source municipal bond transaction-level prices and yields from MSRB, but here we extend our sample back to January 2013, which is the earliest date for which we have transaction data that includes counterparty indicator (i.e., D for interdealer trade, P for a dealer purchase from a client, and S for a dealer selling to a client). In addition to the counterparty indicator, each trade record includes bond identifier (CUSIP), trade time, bond price, yield, par value traded, buy/sell indicator. We follow the cleaning procedure of MSRB transactions data that is common in the literature (see, e.g., Green et al., 2010), and exclude bonds with missing coupon and maturity information (which effectively removes variable rate bonds), a listed coupon greater than 20%, or a listed maturity over 100 years. These are likely to be data errors.

To mitigate the effect of outliers, we further drop trades that occur on weekends and SIFMA holidays, have a price less than 50 or greater than 150, a when-issued flag equal to "Y", a non-missing Brokers Broker Indicator, occur within 90 days of issuance, occur within 365 days of maturity, and any trade date after the maturity date of the bond. We also only keep CUSIPs that traded more than 10 times over the entire sample. This clean trades sample includes 59,907,262 trades and 653,692 bonds.

Next, we use bond characteristics from Bloomberg and Mergent's Municipal Bond Securities Database, including maturity, offering amount, coupon rate, state of issuance, issue series, issuance date, whether it was a negotiated or competitive sale, whether the bond is general obligation, revenue, insured or callable, and ratings from S&P, Moody's, and Fitch, to further filter the data. We exclude variable rate bonds, insured bonds, AMT bonds, and bonds that are only subject to federal taxes (for the decomposition), as these characteristics will add noise to spreads. The filtered transactions sample of state, city and county issuers include 8,052,129 trades and 157,259 bonds. The sample of city and county issuers in 2020 covers 1,089,760 trades and 73,556 bonds.

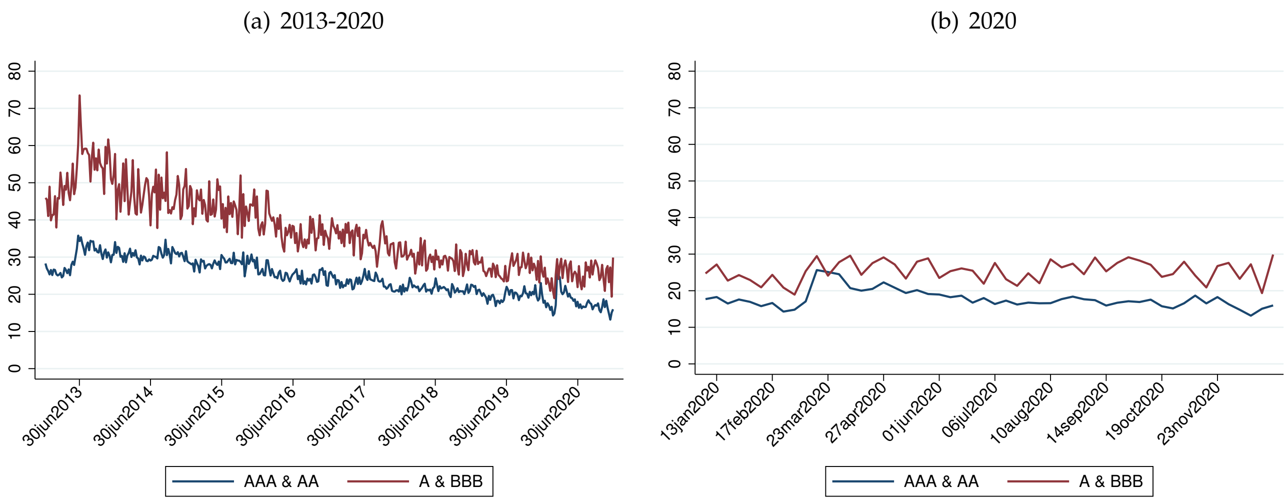
We estimate five measures of liquidity: Amihud price impact, effective bid-ask spread, imputed round-trip cost, Roll measure, and price dispersion. First, we calculate each liquidity measure at the bond-day level, and then we collapse to the bond-week level by taking the mean of the daily observations. Since each measure captures a different aspect of trading costs, we use this set of liquidity measures as an input to generate the first principal component of liquidity, our main metric of interest.

