Online Appendix to "Adverse Selection Dynamics in Privately-Produced Safe Debt Markets"*

Nathan Foley-Fisher[1], Gary Gorton[2], and Stéphane Verani[1]

[1]Federal Reserve Board
[2]Yale School of Management and NBER

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Abstract

This online appendix provides additional data description and results for the paper, "Adverse Selection Dynamics in Privately-Produced Safe Debt Markets."

*Corresponding author email: nathan.c.foley-fisher@frb.gov The views in this paper are solely the authors' and should not be interpreted as reflecting the views of the Board of Governors of the Federal Reserve System or of any other person associated with the Federal Reserve System.

A Data

See full replication package 'openicpsr-185644' available at https://www.openicpsr.org/openicpsr/.

A.1 Data citations

- Bloomberg Finance LP, ABS Backoffice, https://www.bloomberg.com/professional/product/reference-data/
- Financial Industry Regulatory Authority, Bond Trade Dissemination System (BTDS) and Trade Reporting and Compliance Engine (TRACE), http://www.finra.org/Industry/Compliance/MarketTransparency/TRACE/index.htm
- Moody's Analytics, Inc., CreditView, https://www.moodys.com/
- Fitch Solutions, Inc. Fitch Ratings Delivery Service: Corporate and Structured Finance Data, https://www.fitchratings.com/products#structured-finance
- Moody's Analytics CLO Finance & Data Solutions, https://www.moodysanalytics.com/-/media/solutions/moodys-analytics-clo-market-solutions-brochure.pdf
- FRED API, accessed using third party R software package fredr, https://fred.stlouisfed.org/docs/api/fred/
  - 'DEXUSEU' — Board of Governors of the Federal Reserve System (US), U.S. Dollars to Euro Spot Exchange Rate [DEXUSEU], retrieved from FRED, Federal Reserve Bank of St. Louis; https://fred.stlouisfed.org/series/DEXUSEU
  - 'DEXUSUK' — Board of Governors of the Federal Reserve System (US), U.S. Dollars to U.K. Pound Sterling Spot Exchange Rate [DEXUSUK], retrieved from FRED, Federal Reserve Bank of St. Louis; https://fred.stlouisfed.org/series/DEXUSUK
- Standard & Poor's Leveraged Commentary & Data (LCD), https://www.lcdcomps.com/lcd/

- Standard & Poor's Morningstar LSTA, `https://indexes.morningstar.com/our-indexes/details/morningstar-lsta-us-leveraged-loan-FSUSA084ZT?tab=overview`
- Overnight Bank Funding Rate (OBFR), `https://www.newyorkfed.org/markets/reference-rates/obfr`
- Chase and Sharon Ross' US Treasury Swap Rate Data, `https://chaseross.com/`, `https://sharonyross.com/`
- Barchart, see details below, `https://www.barchart.com/stocks/sectors/rankings`

A.2 Barchart data details

Download the seven sectors listed in the table below from the website and stack the files in a single *.csv* file. Our measure of volatility is the difference between the intra-day high and low log prices. We combine the seven sectors into a single weighted-average measure of volatility in the vulnerable sectors, where the weights are the volumes.

Table 1: Mapping Moody's vulnerable sectors to Barchart sectors. The table below provides the seven sectors we used to calculate our measure of volatility.

Moody's Sector	Barchart Sector
Automotive	Automobiles
Consumer Goods: Durable	Consumer Goods: Durable Household Products
Energy: Oil & Gas	Oil & Gas Producers
Hotel, Gaming & Leisure	Hotels
Retail	Retail
Transportation: Cargo	Industrial Transportation
Transportation: Consumer	Transportation Services

B Additional results

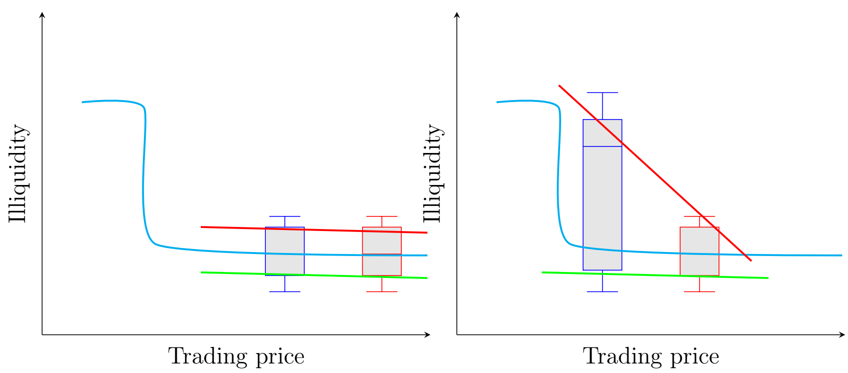
B.1 Alternative specification with continuous price variable

In the analysis of section 4, we used a dummy variable for high and low CLO prices. In this appendix, we replace the dummy variable with a continuous price variable. We find similar results with the caveat that the relationship between IRC and prices is unlikely to be linear.

