Adverse Selection Dynamics in Privately-Produced Safe Debt Markets*

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Abstract

Privately-produced safe debt is designed so that there is no adverse selection in trade. But in some macro states, here the onset of the pandemic, it becomes profitable for some agents to produce private information, and then agents face adverse selection when they trade the debt (i.e., it becomes information-sensitive). We empirically study these adverse selection dynamics in a very important asset class, collateralized loan obligations (CLOs), which finance loans to below investment-grade firms. We decompose the bid-ask spreads on the AAA bonds of CLOs into a component reflecting dealer bank balance sheet costs and the adverse selection component.

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1 Introduction

In this paper we test the proposition that information-insensitive debt can become information-sensitive leading to adverse selection when a large shock, namely the COVID pandemic, hits. We measure the resulting lemons premium by decomposing bid-ask spreads in a quantile fixed effects regression framework. We find that those CLOs with a lemons premium experienced, on average, 12 percentage points higher bid-ask spread accounting for about half of the total increase during the pandemic.

"Information-insensitive" means that the debt can store value through time safely and can be traded without fear of adverse selection. Such debt is designed such that no agent finds it profitable to produce private information about its fundamentals and all agents know this. This debt is senior, complicated, and opaque, making the cost of understanding it high. It is information-insensitive. It provides protection against adverse selection; it is rated AAA/Aaa (S&P/Moody's) and it trades at par (minus a small bid-ask spread).

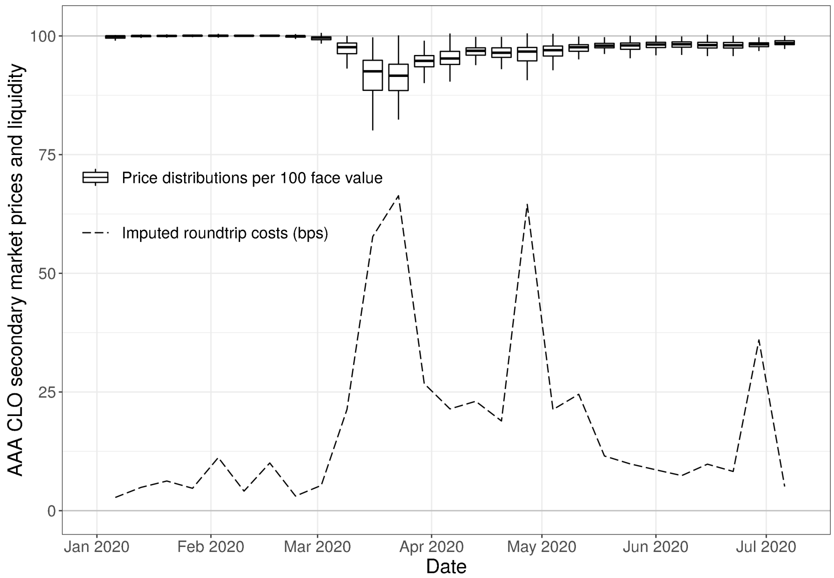
But bad public news about the fundamental value of the debt's backing can prompt sophisticated investors to acquire private information creating adverse selection; see Dang, Gorton and Holmström (2019). We study the appearance of adverse selection in the market for AAA/Aaa-rated collateralized loan obligations (CLOs) when the pandemic hit. Following

Glosten and Milgrom (1985) we focus on the bid-ask spread as a measure of adverse selection.[1] We decompose the bid-ask spreads of these bonds into a component reflecting the individual dealer bank balance sheet costs and a component reflecting adverse selection. We find that significant adverse selection developed in this market with the onset of the pandemic.

CLOs provide an ideal asset class for investigating the onset of adverse selection in otherwise safe bonds. A CLO is a legal entity that buys loans from banks and finances them by issuing debt in the capital market. The CLO manager can subsequently buy and sell assets. The CLO liabilities, called "tranches", have ratings that range from AAA/Aaa to B. CLOs play a very significant role in financing below investment-grade firms, whose loans are called "leveraged loans". For our purposes it is important that the portfolios of loans held by CLOs are heterogeneous and change through time. This distinguishes CLOs from, for example, mortgage-backed securities which are static and homogeneous (across distributions of loan-to-value ratios, credit scores, geographical dispersion, etc). Furthermore, CLOs are an important asset class. According to Fed Chair Jerome Powell (2019): "Collateralized loan obligations are now the largest [nonbank] lenders, with about 62 percent of outstanding leveraged loans." The leveraged loan market is about $1.1 trillion, and is used by

[1]The bid-ask spread is a common measure of adverse selection in fixed income markets. For example, Benmelech and Bergman (2018) use it in their study of corporate bonds and Wittenberg-Moerman (2008) uses it in her study of the secondary loan market.

Figure 1: Trading conditions for AAA-rated CLO debt securities. The boxplots in the figure show the distribution of prices for AAA-rated CLO tranches. The central boxes show the interquartile range (IQR) of prices bisected by the median as a horizontal line. The whiskers show the distribution of prices outside the IQR, up to $\pm 1.5\times$IQR. For each CLO tranche, we calculate a daily weighted-average price, where the weights are transaction volumes. We then average the daily prices to obtain a weekly average weighted by CLO tranche par amount. The dashed line is the imputed round trip cost for agency trades in AAA-rated CLO tranches. Source: Authors' calculations from data provided by TRACE, Bloomberg LP., Moody's Analytics, S&P, and Fitch.



about 70 percent of U.S. companies, including companies like Burger King, United Airlines, Avis Rent a Car, and Equinox Fitness.

When COVID hit there was an increase in AAA CLO bid-ask spreads (measured as the imputed round-trip cost of trade, explained below) and in price dispersion, reflecting the differential pricing based on information. In Figure 1 the dashed line at the bottom is the bid-ask spread for agency trades (i.e., trades where clients are matched in advance but are not committed, one side might fail leaving the bond on the bank's balance sheet) in AAA-rated CLO tranches. The boxplots at the top of the figure show the interquartile range of AAA prices bisected by the median as a horizontal line. The whiskers show the distribution of prices beyond the interquartile range, excluding outliers.

The figure summarizes our argument. Prior to the pandemic all AAA tranches traded at very small bid-ask spreads and at par of $100, consistent with information-insensitivity. When the pandemic hits, the bid-ask spread widens and the price distribution also widens out below par as shown by the box plots.[2] Importantly, if it were an economy-wide shock that introduced a risk premium for AAA-rated CLOs, then their prices would drop uniformly and there would not be price dispersion across CLOs. At no point during the pandemic did any AAA-rated CLO tranche experience a rating downgrade, or even a negative outlook. In the analysis presented below, we will provide formal tests of the information shown in Figure 1.