1. Amihud Illiquidity Measure: Amihud (2002) is a measure of the price impact of a trade, i.e., how much the price moves per $1 million trade. The Amihud measure for bond b on day t is calculated as:

$$Amihud_{b,t} = \frac{1}{N_t}\sum_{j=1}^{N_t}\frac{|r_j|}{Q_j} = \frac{1}{N_t}\sum_{j=1}^{N_t}\frac{\left|\frac{P_j - P_{j-1}}{P_{j-1}}\right|}{Q_j} \tag{7}$$

where N_t is the number of trades on day t, P_j is the price of the bond at trade j, and Q_j is the par amount of trade j. Weekly estimates of the Amihud measure are obtained by taking the mean of CUSIP-day estimates in a week, and are shown in Figure A.11.

Figure A.11: Amihud Illiqudity Measure Evolution in the Municipal Bond Market



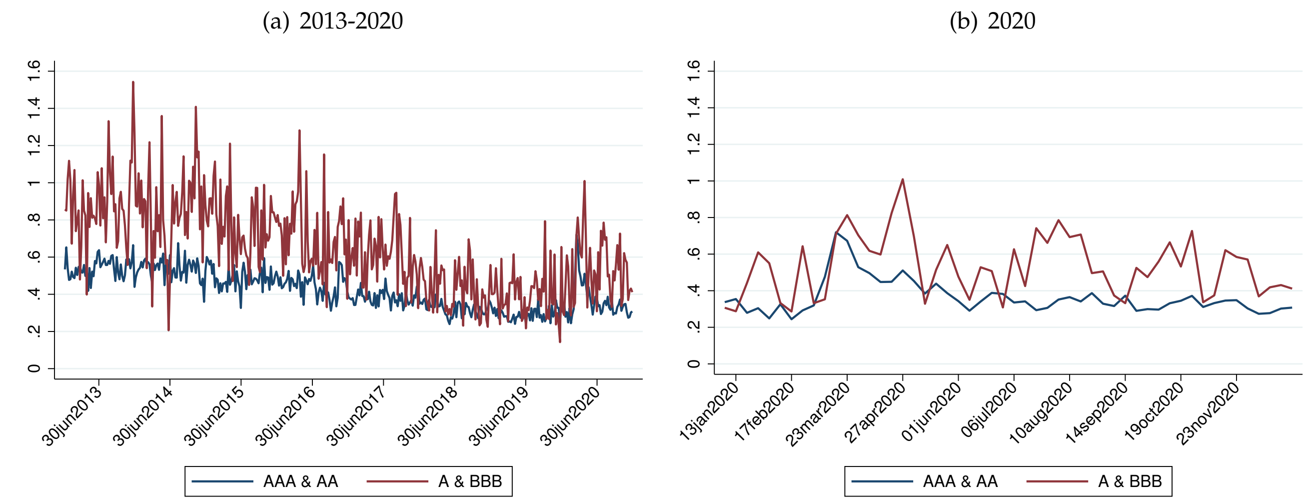
NOTES—Figure shows Amihud measure (the mean of CUSIP-days) over time for city and county bonds by January plurality ratings.

2. Effective Bid-Ask Spread (BAS): The effective bid-ask spread is meant to capture dealer compensation for the information advantage possessed by informed traders in a context of few buyers and sellers at desired price ranges. We calculate the effective BAS for each bond as the difference between the size-weighted buy price within the week and the size-weighted sell price within the week, divided by the midpoint of the two prices. Specifically:

$$BAS_{bt} = \frac{\sum_{n \in bt} w^B_{nbt} p^B_{nbt} - \sum_{n \in bt} w^S_{nbt} p^S_{nbt}}{0.5 \times \left(\sum_{n \in bt} w^B_{nbt} p^B_{nbt} + \sum_{n \in bt} w^S_{nbt} p^S_{nbt}\right)}. \tag{8}$$

Figure A.12 plots the weekly time-series of the average BAS across all city and county bonds separately by January 2020 plurality ratings.