Figure 1 adapts Figure 7 of the main text to show the intuition for identification with a continuous price variable in the quantile regression. The linear functional form estimates the slopes of the red and green lines i.e. the locus of points in the IRC distributions conditional on prices. By interacting the continuous price variable with the pandemic dummy, we compare these slopes in normal and pandemic times. The emergence of adverse selection in the CLO market when prices fall during the pandemic makes the red line steeper while the slope of the green line is unchanged.

The results are shown in Table 2. The F-test in the last line of the table indicates that the interaction term is significantly different between the 75^{th} and 25^{th} percentiles of the IRC distributions. We would caution that imposing the linear functional form (continuous price variable) may not be appropriate. As suggested by the latent blue line in the schematic figure 1, the relationship between IRC and prices is likely to be nonlinear.

Figure 1: Schematic linear relationship between imputed roundtrip costs and prices. The figure adapts Figure 7 of the main text to show the intuition for identification with a continuous price variable in the quantile regression. As before, the blue line represents a single AAA-rated CLO tranche and the boxplots represent IRC distributions. The green and red lines are new. They represent the estimated linear relationship between IRC and prices at different quantiles in the distribution of IRC. The panel on the left represents normal times, when the slopes of the red and green lines are the same. The panel on the right represents pandemic times, when the slope of the red line is significantly steeper and the slope of the green line remains the same as in normal times. This differential effect arises from latent discontinuities in the relationship between the IRC and prices.



(a) Normal times **(b)** Pandemic times

Table 2: Adverse selection in AAA-rated CLOs during the pandemic – quantile fixed effect regression. This table shows an increase in the negative correlation between the imputed roundtrip cost (IRC) and the prices of AAA-rated CLOs during the pandemic. The dependent variable is the imputed round trip cost of CLO tranche i for dealer k on day t. Covid_t takes the value 0 before March 1, 2020 and 1 thereafter. WtPrice_{it} is the weighted-average price of CLO i on day t. See the main text for an explanation of the additional controls. The quantile fixed effect regressions are implemented using the penalized fixed-effects estimation method proposed by Koenker (2004). Percentiles are indicated in the square parentheses. Clustered bootstrapped standard errors (2,000 replications) are implemented using the generalized bootstrap of Chatterjee and Bose (2005) with unit exponential weights sampled for each individual CUSIP, and reported in parentheses. Source: Authors' calculations from data provided by TRACE, Bloomberg LP., Moody's Analytics, S&P, and Fitch. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

	(1) AAA	(2) AAA	(3) AAA	(4) AAA	(5) AAA
[0.25]Covid_t	31.77	30.2	29.7	26.82	-0.6
	(227.86)	(171.85)	(207.28)	(206.52)	(406.45)
[0.25]WtPrice_t	-0.64	-0.68	-0.35	-0.64	-0.77
	(2.23)	(1.65)	(2.08)	(2)	(4.03)
[0.25]$\text{Covid}_t \times \text{WtPrice}_t$	-0.32	-0.29	-0.3	-0.28	0.01
	(2.28)	(1.72)	(2.07)	(2.07)	(4.07)
[0.5]Covid_t	9.41	122.51	76.98	-35.47	121.86
	(243.5)	(172.07)	(219.05)	(228.35)	(466.08)
[0.5]WtPrice_t	-2.78	-1.82	-0.99	-3.21	-1.02
	(2.38)	(1.63)	(2.2)	(2.23)	(4.61)
[0.5]$\text{Covid}_t \times \text{WtPrice}_t$	-0.11	-1.04	-0.78	0.34	-1.22
	(2.44)	(1.72)	(2.19)	(2.28)	(4.66)
[0.75]Covid_t	418.39	469.92**	273.24	157.5	468.37
	(284.19)	(182.13)	(273.95)	(285.15)	(454.18)
[0.75]WtPrice_t	-2.19	-1.82	-1.69	-4.74*	-1.02
	(2.78)	(1.73)	(2.73)	(2.79)	(4.45)
[0.75]$\text{Covid}_t \times \text{WtPrice}_t$	-4.21	-4.51**	-2.75	-1.54	-4.53
	(2.84)	(1.83)	(2.74)	(2.85)	(4.55)
Fixed effects:					
CUSIP	Y	Y	Y	Y	Y
Additional controls:					
Dealer	Y	Y	Y	Y	Y
COVID×Dealer	N	Y	N	N	N
2yr-Carry rate×Dealer	N	N	Y	N	N
OBFR×Dealer	N	N	N	Y	Y
Observations	2,666	2,666	2,486	2,666	985
	H_0: [0.25]$\text{Covid}_t \times \text{Traded price}_{it}$ = [0.75]$\text{Covid}_t \times \text{Traded price}_{it}$				
F test	3.95**	12.5***	1.82	0.37	1.51

B.2 Quantile regression information sensitivity test

We test for the switch to information sensitivity using a quantile regression to study the relationship between the dispersion of AAA CLO tranche prices and uncertainty about vulnerable industries. The test consists of showing that 1) uncertainty about those vulnerable industries is uncorrelated with AAA-rated tranche prices in normal times and become positively correlated during the pandemic, and 2) that the impact is not uniform across the distribution of prices. Under the null hypothesis of information sensitivity, the lower part of the distribution of AAA tranche price should be a lot more sensitive to new information about the vulnerable industries because investors are distinguishing those AAA CLO tranche that became information sensitive.