Two strands of literature are related to our work. The first is the industrial organization literature on adverse selection in insurance and health markets where researchers seek to empirically determine if there is adverse selection. For surveys of this literature see Einav and Finkelstein (2011) and Einav, Finkelstein and Mahoney (2021). The second literature concerns empirical work showing that information-insensitive debt (corporate bonds and money market funds) became information-sensitive during 2007-2008. This literature is surveyed by Dang et al.

[2]The size of the increase in the bid-ask spread is far larger than occurred in the Treasury market as reported by, for example, Dobrev and Meldrum (2020).

(2019). We add to the literature by *quantifying* the lemons premium that arises when there is switch from insensitive to sensitive.

The paper proceeds as follows. In Section 3 we briefly describe the data, provide some background on CLOs, and some background on the loans in CLO portfolios. When the pandemic hit some traders became informed while others did not. Section 3.3 studies these two groups: the informed and the uninformed. The arrival of adverse selection in the AAA CLO debt marketplace is studied in Section 4. Section 5 analyzes the switch from information-insensitive to information-sensitive debt that arises as a consequence of the arrival of adverse selection. In Section 6 we describe how issuers of CLOs altered their structure during the pandemic to avoid adverse selection. Section 7 concludes.

2 Data

In this section we discuss the dataset that we constructed to measure adverse selection in the CLO debt secondary market during the pandemic. We combined several large datasets, including transactions on individual CLO debt tranches, tranche-level credit ratings, loan-level information about the underlying pools of collateral, and loan transactions by CLO managers. The combination of these data create a window to study how information about CLO tranches can affect the trading decisions of CLO investors.

We identify CLO tranches using Bloomberg's Backoffice data on asset-backed securities. We match these data by CUSIP identifiers to dealer transaction data reported in the regulatory version of the Trade Reporting and Compliance Engine (TRACE), created by the Financial Regulatory Authority (FINRA).[3] Bloomberg provides information on individual CLO tranche characteristics, including offering amount, offering yield, and amount outstanding. After merging these two large data sets, we add Moody's, Fitch, and Standard & Poor's credit ratings and credit watch list information for each CLO tranche at a daily frequency.

Our data on secondary market over-the-counter trading of CLO debt is from TRACE. Under regulations introduced in 2002 by FINRA, dealers are required to file detailed reports of their transactions, including trade time, quantity, price, and counterparty. FINRA made asset-backed security secondary market trading data available from 2011 as part of an effort to increase transparency in this over-the-counter market after the 2007-09 financial crisis. The limitation on data availability means that, unfortunately, we cannot compare CLO trading during the pandemic to the financial crisis. We follow standard procedures for cleaning these data.[4] We use confidential regulatory data with dealer bank identifiers, which allows

[3]CUSIP stands for Committee on Uniform Securities Identification Procedures and is a unique identifier for most financial instruments, including privately-placed securities.

[4]See, for example, Dick-Nielsen (2009) and Bao, O'Hara and Zhou (2018).

us to match trades by buyer, seller, amount, and trade time while removing duplicates. The regulatory version of TRACE allows us to identify dealers and observe the trading behavior of every dealer.

We construct daily aggregates for each CLO tranche using the transaction-level data. The daily trading price is defined as the weighted average price on transactions, where the weights are the transaction volumes. This measure is designed to approximate the mid price for each CLO tranche as the vast majority of trades are matched in advance. We also calculate the total volume transacted.

The data we use to study the loans held by CLOs are from Moody's Analytics, which are based on trustee reports issued by each CLO each month and vastly augmented by Moody's proprietary leveraged loan analytics. These data contain details of the entire portfolio of assets held, including type of asset, credit rating, maturity, par value, market value, creditor information, as well as multiple individual loan prices provided by Markit, Reuters, and the CLO trustees. Moody's also provides information about the performance of the CLO, such as details of the internal triggers for cash flows, discussed below.

Table 1 presents summary statistics from the baseline dataset where the unit of observation is CLO tranche i on day t, conditional on at least one transaction occurring. Our sample data cover the period from January 1, 2020 onwards. We separate the period into two subsamples:

Table 1: Summary statistics This table reports summary statistics for the CLO tranche secondary market trading data used in the analysis. Trade_price_{it} is the weighted average transaction price, where the weights are the transaction volumes. Trade_volume_{it} is the sum of transaction volumes. Our sample begins on January 1, 2020 and is divided on March 1, 2020 into the pre-pandemic period and the pandemic period. Source: TRACE, Bloomberg LP., Moody's Analytics, S&P, and Fitch.

Variable	Statistic	AAA-rated tranches			Class E tranches		
(units)		Pre	Post	*p-value*	Pre	Post	*p-value*
Trade_price_{it}	Mean	99.91	96.48	0	95.69	72.08	0
($ per 100 face)	SD	0.38	3.17	0	4.9	14.87	0
	N	1,125	4,000		581	1,222	
Trade_volume_{it}	Mean	9.77	11.36	0.95	5.3	5.33	0.56
($'000s)	SD	30.11	24.33	1	5.03	4.83	0.88
	N	1,125	4,000		581	1,222	

The dates prior to March 1, 2020 are in the "pre-pandemic period" and the dates thereafter are in the "pandemic period." The tests of equality of the means and standard deviations between the two subsamples are reported in the columns labeled "*p-value*". During the pandemic there was a drop in the average transaction prices, together with an increase in the dispersion of transaction prices, while there was no change in aggregate trading volumes. These statistics suggest that investors' trading behaviour changed significantly as investors sought information about underlying risks. We investigate the role of information production below.

Dang, Gorton and Holmström (2018) have no prediction about the trading volume once there is a switch to information-sensitive. While the market might collapse, as in Akerlof (1970), uninformed agents may choose to trade anyway, accepting the adverse selection. And, in reality, fearing that the AAA-rated tranches may be downgraded may motivate some institutions to sell.

3 CLO Background

In this section we provide some background information on CLOs. We begin with a high-level overview of their structure and then provide descriptive statistics for the underlying loan portfolios.

3.1 CLO Rationale and Structure

Why do banks sell their loans? The answer is that it is profitable to do so. And it reduces the cost of credit to the borrowing firms. Nadauld and Weisbach (2012) found that bank loans that are eligible to be securitized, i.e., sold to a CLO, cost borrowers 17 basis points less than otherwise (100 basis points equals one percent). The bank can make up this difference because the AAA/Aaa-rated debt sold by the CLO has a convenience yield (due to it being information-insensitive), that is investors value it for safety in addition to the interest rate it pays, so its pecuniary coupon rate is lower than it otherwise would be.