Figure A.12: Bid-Ask Spread Evolution in Municipal Bond Markets



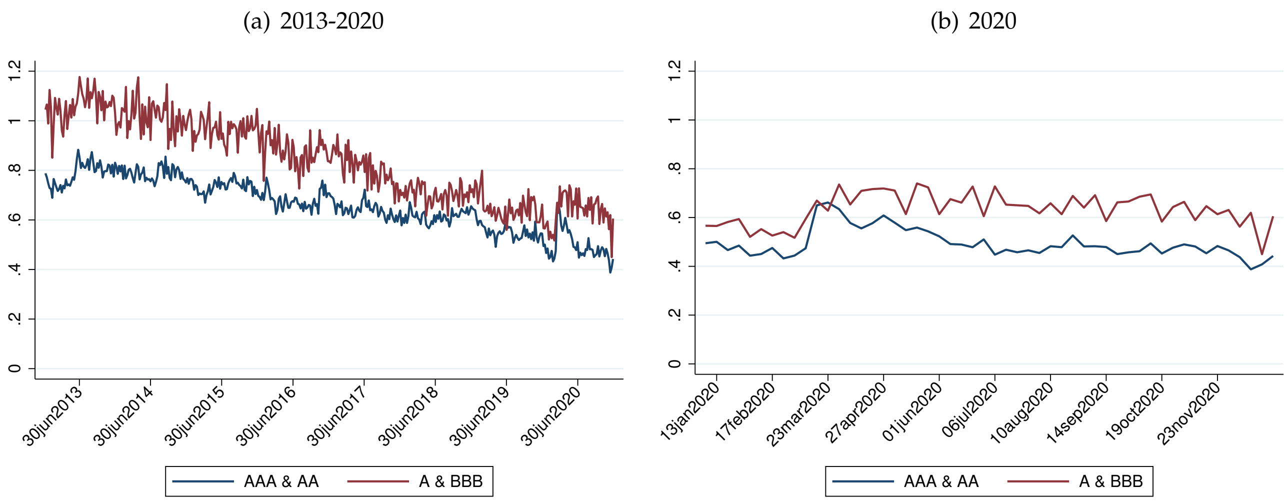
NOTES—Figure shows the average effective bid-ask spread over time for city and county bonds. We calculate the effective bid-ask at the bond-week level as the volume-weighted difference between transacted buy price and sell price from the client's perspective, adjusted by the midpoint level of the two prices. We show results separately by January 2020 issuer plurality ratings.

3. Imputed Round-trip Cost (IRC): Following Feldhütter (2012), we identify imputed round-trip trades for a given bond on a given day if there are exactly two or three trades for a given volume that occur within fifteen minutes. Those trades are likely a part of a pre-matched arrangement in which a dealer has matched a buyer and seller. In an imputed round-trip trade, the highest price is assumed to be an investor buying from a dealer, while the lowest price assumed to be an investor selling to a dealer. The investor round-trip cost for bond b and day t is then calculated as the highest minus the lowest price. Specifically:

$$IRC_{bt} = \frac{P_{max} - P_{min}}{P_{min}} \tag{9}$$

where P_{max} is the highest price and P_{min} is the lowest price in an imputed round-trip trade. Weekly IRC estimates at the bond-level are obtained by taking the mean of daily estimates in a given week, and are shown in Figure A.13.

Figure A.13: Imputed Round-Trip Costs in Municipal Bond Markets



NOTES—Figure shows the average imputed round-trip cost over time for city and county bonds, separately by January 2020 plurality ratings.