The dependent variable $\text{Trading price}_{it}$ is the weighted-average price of CLO tranche i on day t, where the weights are the transaction volumes. The variable Covid_t takes the value 0 before March 1, 2020 and 1 thereafter. Volatility_t is the volume-weighted average daily difference between the high and low log prices on seven vulnerable industries (Sallerson, 2020).[1] We estimate the conditional quantile functions $Q_{\text{Trading price}_{it}}(\tau|\text{Covid}_t, \text{Volatility}_t)$ of the response of the t-th

[1] Appendix B.3 reports a robustness check where we replace our measure of realized volatility with a measure of forward volatility.

observation on the i-th CLO tranche's Trading price$_{it}$ given by

$$
\begin{aligned}
Q_{\text{Trading price}_{it}}(\tau|\text{Covid}_t, \text{Volatility}_t) = \alpha^i &+ \beta_1(\tau)\text{Covid}_t \\
&+ \beta_2(\tau)\text{Volatility}_t \\
&+ \beta_3(\tau)\text{Covid}_t \times \text{Volatility}_t \ , \qquad (1)
\end{aligned}
$$

with quantile $\tau \in \{0.25, 0.5, 0.75\}$ and where α^i is the CUSIP fixed effect. The CUSIP fixed effects absorb all time-invariant cross-sectional differences in the CLOs that were traded during the period. The quantile fixed effect regressions are implemented using the penalized fixed-effects estimation method proposed by Koenker (2004).

Table 3 shows the results. The columns in the table refer to the different CLO tranches by seniority. The industry calls the most senior debt tranche the A Class and the most junior debt tranche the E Class. Class A tranches are designed to attract a AAA rating by a credit rating agency at issuance. Therefore, the majority of AAA-rated tranches are Class A debt securities. In our sample of CLO trades, about 92 percent of the CLO tranches rated AAA by at least one of the main credit rating agencies (S&P, Moody's, and Fitch) are Class A tranches. The remaining AAA CLO tranches in our sample are below Class A. In the table, the first column is all AAA tranches. Columns 2 through 6 follow the CLO capital structure from the most senior debt tranches (Class A) to the most subordinate debt tranches

Table 3: Information sensitivity of CLO debt tranches – quantile fixed effect regression. This table shows that highly-rated CLO debt tranches became information-sensitive during the pandemic. The dependent variable is the weighted average price of CLO tranche i on day t, where the weights are the transaction volumes. Covid_t takes the value 0 before March 1, 2020 and 1 thereafter. Volatility_t is the weighted average daily difference between the high and low log prices on the seven vulnerable industries identified by Moody's, where the weights are the transaction volumes. Column 1 includes only the CLO tranches rated AAA by at least one of the three main credit rating agencies. The quantile fixed effect regressions are implemented using the penalized fixed-effects estimation method proposed by Koenker (2004). Percentiles are indicated in the square parentheses. Clustered bootstrapped standard errors (1,000 replications) are implemented using the generalized bootstrap of Chatterjee and Bose (2005) with unit exponential weights sampled for each individual CUSIP, and reported in parentheses. Source: Authors' calculations from data provided by TRACE, BarChart, Bloomberg LP., Moody's Analytics, S&P, and Fitch. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Dep. var.:		Debt class				
Trading price	AAA	A	B	C	D	E
	(1)	(2)	(3)	(4)	(5)	(6)
[0.25]Covid_t	-0.59***	-0.6***	-1.14*	-3.51***	-12.37***	-22.05***
	(0.21)	(0.22)	(0.59)	(0.89)	(1.27)	(1.97)
[0.25]Volatility_t	-2.32	-4.76**	-24.25***	-52.08***	-0.07	-63.64**
	(1.86)	(2.29)	(6.87)	(14.56)	(13.95)	(30.07)
[0.25]$\text{Covid}_t \times \text{Volatility}_t$	-78.76***	-83.3***	-153.7***	-188.56***	-235.28***	-201.51***
	(7.69)	(8.39)	(23.28)	(32.33)	(36.81)	(60.83)
[0.5]Covid_t	-1.22***	-1.22***	-2.1***	-3.78***	-10.78***	-18.58***
	(0.17)	(0.18)	(0.33)	(0.63)	(1.03)	(1.8)
[0.5]Volatility_t	-1.23	-1.59	-18.22***	-23.12*	0.36	-47.26*
	(0.94)	(1.32)	(5.38)	(12.46)	(7.39)	(26.81)
[0.5]$\text{Covid}_t \times \text{Volatility}_t$	-36.21***	-40.41***	-76.63***	-108.15***	-150.42***	-103.83*
	(5.98)	(6.54)	(13.38)	(25.1)	(28.77)	(56.76)
[0.75]Covid_t	-1.54***	-1.54***	-2.09***	-3.68***	-8.77***	-13.62***
	(0.16)	(0.17)	(0.33)	(0.51)	(0.76)	(1.6)
[0.75]Volatility_t	1.3	0.32	-11.79**	-7.82	0	-27.23
	(2.03)	(1.43)	(5.85)	(10.09)	(7.79)	(26.58)
[0.75]$\text{Covid}_t \times \text{Volatility}_t$	-12.9**	-16.23***	-44.17***	-54.76***	-83.9***	-51.16
	(5.33)	(5.4)	(11.7)	(18.83)	(18.65)	(46.1)
CUSIP FE	Y	Y	Y	Y	Y	Y
Observations	16,529	18,333	5,938	6,775	8,471	6,074
	H_0: [0.25]$\text{Covid}_t \times \text{Volatility}_t$ = [0.75]$\text{Covid}_t \times \text{Volatility}_t$					
χ^2_1 test statistic	81.76***	81.61***	20.13***	15.22***	15.91***	5.67**