In our sample about 65 percent of a typical CLO is rated AAA. This means that to recover the 17 basis points, the convenience yield must be at least 26 basis points. By comparison, Krishnamurthy and Vissing-Jorgensen (2012) find that the yield on U.S. Treasuries over 1926-2008 was, on average, 73 basis points lower than it otherwise would have been, due to the "moneyness" and safety of U.S. Treasury securities. Using higher frequency data, van Binsbergen, Diamond and Grotteria (2019) estimate the convenience yield on Treasuries to be about 40 basis points.

To value a CLO tranche, the companies whose leveraged loans are in the underlying portfolio have to be studied and the correlations between all the loans in the CLO portfolio have to be determined. This requires credit analysts and a model to simulate outcomes. Also, as we explain below, CLOs have complicated and opaque internal structures. All these attributes make it very expensive for agents to produce private information about the value of the AAA tranche, allowing buyers of this debt to avoid adverse selection because it is very expensive to produce private information. But, in bad times this is exactly the problem!

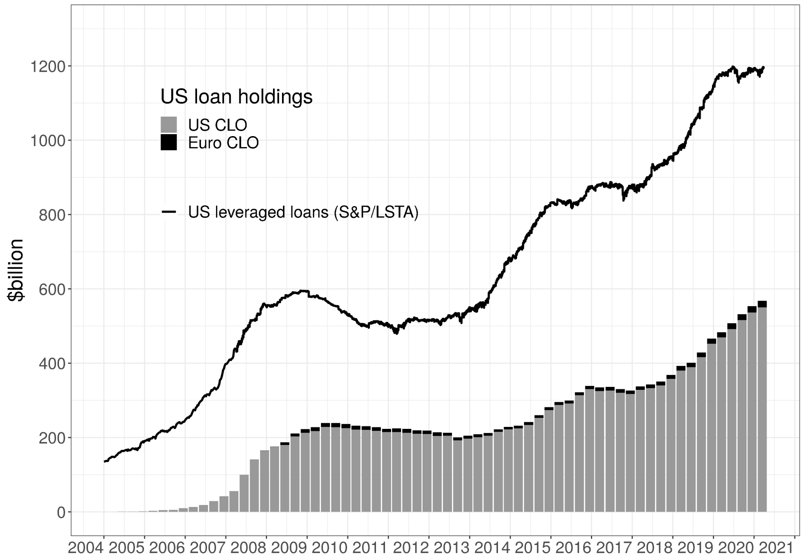
CLOs allocate the effects of default risk in the underlying pool of loans in several ways. First, there is subordination. For example the AAA-rated tranche is protected by the mezzanine (middle) tranche and the junior tranche. Second, there are over-collateralization tests. Over-collateralization tests are calculated by dividing the principal balance of the portfolio by the total cumulative balance of the tranche (and, if it is not the senior tranche then all tranches senior to it). The numerator is adjusted when some of the loans face stress: they become more risky, default, or are worth significantly less than their face value. There are specific haircuts for loans in these categories.

When an over-collateralization test is violated, there is a reallocation of excess spread. Excess spread is the interest earned on the portfolio of loans in excess of the interest due on the CLO tranches. If there are no defaults and the CLO can make its obligated payments to the note holders, then the excess spread flows to the equity holders (on a monthly basis). But, if the portfolio experiences stress in the form of defaults, ratings downgrades, etc., such that over-collateralization tests fail, then excess spread is directed away from equity, and sometimes away from junior tranches, and used to pay down principal on the AAA debt.

CLO managers are large sophisticated entities that usually manage multiple CLOs. According to the fourth-quarter 2019 manager rankings from CreditFlux, the average CLO manager had 10 CLOs with a total par value of $5.3 billion. CLO managers are often affiliated with private equity funds, hedge funds, asset managers, banks, or insurance companies. These firms have large teams of credit analysts and loan traders, which contribute to the CLO managing and trading its portfolios.

CLOs are an important way for banks to offload large amounts of risky loans that would otherwise reside on their balance sheets. Figure 2 compares the amounts of leveraged loans and CLOs outstanding. As of

Figure 2: Leveraged loans outstanding and held by CLOs. The time series in the figure below show the amount of outstanding U.S. leveraged loans. The bars in the figure show the aggregate amount of U.S. leveraged loans held by U.S. CLOs (grey) and European CLOs (black). Source: S&P and Moody's Analytics.



2019, according to the Loan Syndications and Trading Association (LSTA), there were more than $1.1 trillion of U.S. leveraged loans outstanding. U.S. CLOs, which are the largest nonbank investors in U.S. leveraged loans, amounted to over $500 billion.[5]

3.2 CLO Loan Portfolios

We use Moody's data largely drawn from CLO trustee reports to examine the typical CLO loan portfolio characteristics. We then use the same data to describe how prices of leveraged loans evolved during the pandemic. We show that variation in the distributions of loan prices depend on whether

[5]These CLOs may hold other types of investments, e.g., junk bonds, but are predominantly backed by U.S. leveraged loans.

the firms belonged to industries that were more vulnerable to the pandemic shock.

Table 2 presents summary statistics across CLOs from the information provided in the trustee reports. The unit of observation is a CLO. The first three columns show statistics for 1,627 CLOs during the pre-pandemic period and are calculated using the last trustee report for each CLO published before February 15, 2020. The second three columns cover 1,599 CLOs during the pandemic period, calculated using the first trustee report published after April 1, 2020. Data constructed by Moody's indicate that the average attachment point for the AAA-rated tranches in these CLOs before the pandemic is about 37 percent. In other words, on average 63 percent of a CLO is rated AAA. The data confirm that loans dominate the asset portfolios of CLOs, with the typical portfolio containing about 370 loans and a total market value of roughly $420 million. Bonds account for less than 3 percent of the principal value of the typical portfolio. The average loan in the portfolio is worth $1-1.5 million and has a residual maturity of 4.5-5 years.

The last line of Table 2 shows that the typical CLO loan portfolio has about 18 percent of its market value in industries that Moody's identified as vulnerable to the pandemic shock. Sallerson (2020) identified seven industries vulnerable to the pandemic shock: Automotive, Consumer goods: Durable, Energy: Oil & Gas, Hotel, Gaming & Leisure, Retail,

Table 2: Summary statistics of CLO loan portfolios. For the pre-pandemic sample of 1,627 CLOs, the statistics are calculated using the last trustee report published before February 15, 2020 for each CLO. The pandemic sample of 1,599 CLOs use the first trustee report published after April 1, 2020. Source: Authors' calculations from data provided by Moody's Analytics.