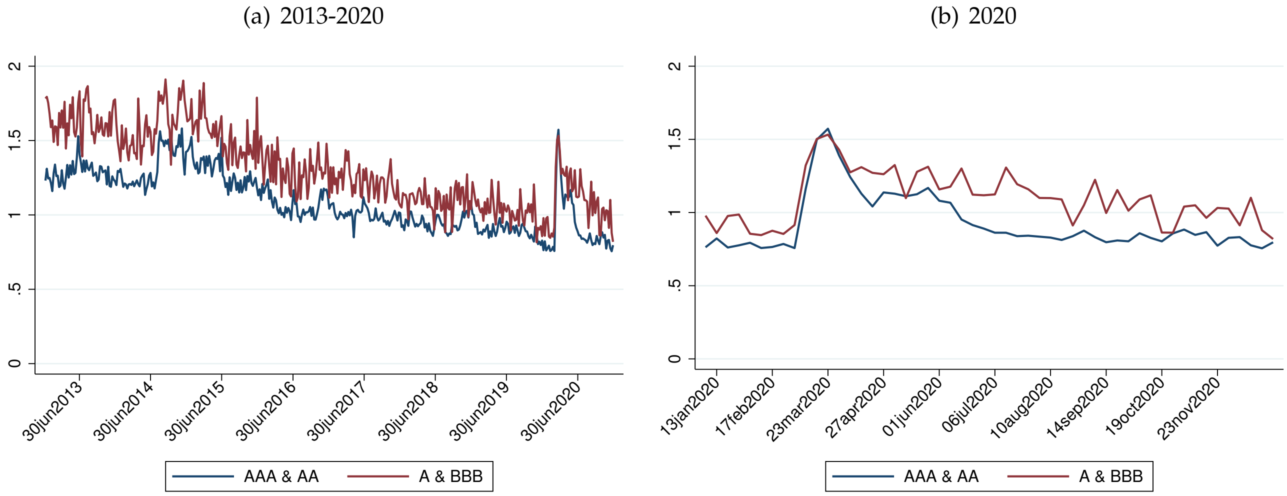
4. Roll's Measure: Roll (1984) provides an alternative construction of the BAS. It requires two strong assumptions. First, the market is informationally efficient. Second, the probability distribution of observed price changes is stationary (at least for short intervals). Under these assumptions, if trading costs are zero, a change in price will occur if and only if unanticipated information is received by market participants. There will be no serial dependence on successive price changes (aside from that generated by serial dependence in expected returns). However, if trading is costly, the dealer will be compensated by the bid-ask spread. When information arrives, both the bid and the ask prices move to different levels such that their average is the new equilibrium value. Thus, the bid-ask average fluctuates randomly in an efficient market. Observed market price changes are no longer independent because recorded transactions occur at either the bid or the ask, not at the average, and a negative serial dependence in observed price changes should be anticipated.

In our context, we calculate Roll's measure for bond b and day t as:

$$Roll_{bt} = 2 \times \sqrt{-Cov\left(\Delta P_n, \Delta P_{n-1}\right)} \tag{10}$$

where P_n is the price at trade n and the measure is set to zero when the covariance between successive price movements is positive. Weekly estimates of the Roll measure are obtained by taking the mean of the daily estimates in a week.

Figure A.14: Roll Measure in Municipal Bond Markets



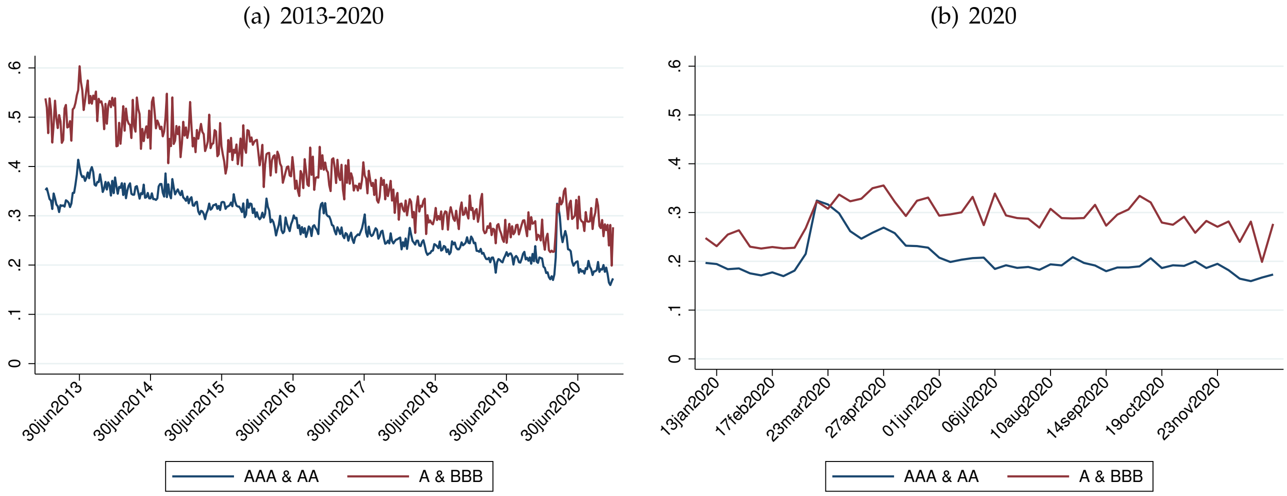
NOTES—Figure show the weekly mean Roll Measure over time for city and county bonds, separately by January 2020 plurality ratings.