(Class E).

The regression reveals how sensitive the CLO prices *within a tranche group* are to the vulnerable industries volatility index. The table includes a row reporting a χ^2 test of the null hypothesis that the 25^{th} and 75^{th} percentile coefficients are the same. The statistical significance of the difference between the two coefficients increases monotonically with the seniority of the tranches and loses significance lower in the capital structure (E class).

Percentiles of the distribution of transaction prices are responding heterogeneously to uncertainty about the vulnerable industries. Appendix B.4 reports a robustness check where we include a measure of volatility in other sectors, to control for aggregate volatility. The variation is strongest for the tranches that were information insensitive in the pre-pandemic period. Before the pandemic, the distribution of transaction prices of AAA tranches was uniformly uncorrelated with the vulnerable industries volatility index. During the pandemic, the lowest transaction prices for AAA-rated CLOs became correlated with an index of the volatility of the vulnerable industries' stock prices, while the highest transaction prices remained relatively uncorrelated with the same index.

Looking at the AAA tranches, the difference in the coefficients between the 25^{th} and the 75^{th} percentile is economically meaningful. The counterfactual price of a AAA CLO tranche that moved from the

75^{th} percentile to the 25^{th} percentile would have been about 180 bps lower, given a one standard deviation increase in the vulnerable volatility index during the pandemic period. That change is almost two dollars per 100 face value, a huge difference. For some perspective on the 180 bps decrease, note that the standard deviation of AAA CLO tranche prices in the pre-pandemic period was about 8 bps.

B.3 Robustness: Table 3 with forward volatility

In this subsection, we check whether the results of our quantile fixed effect regression used in section 5 of the main text are sensitive to the use of realized volatility as a measure of information. We replace the realized volatility measure with lagged values, which are a proxy for forward volatility.

Table 4 shows the results from repeating the quantile regression specification, replacing Volatility_t with the values lagged by one week ($\text{Volatility\_1wk\_lag}_t$). The lagged variable is a proxy for forward volatility. The coefficient estimates and the χ^2_1 test statistic in the last row of the table further suggest that AAA-rated CLO debt tranches became information sensitive. The lowest transaction prices for AAA CLOs became correlated with a proxy for *forward* volatility of the vulnerable industries' stock prices, while the highest transaction prices remained relatively uncorrelated with the same proxy.