	Pre-pandemic, 1,627 CLOs				Pandemic, 1,599 CLOs		
Characteristic	Mean	Median	SD		Mean	Median	SD
AAA tranche attachment point (%)	36.9	35.7	5.5		36.7	35.6	5.9
Loans per CLO	369.6	344	233		390.3	349	285
Bonds per CLO	7.7	0	25	9.8	0	35	
CLO market value (loans, $mn)	421.4	408.9	175.7		367.7	353.7	157.7
CLO principal value (nonloans, $mn)	10.7	1.4	24.2	12.1	1.1	28.2	
Mean loan value ($mn)	1.5	1.3	0.9		1.3	1.2	0.8
Median loan value ($mn)	1.2	1	0.9		1	0.9	0.7
Mean loan maturity (yrs)	4.5	4.8	0.9		4.5	4.8	0.9
Median loan maturity (yrs)	4.7	5	0.9		4.7	4.9	0.9
Principal value in bonds (%)	2.7	0	8.6		3.4	0	11.4
Vulnerable loans (market value, %)	18.4	18.1	9.6		16.4	16.2	9

Transportation: Cargo, and Transportation: Consumer. Appendix 8 describes how we map these industries to other data. We use these sectors throughout our analysis to tease out a differential impact of the pandemic.

Table 3 presents summary statistics from the leveraged loan transactions reported in the trustee reports. We separate the transactions since January 1, 2020 into two time periods: The pre-pandemic period up to March 1 and thereafter the pandemic period. The table reports both the number and average transaction value of sales and purchases *per CLO*. The table is divided into three parts. The first three columns provide summary statistics for all leveraged loan transactions. The middle three columns provide statistics for transactions on loans to the sectors identified by Moody's as vulnerable to the pandemic shock. The final

Table 3: Loan transactions summary statistics. The table shows summary statistics for leveraged 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). Source: Authors' calculations from data provided by Moody's Analytics.

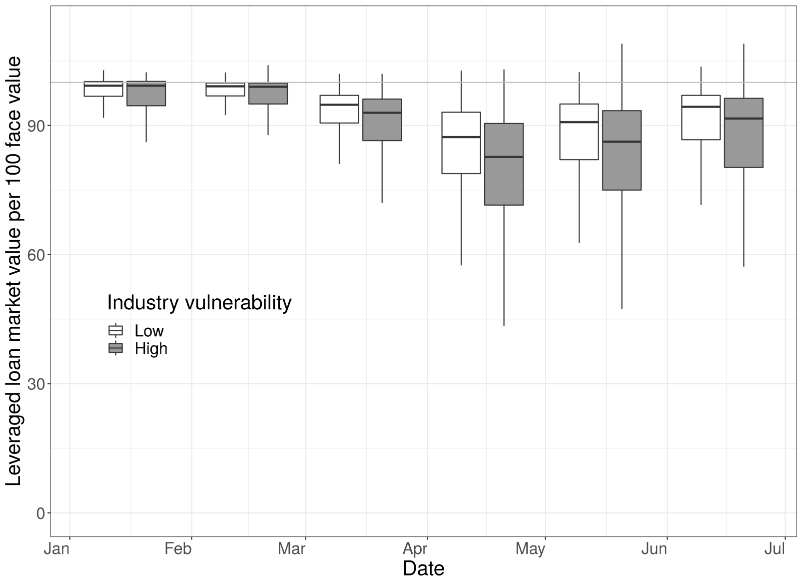
Variable	Statistic	All transactions			Vulnerable sector			Non-vulnerable sector		
(units)		Pre	Post	*p-value*	Pre	Post	*p-value*	Pre	Post	*p-value*
Number of sales	Mean	47.16	82.79	0	6.83	10.99	0	45.09	78.77	0
(per CLO)	SD	59.33	136.29	0	16.41	23.03	0	53.49	127.75	0
	N	1,581	1,625		493	603		1,579	1,624	
Mean sales value	Mean	0.8	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	

three columns provide statistics for transactions on the non-vulnerable loans. The statistics generally indicate that loan portfolio turnover (sales and purchases) increased, including for loans to firms in vulnerable sectors. There was no change in the average value of the loan transactions per CLO. As a robustness check on the summary statistics reported in the table, we excluded loan transactions that took place during a CLO's ramp-up period and report the results in Table 13 in appendix 9.

The trustee reports also reveal greater deterioration in the market value of leveraged loans in the seven vulnerable sectors. CLO managers provide monthly updates through the trustee reports on the market value of the leveraged loans in their portfolios.[6] We use these data to construct

[6]We compared the loan market values in the trustee reports to the bid prices provided by Reuters and Markit. These pricing services obtain their data using a combination of polling traders and modelling. We found that the vast majority of CLO managers

Figure 3: Loan collateral price distribution The boxplots in this figure show the distributions of loan prices reported in CLO trustee reports of U.S. leveraged loans. The shaded boxplots include loans to firms in the industries identified by Moody's as vulnerable to the pandemic shock. The unshaded boxplots contain loans to firms in all other industries. Source: Moody's Analytics.



distributions of loan market values over time. For each month, we plot the distributions separately for loans to firms in the vulnerable and not vulnerable industries. Figure 3 shows that the values of loans to firms in the vulnerable industries (shaded boxplots) fell further and were more variable than the values of loans to firms in other industries.

3.3 Informed and Uninformed Traders of CLOs

According to a Bloomberg article, on May 20, 2020, J.P. Morgan sent an extraordinary email to its clients warning them of "information

report market values identical to Markit bid prices.

asymmetries" in the fast-moving CLO market.[7] The cited cause for concern was originators, sponsors, and even managers that were interested in *buying* their own CLO tranches based on nonpublic information about "the potential effects of Covid-19 on the portfolio" that "may constitute insider information". In this section we examine the risk to investors from such information asymmetries.

Investors produce information about investment-grade debt securities when it is profitable to do so. After a corporate bond has been issued there are few subsequent analyst reports. Resources are only devoted to information production when the bond starts to deteriorate. Johnson, Markov and Ramath (2009) write that: "the amount of resources devoted to debt research depends on the debt's price sensitivity to information about the value of the asset. Intuitively, the sensitivity of the price of debt determines how much one can profit from information about the company's assets in the debt market" (p. 92).

In the case of AAA-rated CLO tranches there are never analysts' reports. But there are monthly CLO trustee reports which contain information about the composition of loans in the CLO portfolio. In the first subsection, we ask whether the information in those reports was more broadly used once the pandemic started. Then we look at a measure of disagreement between third-party loan price suppliers. These agents see

[7] "JPMorgan Warns on Insider Trading Risk in Fast-Moving CLO Market" by Alastair Marsh and Sally Bakewell, published May 20, 2020, 9:58AM EDT.

the trustee reports but have no direct knowledge of the loan market. They proxy for uninformed agents.