5. Price Dispersion: We also consider an alternative measure following Jankowitsch et al. (2011), who use the wedge between expected and traded prices to estimate liquidity. We calculate the dispersion of traded prices around a market "consensus valuation". Although this measure is similar to the other liquidity measures, it is not perfectly correlated and seems to contribute additional information about the market liquidity. So, for each bond b on day t we calculate:

$$Dispersion_{bt} = \sqrt{\left(\sum_{n=1}^{N_{bt}} Q_{bn} \sum_{n=1}^{N_{bt}} (P_{bn} - M_{bt})^2 Q_{bn}\right)^{-1}} \tag{11}$$

where N_{bt} is the number of trades of bond b on day t, P_{bn} is the price of the bond at trade n, Q_{bn} is the par amount of trade n, and M_{bt} is the market "consensus valuation" for bond b, which is calculated as the daily volume-weighted average price of the bond. Weekly estimates of the price dispersion measure at the bond-week level are obtained by taking the mean of the daily estimates in a week, and are shown in Figure A.15.

Figure A.15: Price Dispersion Measure in Municipal Bond Markets

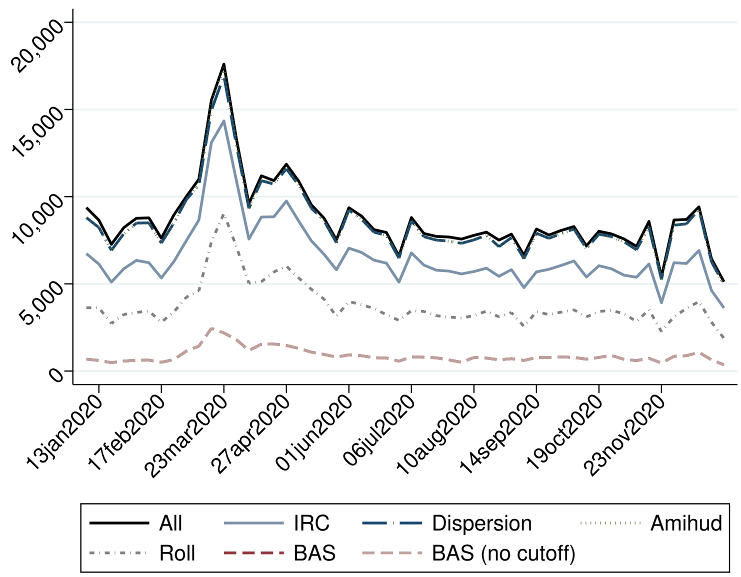


NOTES—Figure shows the average weekly Price Dispersion measure over time for city and county bonds, separately by January 2020 plurality ratings.