Table 4: Information sensitivity of CLO debt tranches – robustness test with forward volatility. This specifications report in this table replicate those of Table 3, replacing Volatility_t with the values lagged by one week. The dependent variable is the weighted average price of CLO tranche i on day t, where the weights are the transaction volumes. Covid_t takes the value 0 before March 1, 2020 and 1 thereafter. $\text{Volatility\_1wk\_lag}_t$ is the one-week lagged weighted average daily difference between the high and low log prices on the seven vulnerable industries identified by Moody's, where the weights are the transaction volumes. Column 1 includes only the CLO tranches rated AAA by at least one of the three main credit rating agencies. The quantile fixed effect regressions are implemented using the penalized fixed-effects estimation method proposed by Koenker (2004). Percentiles are indicated in the square parentheses. Clustered bootstrapped standard errors (1,000 replications) are implemented using the generalized bootstrap of Chatterjee and Bose (2005) with unit exponential weights sampled for each individual CUSIP, and reported in parentheses. Source: Authors' calculations from data provided by TRACE, BarChart, Bloomberg LP., Moody's Analytics, S&P, and Fitch. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Dep. var.:		Debt class				
Trading price	AAA	A	B	C	D	E
	(1)	(2)	(3)	(4)	(5)	(6)
[0.25]Covid_t	-0.13	-0.17	0.1	-1.71**	-9.43***	-15.59***
	(0.17)	(0.17)	(0.42)	(0.7)	(1.09)	(1.44)
[0.25]$\text{Volatility\_1wk\_lag}_t$	4.96***	4.42**	10.1	-5.79	-4.26	-58.76**
	(1.89)	(2.11)	(7.21)	(15.73)	(16.11)	(25.8)
[0.25]$\text{Covid}_t \times \text{Volatility\_1wk\_lag}_t$	-90.49***	-93.42***	-194.85***	-234.73***	-284.99***	-310.87***
	(6.25)	(6.54)	(15.83)	(25.32)	(30.49)	(43.18)
[0.5]Covid_t	-0.68***	-0.72***	-0.45	-1.31**	-7.82***	-11.63***
	(0.12)	(0.12)	(0.36)	(0.56)	(0.94)	(1.42)
[0.5]$\text{Volatility\_1wk\_lag}_t$	2.44**	3**	4.87	-3.65	-15.08	-63.32***
	(1.1)	(1.27)	(3.04)	(6.18)	(11.18)	(16.81)
[0.5]$\text{Covid}_t \times \text{Volatility\_1wk\_lag}_t$	-53.16***	-56.9***	-137.42***	-184.03***	-212.7***	-272.78***
	(4.01)	(3.92)	(11.95)	(16.51)	(26.12)	(36.04)
[0.75]Covid_t	-0.8***	-0.92***	-1.19***	-0.97	-5.03***	-6.67***
	(0.11)	(0.11)	(0.45)	(0.63)	(0.91)	(1.67)
[0.75]$\text{Volatility\_1wk\_lag}_t$	2.45	0.9	1.12	-5.94	0.7	-59.46***
	(2.3)	(1.95)	(3.24)	(5.94)	(11.68)	(18.79)
[0.75]$\text{Covid}_t \times \text{Volatility\_1wk\_lag}_t$	-35.11***	-34.29***	-78.27***	-135.08***	-189.19***	-240.47***
	(3.54)	(3.38)	(14.51)	(18.43)	(25.15)	(39.63)
CUSIP FE	Y	Y	Y	Y	Y	Y
Observations	15,779	17,479	5,551	6,320	8,049	5,817
	H_0: [0.25]$\text{Covid}_t \times \text{Volatility\_1wk\_lag}_t$ = [0.75]$\text{Covid}_t \times \text{Volatility\_1wk\_lag}_t$					
χ^2_1 test statistic	78.7***	84.54***	41.59***	11.94***	6.85***	1.74

B.4 Robustness: Table 3 with other sectors' volatility

In this subsection, we check whether the results of our quantile fixed effect regression used in section 5 of the main text are driven by higher volatility in all sectors. We include an index of the stock price volatility of the ten largest sectors traded, as measured by the 30-day average volume reported by barchart.com. We use the largest sectors because we have no prior on the sectors that are *least* affected by the pandemic. We exclude the sectors already identified by Moody's as being vulnerable to the pandemic. The ten other sectors are: Banks, Consumer Services, Financials, Industrial Goods & Services, Industrials, Software & Computer Services, Tech Hardware & Equipment, Technology, Software, and Semiconductors. We construct the new index as the weighted average daily difference between the high and low log prices for each sector, where the weights are the transaction volumes. This construction is analogous to the construction of the stock price volatility index for the sectors that Moody's identified as vulnerable to the pandemic.

Intuitively, the volatility index for the most-traded sectors is a proxy for widespread financial market volatility that is *not* related to information specific to the vulnerable sectors. We prefer this proxy to an aggregate measure–such as VIX–whose variation is potentially also related to information about the vulnerable sectors.

Table 5 shows the results. We find that even after controlling for volatility in the most-traded other sectors, the distribution of CLO prices is differentially related to stock price volatility of the vulnerable industries. To be sure, the χ_1^2 test statistic reported in the last row of the table indicates that volatility in the other sectors is also differentially affecting the distribution of AAA-rated CLO prices. This suggests that widespread volatility–or information about those other sectors–is creating dispersion in CLO prices. Nonetheless, the significant effect of the vulnerable industries' volatility, in combination with the other results documented in the paper, continue to suggest that AAA-rated CLOs became information-sensitive during the pandemic.