To be clear, informed agents are those who have produced private information, meaning credit analysis of the loans in a CLO portfolio. These agents need to invest significantly in the technology required to produce the information. As Guggenheim Partners put it: "[analyzing a CLO] requires the expertise to perform rigorous bottom-up research on individual bank loans . . . managers must have significant corporate credit research capabilities".[8] This costly technology is the reason that investment firms manage multiple CLOs and may well have other credit products. Bain Capital, for example, has 310 employees in Bain Capital Credit.[9]

The first step in producing information about a CLO tranche is finding out what loans are in the portfolio. This must be checked repeatedly because the CLO manager can trade the loans in the portfolio. Portfolio information comes from studying trustee reports, which are published monthly for each CLO. Each CLO has a trustee, a fiduciary, who carries out a number of tasks including reporting on the CLO's portfolio composition, as well as its compliance with the many requirements of the CLO's indenture, e.g., checking over-collateralization tests, the loan ratings, and the account balances. The trustee also maintains the CLO assets in custody

[8]See `https://www.guggenheimpartners.com/perspectives/portfolio-strategy/collateralized-loan-obligations-clos`.

[9]See `https://www.baincapitalcredit.com/approach`.

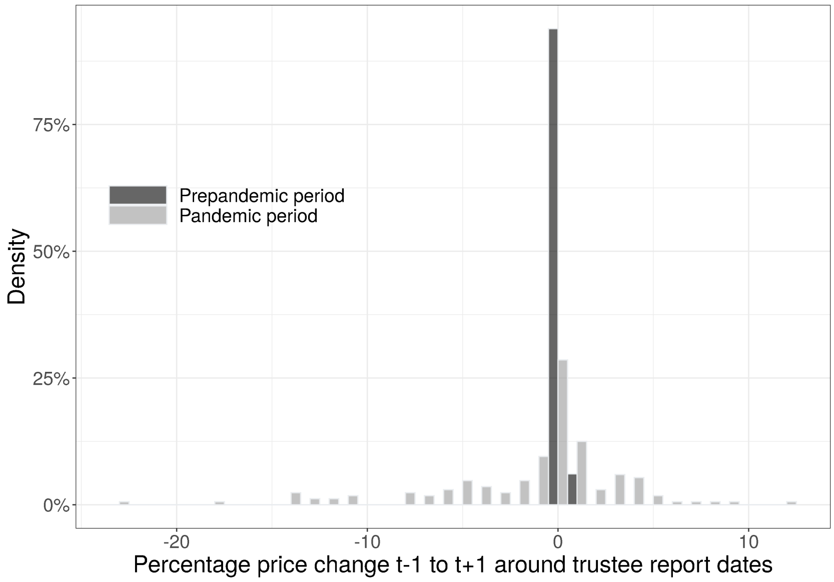
and is responsible for paying funds to investors on coupon dates.

The trustee reports are informative but, as mentioned above, they are only the starting point. The second step is credit analysis of the firms which borrowed money and whose loans are in the portfolio. Credit analysts are necessary to take the information in the trustee reports and make it meaningful. We do not observe this second step except insofar as the AAA-tranche price changes. Further, and perhaps most importantly, the correlations between loans in the portfolio have to be studied.

Figure 4 shows the percentage change in the price of AAA-rated tranches on the day the trustee report is released and the day after. Prior to the pandemic, the percentage price change was essentially zero (the tall bar), while after the pandemic the price changes are spread out, suggesting that there was valuable information in the trustee reports. Note that sometimes the percentage price change is positive. This can happen if the CLO manager took positive trading actions or a loan improved in credit quality.

Bonds and loans are traded over-the-counter so there is no price discovery in the sense that a price aggregates many agents' information sets. Like bond mutual fund managers, CLO managers engage a third-party pricing service to track the value of their loans, that is obtain a "price" for each loan. Loans do not trade frequently so these prices are essentially informed guesses. Pricing services use models and rely heavily

Figure 4: Price changes around trustee report dates. The histogram shows the distribution of percentage price changes of AAA-rated CLO tranches traded on the same day or the day after each trustee report was released. Source: Authors' calculations from data provided by TRACE, Moody's Analytics, Bloomberg LP, Moody's Analytics, S&P, and Fitch.



on communication from traders and the trustee reports. In other words, it is hard to come up with such prices.[10]

In the case of loans, Markit and Reuters provide loan marks, "prices". The basis for these prices is proprietary, but likely involve anecdotal evidence from loan traders and models. These companies do not have large teams of credit analysts. Because these companies also see the trustee reports, they can proxy for uninformed traders who cannot analyze

[10]This difficulty has been shown by Cici, Gibson and Merrick (2011) who study corporate bonds. In the case of bonds, the "prices", called "marks", are supplied by dealers using different methodologies. These are not transaction prices. Cici et al. (2011) study the dispersion of month-end mark-to-market prices for identical bonds held by many bond mutual funds. The marks from different dealer banks differ substantially (in normal times), even for AAA-rated bonds and the dispersion increases the lower the rating.

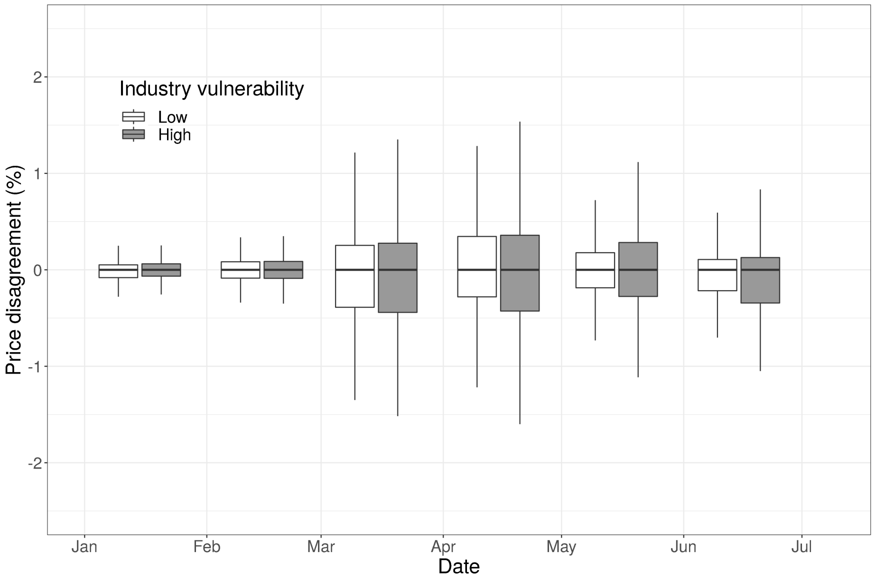
or fully understand the reports. To measure the degree to which the pandemic created problems and/or disagreements between these essentially uninformed agents we can measure the percentage difference between Markit and Reuters prices for the same vulnerable leveraged loan on the same date and compare that distribution to the distribution of the mark difference in pre-pandemic times.