Choice of Liquidity Measures: In the main text we choose to present results using a liquidity factor that is calculated based on only four illiqudity measures, excluding the bid-ask spread. Given the relationship between transaction costs and trade size, we would have liked to compare buy and sell prices of trades with similar sizes. As Green et al. (2010) has observed, dealers often provide liquidity to institutional traders by purchasing large blocks of bonds and selling smaller blocks off to retail investors, or to regional dealers with retail distribution capability. This results in asymmetry of the trade size of buys and sales. A reasonable condition such as requiring at least one buy and one sale, each with a trade size greater than $100,000 results in a very restrictive sample, as shown in Figure A.16. Relaxing this restriction indeed results in a similar coverage of bonds as the other illiquidity measures, but we prefer not to use a measure that "mixes" transaction costs of large and small trades without properly "controlling" for the trade size (as the IRC does for example). In either case, our results are robust to including or excluding BAS, and to including BAS without the >$100,000 restriction.

To illustrate the number of bonds that contribute to each measure in a given week, Figure A.16 shows the number of distinct CUSIPs that are in our Baseline sample each week, both overall, and by measure.

Figure A.16: CUSIP Coverage of Each Illiquidity Measure



Summary of Liquidity Measures and Liquidity First Principal Component Method: The different illiquidity measures above capture the expected transaction costs and the risk of these costs changing. Historically, as expected, we observe that lower rated bonds (A and BBB) are less liquid than higher rated bonds (AAA and AA).

Table A.3 summarizes the distributive properties of the four illiquidity measures used for the analysis. While the measures are correlated, each individual measure still contains additional distinct information, as observed in Table A.4 which reports the correlation between measures. We also observe that transaction costs are high, though liquidity in the market has been improving over the past decade. We normalize each liquidity measure by subtracting its mean and dividing by its standard deviation over the sample period (January 2013 - December 2020):

$$\lambda_{bt} = \frac{L^k_{bt} - \mu_b}{\sigma_b} \,,$$

where L^k_{bt} is one of the liquidity measures k (Amihud, BAS, IRC, Roll, or Price Dispersion) for bond b on week t. We then consider the first principal component of the four liquidity measures (excluding BAS) as the liquidity factor λ_{bt}. When we present the results for the calendar year 2020, we restrict the sample only after following the procedure described above. That is, the weekly liquidity factors are based on normalization that is based on a longer time series, from January 2013 to December 2020.

Figure A.17 plots the first principal component of the four normalized illiquidity measures. Panel (a) shows the time series of average illiquidity variable λ_t from 2013 to 2020, exhibiting a long term improvement in liquidity in the municipal bond market consistent with evidence in the literature (e.g., Wu, 2018). Panel (b) takes a closer look at the liquidity during 2020. We see that liquidity worsened in early March during COVID-19 market dislocation across all rating groups. While AAA/AA liquidity improved post-MLF announcement and other Federal interventions that were introduced between mid-March and the end of April 2020, liquidity of the lower rated bonds (A and BBB) has continued to be a problem throughout 2020.

Table A.3: Illiquidity Measures Summary Statistics. This table reports summary statistics for the bond-week illiquidity measures.

	Mean	SD	p1	p10	p50	p90	p99	# Observations	# Bonds
Amihud (% per $1m)	25.8	45.8	0	0	7.51	74.8	236.8	2,113,646	157,132
BAS	0.43	0.60	0	0.011	0.17	1.31	2.63	189,517	154,415
IRC (%)	0.68	0.68	0.031	0.090	0.41	1.78	2.72	1,664,143	157,146
Roll	1.13	1.19	0	0	0.75	2.82	5.09	907,006	131,561
Dispersion	0.29	0.34	0	0	0.13	0.84	1.32	2,121,035	67,101

Table A.4: Correlations between Illiquidity Measures. This table reports correlations between illiquidity measures on a weekly basis.

	Amihud	BAS	IRC	Roll	Dispersion
Amihud	1	0.2363	0.4245	0.3743	0.4718
BAS	0.2363	1	0.7283	0.4086	0.8202
IRC	0.4245	0.7283	1	0.4930	0.8379
Roll	0.3743	0.4086	0.4930	1	0.5177
Dispersion	0.4718	0.8202	0.8379	0.5177	1

Figure A.17: First Principal Components This figure plots the first principal component of illiquidity measures on a weekly basis, calculated separately for cities and counties by January 2020 plurality ratings.