Table 5: Quantile fixed effect regression with vulnerable sectors' and other sectors' stock price volatility. The dependent variable is the weighted average price of CLO tranche i on day t, where the weights are the transaction volumes. Covid_t takes the value 0 before March 1, 2020 and 1 thereafter. Vul_Volatility_t is the weighted average daily difference between the high and low log prices on the seven vulnerable industries identified by Moody's, where the weights are the transaction volumes. $\text{Other\_Volatility}_t$ is the weighted average daily difference between the high and low log prices on the ten most traded non-vulnerable industries, where the weights are the transaction volumes. Column 1 includes only the CLO tranches rated AAA by at least one of the three main credit rating agencies. See the note to Table 3 for additional details. Source: Authors' calculations from data provided by TRACE, BarChart, Bloomberg LP., Moody's Analytics, S&P, and Fitch. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Dep. var.:		Debt class				
Trading price	AAA	A	B	C	D	E
	(1)	(2)	(3)	(4)	(5)	(6)
[0.25]Covid_t	-0.57***	-0.6***	-1.15*	-3.66***	-12.47***	-22.52***
	(0.21)	(0.21)	(0.67)	(0.91)	(1.25)	(2.13)
[0.25]Vul_Volatility_t	5.59	8.09*	17.94**	29.25	39.58**	42.03
	(4.05)	(4.36)	(7.04)	(18.6)	(16.04)	(32.94)
[0.25]$\text{Other\_Volatility}_t$	-10.07**	-16.58***	-53.01***	-113.64***	-76.69***	-158.26***
	(5.1)	(5.79)	(11.75)	(25.71)	(29.04)	(47.53)
[0.25]$\text{Covid}_t \times \text{Vul\_Volatility}_t$	-51.03***	-53.03***	-184.55***	-242.64***	-350.24***	-374.91***
	(12.11)	(14.96)	(29.78)	(46.37)	(68.67)	(94.39)
[0.25]$\text{Covid}_t \times \text{Other\_Volatility}_t$	-37.64**	-38.1**	38.78	76.36	165**	259.38**
	(15.07)	(17.61)	(45.48)	(65.03)	(79.58)	(130.26)
[0.5]Covid_t	-1.21***	-1.2***	-2.24***	-4.71***	-11.3***	-20.28***
	(0.19)	(0.18)	(0.38)	(0.64)	(1.02)	(1.58)
[0.5]Vul_Volatility_t	1.88	4.03	5.75	10.6	23.92**	30.78
	(1.98)	(2.54)	(4.7)	(10.75)	(10.04)	(23.45)
[0.5]$\text{Other\_Volatility}_t$	-4.66*	-7.27**	-35.55***	-50.73***	-37.47**	-124.8***
	(2.58)	(3.41)	(8.86)	(19.14)	(16.15)	(37.62)
[0.5]$\text{Covid}_t \times \text{Vul\_Volatility}_t$	-34.21***	-36.17***	-157.09***	-213.28***	-231.81***	-374.32***
	(11.29)	(13.99)	(24.5)	(26.76)	(52.64)	(75.76)
[0.5]$\text{Covid}_t \times \text{Other\_Volatility}_t$	-2.96	-7.12	115.36***	182.13***	125.65*	433.53***
	(12.39)	(16.13)	(34.78)	(53.85)	(74.74)	(97.32)
[0.75]Covid_t	-1.56***	-1.55***	-2.5***	-3.76***	-8.74***	-13.7***
	(0.14)	(0.13)	(0.34)	(0.48)	(0.78)	(1.61)
[0.75]Vul_Volatility_t	5.54*	4.5*	-1.1	4.92	13.72	18.09
	(2.97)	(2.52)	(4.98)	(9.2)	(13.35)	(27.6)
[0.75]$\text{Other\_Volatility}_t$	-6.3*	-6.02*	-18.96**	-22.22	-24.51	-91.66**
	(3.61)	(3.22)	(9.43)	(17.29)	(18.61)	(42.23)
[0.75]$\text{Covid}_t \times \text{Vul\_Volatility}_t$	-18.21	-19.09	-107.06***	-189.9***	-153.5***	-184.96
	(12.36)	(13.94)	(26.71)	(26.82)	(51.76)	(129.83)
[0.75]$\text{Covid}_t \times \text{Other\_Volatility}_t$	7.73	4.16	95.5***	177.93***	97.42	191.32
	(13.61)	(14.85)	(36.13)	(39.43)	(63.82)	(144.53)
CUSIP FE	Y	Y	Y	Y	Y	Y
Observations	16,529	18,333	5,938	6,775	8,471	6,074
	H_0: [0.25]$\text{Covid}_t \times \text{Vul\_Volatility}_t$ = [0.75]$\text{Covid}_t \times \text{Vul\_Volatility}_t$					
χ^2_1 test statistic	6.99***	7.86***	5.08**	0.98	6.77***	2.4
	H_0: [0.25]$\text{Covid}_t \times \text{Other\_Volatility}_t$ = [0.75]$\text{Covid}_t \times \text{Other\_Volatility}_t$					
χ^2_1 test statistic	7.53***	7.4***	1.13	1.96	0.55	0.18

B.5 Testing the difference between IRC distributions

Figure 6 of the main text showed that the imputed roundtrip cost (IRC) of trading a CLO depends on whether that CLO is more or less exposed to the industries identified by Moody's as vulnerable to the pandemic shock. We formally test this hypothesis using the Anderson-Darling and Kruskal-Wallis rank tests for whether k samples are drawn from a common distribution. We divide all the IRC observations in the month following the declaration of the pandemic into two samples: Above and below the median market value of loans in the CLO collateral pool. Table 6 reports that there were roughly equal number of observations in the two samples.