Figure 5 shows that disagreement increased significantly once the pandemic started. But there is no statistical difference between the disagreement about vulnerable and non-vulnerable industries. Neither a common nor a sector-specific nor a firm-specific increase in risk can explain this greater disagreement in loan pricing. Such an increase in risk would result in a loan-specific premium, but not greater disagreement in pricing at the loan level.

4 The Arrival of Adverse Selection

In this section we look at evidence of adverse selection. In the first subsection below we look at the imputed roundtrip trading cost (IRC), a measure of the bid-ask spread. Then in the second subsection we look at the evidence for adverse selection using the IRC. The bid-ask spread is a common measure of adverse selection in fixed income markets. For example, Benmelech and Bergman (2018) use it in their study of

Figure 5: Loan price disagreement by industry vulnerability. The figure shows monthly distributions of the percentage difference between Markit and Reuters prices for the same leveraged loan on the same date. Source: Authors' calculations from data provided by Moody's Analytics.



corporate bonds and Wittenberg-Moerman (2008) uses it in her study of the secondary loan market.

4.1 Analysis of AAA CLO tranche trading Costs

We measure trading costs in the secondary trading market for CLO tranches using the method proposed by Feldhütter (2012). The imputed roundtrip trading cost (IRC) is the difference in the price paid by a dealer to purchase a bond from a client and the price charged by a dealer to sell the same amount of the same security to a client.[11] Measuring the time between

[11]We also estimated the realized bid-ask spread, calculated as the difference between the volume-weighted average prices paid to dealers by their clients and the volume-weighted average prices paid by dealers to clients. The two measures of liquidity are highly correlated.

trades is important for markets with relatively thick trading and where the dealer is willing to carry risk in so-called "principal" trades. When trading CLO tranches, dealers almost always match clients in advance, in "agency" trades, and make very few principal trades.[12] However, in an agency trade the buyer is not committed to buy, so the dealer could end up holding the tranche. We identify agency trades as those in a given CLO tranche with the same trade size that take place within a calendar day.[13]

To calculate the dealer-level IRC, we first identify within-day roundtrip trades, composed of a sale from a client to a dealer and a purchase by a client from the same dealer. Following Dick-Nielsen et al. (2012), if we observe trades in a given CLO tranche with the same trade size on the same day, and there are no other trades with the same size on that day, we define the transactions as part of a roundtrip trade.[14]

Taking the average IRC across tranches and dealers, Figure 6 shows the estimated structural breaks in the average IRC time series from applying the method of Bai and Perron (2003) for identifying multiple structural breaks in a single time series. The shaded areas are 95 percent confidence

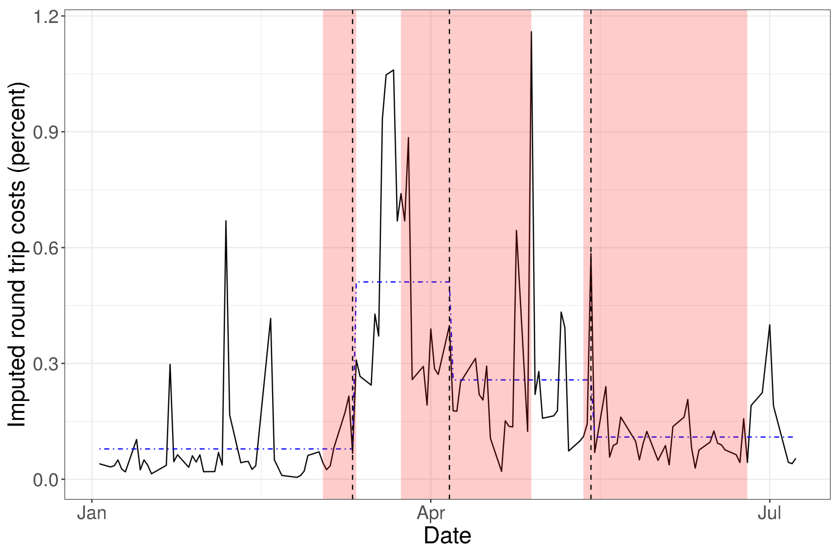
[12]For this reason, the liquidity measure based on principal trades proposed by Choi and Huh (2017) is uninformative in our setting. The ratio of agency trades to principal trades, both by number and by volume, is close to one. This measure underestimates the number and volume of agency trades because it treats as principal trades those transactions that the dealer split over two or more clients.

[13]Dick-Nielsen, Feldhütter and Lando (2012) calculate a similar measure of agency trades using corporate bond transactions within one day

[14]For each such trade, we calculate the IRC as the percentage difference between the maximum and minimum prices. We then calculate a dealer-specific daily weighted-average IRC over all roundtrip trades, where the weights are the volume of each trade.

intervals.

Figure 6: Structural breaks in the imputed roundtrip cost (IRC). 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. Source: Authors' calculations from data provided by TRACE, Bloomberg LP, Moody's Analytics, S&P, and Fitch.



The first structural break is estimated to have occurred between March 3 and March 12, 2020, overlapping with the first break in the standard deviation of trading prices (Figure 14) and coinciding with the March 11 declaration by the World Health Organization of the pandemic.

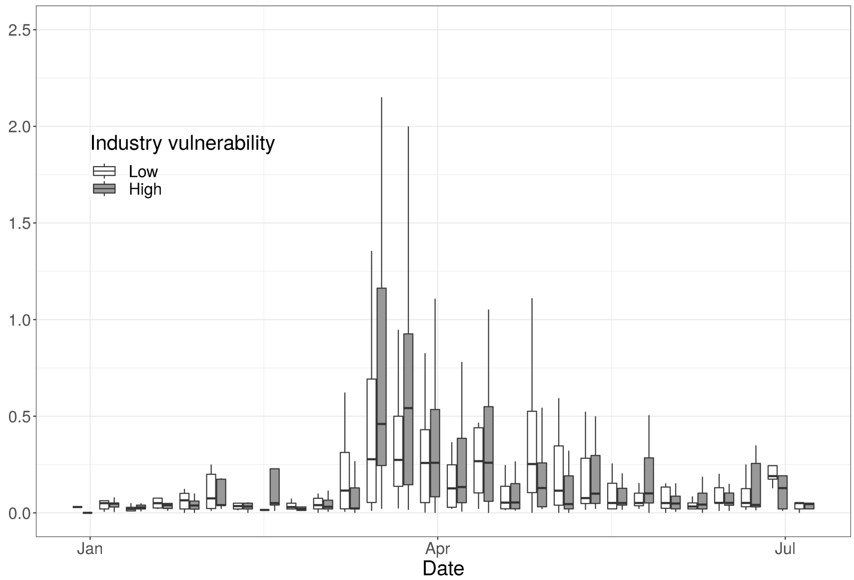
The second structural break in the IRC occurred between March 24 and April 23, 2020, with a point estimate of April 2. This break likely reflects the significant actions taken by the Federal Reserve to improve financial intermediation. In particular, on March 20, the PDCF became operational and accepted AAA-rated CLO tranches. On March 23, the Board of Governors announced the establishment of the Term Asset-Backed

Securities Loan Facility (TALF), Primary Market Corporate Credit Facility (PMCCF), and Secondary Market Corporate Credit Facility (SMCCF) as well as expanding the role of the Money Market Mutual Fund Liquidity Facility (MMLF) and Commercial Paper Funding Facility (CPFF). On April 1, the Board announced that it was relaxing the supplementary leverage ratio requirements "to allow banking organizations to expand their balance sheets as appropriate to continue to serve as financial intermediaries".