The left-hand panel and right-hand panels of Table 6 report the results from the Anderson-Darling and Kruskal-Wallis tests, respectively. The tables report both the asymptotic and simulated p-values, as well as two versions of the Anderson-Darling test that differ in how they treat "ties" i.e. identical values in a sample. For details of the two versions of the test, see Scholz and Stephens (1987). In all cases, we can reject the null hypothesis that the two samples are drawn from a common distribution.

Table 6: Testing for significant differences between distributions of imputed roundtrip costs by vulnerability. Panels A and B show the results from Anderson-Darling and Kruskal-Wallis rank tests for differences in two distributions of imputed roundtrip costs (IRC). The two distributions are formed by separating CLOs into those above and those below the median share of their market value that is exposed to the industries identified by Moody's as vulnerable to the pandemic shock. We calculate the exposure from the last trustee report prior to the pandemic. For details of the two versions of the test, see Scholz and Stephens (1987). Source: Authors' calculations from data provided by TRACE, Bloomberg LP, and Moody's.

(a) Anderson-Darling Test

Number of samples: 2
Sample sizes: 296, 393
Number of simulations: 10,000

	AD	T.AD	asympt. p-val.	sim. p-val.
version 1:	2.90	2.51	0.03	0.03
version 2:	2.91	2.52	0.03	0.03

(b) Kruskal-Wallis Test

Number of samples: 2
Sample sizes: 296, 393
Number of simulations: 10,000

test stat.	asympt. p-val.	sim. p-val.
2.79	0.09	0.09

B.6 Loan transaction summary statistics without ramp-up period

This table repeats the analysis in Table 3 of the main text excluding the transactions that occurred during the ramp-up period between the CLO closing date and the completion of the initial portfolio purchases. Because the data do not include a date for the end of the ramp-up period, we excluded all transactions that occurred in the two months after a CLO's closing date. The ramp-up period typically lasts one or two months, so this is a conservative approach.[2]

B.7 Structural breaks in Class E CLO tranches

Figure 2 presents the structural breaks in both the AAA rated CLO tranches (Panel A) and the Class E CLO tranches (Panel B). The Class E tranches in Panel B are the most junior tranches that are debt. CLO equity is junior to the Class E tranche and does not trade. The results from the quantile fixed effects regression in Table 3 showed that Class E tranches were information-sensitive prior to the pandemic.

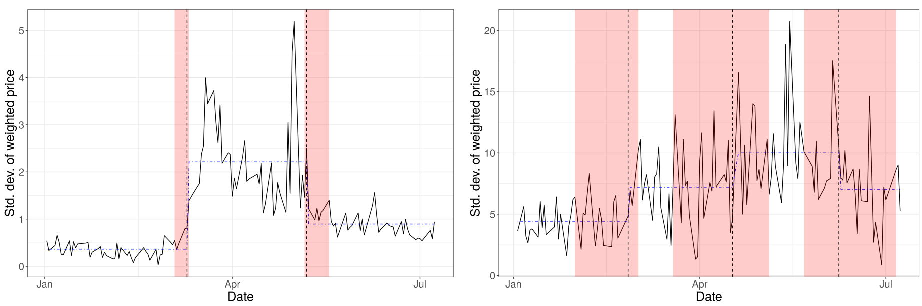
[2] https://www.pinebridge.com/insights/investing/2019/09/clo-beyond-the-complexity

Table 7: Loan transactions summary statistics. The table shows summary statistics for leverage loan transactions per CLO in the pre-pandemic period (January 1, 2020—March 1, 2020) and the pandemic period (March 2, 2020—June 30, 2020). These summary statistics exclude transactions in a CLO's ramp-up period by removing transactions in the two months immediately after a CLO's closing date. The statistics are provided for all leveraged loans and separately for the sectors that Moody's identified as vulnerable to the pandemic shock. Source: Moody's Analytics.

Variable *(units)*	Statistic	All transactions Pre	All transactions Post	All transactions *p-value*	Vulnerable sector Pre	Vulnerable sector Post	Vulnerable sector *p-value*	Non-vulnerable sector Pre	Non-vulnerable sector Post	Non-vulnerable sector *p-value*
Number of sales	Mean	47.16	82.79	0	6.83	10.99	0	45.09	78.77	0
(per CLO)	SD	59.33	136.29	0	16.41	23.03	0	53.49	127.75	0
	N	1,581	1,625		493	603		1,579	1,624	
Mean sales value	Mean	0.80	0.72	1	0.57	0.53	0.82	0.81	0.73	1
($mn per CLO)	SD	0.76	0.78	0.1	0.64	0.62	0.25	0.76	0.79	0.08
	N	1,581	1,625		493	603		1,579	1,624	
Number of purchases	Mean	62.66	102.43	0	6	12.73	0	58.79	94.8	0
(per CLO)	SD	63.55	146.42	0	13.52	29.2	0	55.96	130.94	0
	N	1,549	1,592		1,001	961		1,549	1,591	
Mean purchase value	Mean	1.16	0.84	1	1.1	0.77	1	1.17	0.85	1
($mn per CLO)	SD	0.91	0.86	0.01	1.01	1	0.37	0.92	0.86	0
	N	1,549	1,592		1,001	961		1,549	1,591	