The third, and final, structural break in the IRC occurred between May 13 and June 17, with a point estimate of May 14. The timing of this break overlaps (partly) with the second structural break in the standard deviation of trading prices. Two proximate actions were intended to further improve banks' financial intermediation services. The Board of Governors modified the liquidity coverage ratio (May 5) and the supplementary leverage ratio (May 15).

Figure 7 shows that imputed roundtrip costs were differentially affected by the pandemic. We separate the CLOs in our sample into two groups: Those above and those below the median holdings of loans to firms in vulnerable industries identified by Sallerson (2020). To avoid any potential confounding effect of secondary loan market trading, we calculate each CLO's exposure to vulnerable industries from the last trustee report prior to the declaration of the pandemic.

Figure 7: The distributions of imputed roundtrip costs by industry vulnerability. The figure shows weekly distributions of imputed roundtrip costs (IRC). The CLOs are separated into two groups that are determined by the portfolio of loans held as collateral. Source: Authors' calculations from data provided by TRACE, Moody's Analytics, Bloomberg LP, S&P, and Fitch.



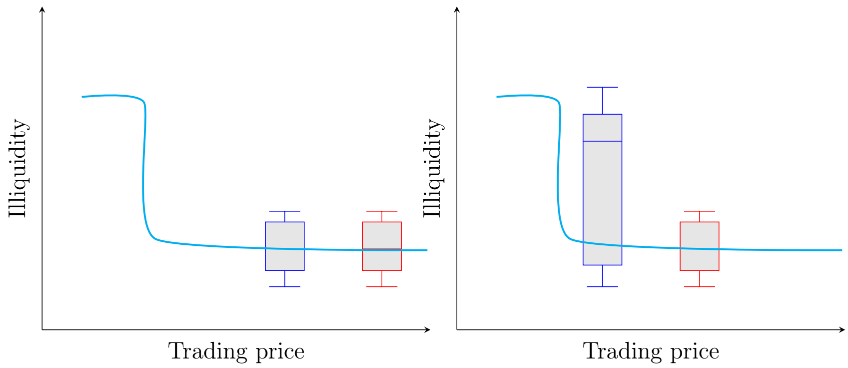
We find generally higher and more variable imputed roundtrip costs of trading CLOs that were more exposed to vulnerable industries during the pandemic. Nonparametric tests confirm that the two distributions are statistically different. We implemented both Anderson-Darling and Kruskal-Wallis rank tests using the trade data after the WHO declared the start of the pandemic. In both cases, we reject with a p-value less than 5 percent the null hypothesis that the samples are drawn from a common distribution. Full details and the results of the tests are provided in appendix 9.

4.2 Quantile regression test of adverse selection

We use the IRC in a quantile difference-in-difference framework to test for the arrival of adverse selection in the AAA CLO secondary market. A unique prediction from the information-based theories of debt is that the potential for adverse selection creates a nonlinear relationship between trading price and IRC of a debt instrument. When the value of the collateral backing the debt decreases, investors have an incentive to acquire information about the collateral. This creates adverse selection, which reduces the liquidity of the debt, as uninformed dealers demand a compensation reflected in the IRC.

Our empirical test consists of comparing the quantiles of the IRC distribution for low- and high-price AAA CLO tranches before and during the pandemic. Under the adverse selection hypothesis, the exogenous COVID shock causes the distribution of IRC to disproportionately widen for tranches that trade at relatively low prices. The disproportionate increase in the IRC distribution is due to the variation in CLO exposure to the vulnerable sectors. Under the adverse selection hypothesis, the effects of a decrease in prices is associated with greater dispersion in illiquidity when tranches start from a relatively lower price—i.e., when the collateral value of some, but not all, of the low-price CLO tranches moves closer to the debt default region.

Figure 8: Schematic relationship between imputed roundtrip costs and prices. The figure shows the intuition for identifying adverse selection. The blue line represents a single AAA-rated CLO tranche, showing the discontinuous relationship between the IRC and price. The latent tranche-specific "step" occurs when prices fall far enough to trigger investors to acquire information, leading to adverse selection. The boxplots represent IRC distributions across AAA-rated CLO tranches. The blue and red boxplots are for relatively low- and high-priced tranches, respectively. The panel on the left represents normal times, when the IRC distributions of relatively low- and high-priced tranches are the same. The panel on the right represents pandemic times, when the IRC distribution of relatively low-priced tranches is more dispersed due to the latent discontinuities.



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

Figure 8 provides a graphical representation of our empirical strategy. The left hand side of Figure 8 represents normal times during which tranches trade at close to their par value. The blue and red boxplots represent the IRC distribution of the low- and high-price AAA CLO tranches, respectively. In normal times, the IRC distributions for low- and high-price AAA CLO tranches are not statistically different because the debt is information insensitive.

The right-hand side of Figure 8 shows the effects of the pandemic under the adverse selection hypothesis. During the pandemic, the entire distribution of prices of AAA CLO tranches exogenously shifts down. For the relatively high-price tranches, this has no effect on the IRC distribution. But for the relatively low-price tranches, the IRC distribution widens as dealers respond to the arrival of adverse selection. In sum, our test uses the pandemic as an exogenous shifter of prices that moves AAA CLO tranches from the left-hand side to the right-hand side of Figure 8.

Table 4 reports summary statistics for IRCs corresponding to points in the distributions shown in Figure 8. The 75^{th} percentile of the IRC distribution increases by relatively more than the median or the 25^{th} percentile during the pandemic *for low-priced CLOs.* Low-priced CLOs are defined as those CLOs that traded below the median price *in a given week* while high-priced CLOs are those above the median price *in the same week.*[15] In the pre-pandemic period, the 75^{th} percentile of the distribution of IRCs is about 5 and 4 percent of the dealers' sale price, respectively, for high- and low-priced CLOs. During the same period, the median of the respective distributions is 3.3 and 2. The distribution in the pandemic is vastly different. The largest *relative* increase reported in the table is the 75^{th} percentile of the IRC distribution, which rose to 53.5 percent. This triple difference effect suggests the arrival of adverse selection in the

[15]In appendix 9.1, we replace the dummy variable with a continuous price variable. We find similar results with the caveat that the estimated relationships between IRC and prices are unlikely to be linear.