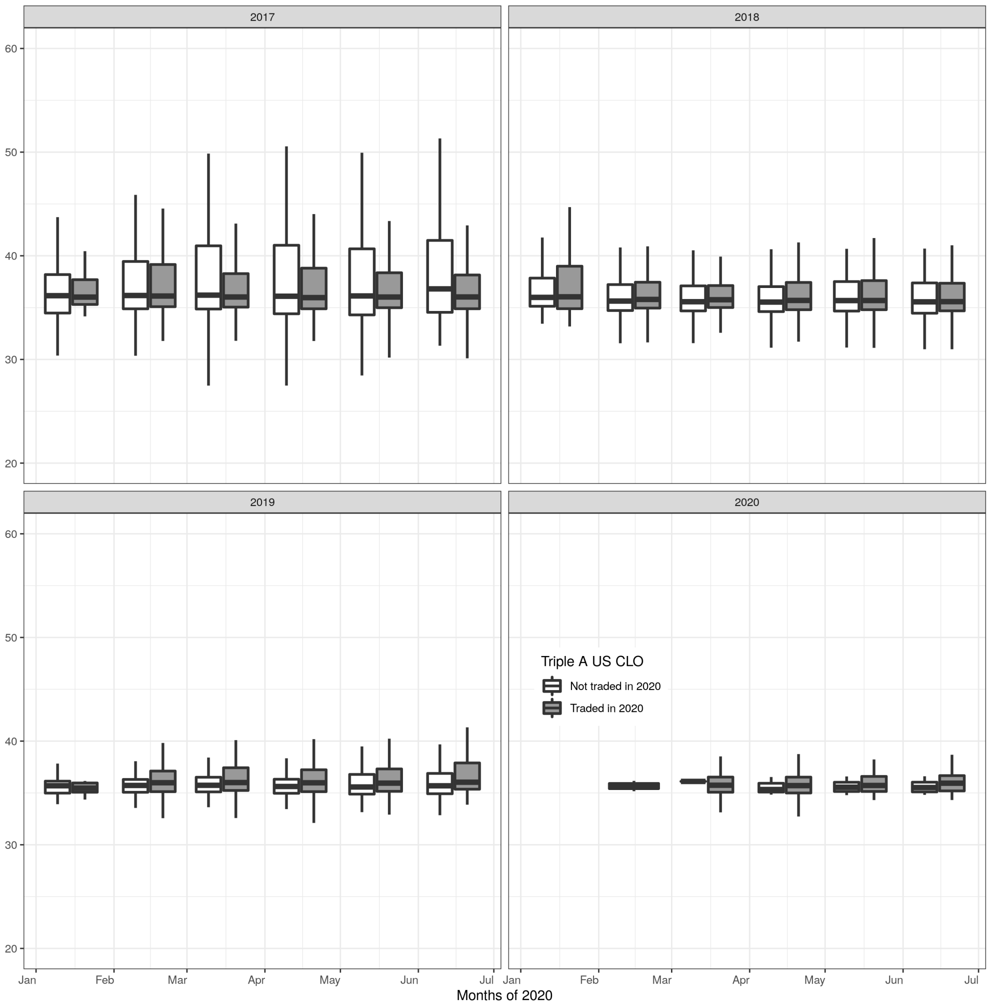
Figure 2: Structural breaks in the standard deviation of CLO prices. This figure shows the estimated structural breaks from applying the method of Bai and Perron (2003) for identifying multiple structural breaks in a single time series. For each tranche, we calculate a daily weighted-average price, where the weights are transaction volumes. We then calculate the standard deviation across tranches. The optimal number of breaks to explain the time series is determined by the Bayesian Information Criterion. The solid line is the standard deviation of daily prices. The blue dot-dashed line is the fitted values of the regression including the structural breaks. The vertical dashed lines are the locations of the structural breaks. Source: Authors' calculations from data provided by TRACE, FRED, and Bloomberg, LP.

(a) AAA rated **(b)** Class E



B.8 Attachment points

Figure 3: The distributions of AAA-rated CLO tranche attachment point by CLO vintages for the current population of CLO outstanding and the population of CLO traded in 2020. Roughly half of the triple-A rated CLO population was traded in 2020 (779 triple-A rated CUSIPs out of 1,684 were traded in 2020). Source: Authors' calculations from data provided by Bloomberg LP, Fitch, Standard & Poor's and Moody's.



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