Table 4: Summary statistics for the distributions of IRC by low- and high-priced CLOs in normal times and pandemic times. Low-priced CLOs are defined as those CLOs that traded below the median price *in a given week* while high-priced CLOs are those above the median price *in the same week.*

	Pre-pandemic		Pandemic	
	Low price	High price	Low price	High price
75^{th} percentile	5.0	4.4	53.5	25.5
Median	3.3	2.0	12.9	8.4
25^{th} percentile	1.0	1.3	3.6	2.1

CLO market. In the next section, we develop a formal test and address endogeneity concerns.

4.2.1 Implementation of the test

The dependent variable in our analysis is the IRC for a dealer bank-specific AAA CLO tranche. As previously explained, we calculate the IRC of matched trades of a dealer bank that occur within one day. This measure is the difference between a dealer's sell price and the same dealer's buy price for the same security on the same day. Intuitively, even though dealers typically arrange trades in advance, there is no commitment of the buyer to trade. There are two possible costs to the dealer banks if they end up holding the tranche. First, dealers require compensation for the risk that they take—as uninformed agents—because they may end up holding the tranche and trading with informed clients. Second, there are bank balance sheet costs. There are bank capital requirements if a tranche is held on-balance sheet. These costs are associated with the Volker Rule (see, e.g., Bao et al. (2018)) and there are costs associated with binding leverage constraints (see, e.g., Koont and Walz (2021)). Later, as a robustness check, we will be more specific about taking such costs into account.

Our identification strategy relies on the causal effect of the pandemic on AAA CLO illiquidity through its effect on prices. It is evident that the pandemic acts as an exogenous shifter of AAA CLO prices. However, it is plausible that the pandemic may also have an effect on the illiquidity of debt securities through its effect on dealers, which is a threat to identification. For example, dealer funding cost may be heterogeneous and may also heterogeneously vary in and out of the pandemic. Variation in dealer funding cost could arise from non-informational frictions such as, for example, search or hedging costs. Another potential confounding effect is unobserved heterogeneity in CLO tranches that could lead to different unobserved equilibrium relationships between a tranche IRC and its trading price—the inverted "hockey stick" relationship in Figure 8.

We address these two potential issues using a quantile regression with fixed effects and by exploiting the identity of dealers that we observe for each individual transaction. The unit of observation is a tranche i traded by dealer k on day t. The dependent variable IRC_{ikt} is the imputed roundtrip cost of a specific dealer bank k trading CLO tranche i on day t, conditional on a trade taking place. Low price_{it} is a binary variable that takes the value 1 if tranche i trades below the median price in a given week. The binary variable Covid_t takes the value 0 before March 1, 2020 and 1 thereafter.

We implement the test by estimating the conditional quantile functions $Q_{\text{IRC}_{ikt}}(\tau|\text{Covid}_t, \text{Low price}_{it})$ given by

$$\begin{aligned} Q_{\text{IRC}_{ikt}}(\tau|\text{Covid}_t, \text{Low price}_{it}) = \alpha^i &+ \beta_1(\tau)\text{Covid}_t \\ &+ \beta_2(\tau)\text{Low price}_{it} \\ &+ \sum_{j=1}^{K} \beta_3^j(\tau)\text{Dealer ID}_{ijt} \\ &+ \beta_4(\tau)\text{Covid}_t \times \text{Low price}_{it} \\ &+ \sum_{j=1}^{K} \beta_5^j(\tau)\text{Covid}_t \times \text{Dealer ID}_{ijt} \ . \end{aligned} \tag{1}$$

with quantile $\tau \in \{0.25, 0.5, 0.75\}$.

The parameter α^i is a tranche fixed effect, which is unrelated to the conditional quantile response function and act as a pure location shift. The role of the tranche fixed effect is to "align" the unobserved relationship between IRC and prices across the different tranches. Our baseline specification controls for the potential effect of dealer funding cost heterogeneity using an interaction between the Covid_t dummy and a set of unique dealer identifier dummy variables Dealer ID_{ijt} for $j = 1, ...K$. Note that these interaction terms can vary across the different quantile response functions and control for potentially heterogeneous dealer funding costs that may vary before and during the pandemic. In the next subsection, we consider alternative controls for dealer funding costs. The coefficients of interest are $\beta_3(\tau)$ for $\tau \in \{0.25, 0.75\}$.

Under the null hypothesis of no adverse selection in the market, $\beta_3(0.25)$ is not statistically different from $\beta_3(0.75)$.

Under the alternative hypothesis consistent with the information-based theories of debt, the pandemic shock shifts all prices lower and those AAA CLO tranches with prices in the lower part of the distribution are now closer to the "kink" on Figure 8 and more likely to experience adverse selection. As a consequence, the distribution of the IRC for those tranches is wider—i.e., $|\beta_3(0.75) - \beta_3(0.25)| > 0$. Once again, this test is conditional on the potentially time-varying dealer funding cost.

An important–but plausible–identification assumption is that all dealer banks are competitive (relatively) uninformed intermediaries. They fear that the relatively low prices imply adverse selection and adjust their IRC accordingly. Alternatively, if dealer banks were informed about every CLO tranche, the correlation between IRC and price could arise from common information about the underlying pool of collateral. We are confident that dealer banks do not scrutinize and assess the collateral quality before intermediating every AAA-rated CLO tranche.

We implement the quantile fixed effect regressions using the penalized fixed-effects estimation method proposed by Koenker (2004). Throughout the analysis, we report clustered bootstrapped standard errors with 1,000 replications that are implemented using the generalized bootstrap of Chatterjee and Bose (2005) with unit exponential weights sampled for each individual CUSIP.

4.2.2 Empirical results

Table 5 shows the results. The estimated coefficients suggest the economic effect of adverse selection due to the pandemic was large. Consider a hypothetical CLO that switched from the 25^{th} percentile of the distribution of IRC to the 75^{th} percentile of the distribution during the pandemic. If that CLO's price had been below the median, the IRC would have been about 12 percentage points higher than if its price had been above the median. To give this estimate some context, the pre-pandemic average IRC was about 5 percentage points.

We use the coefficients in column 2 of Table 5 to estimate the adverse selection component. The combination of all the pandemic terms is the estimated increase in the 75^{th} percentile, where we identify adverse selection.[16] Averaging across dealer fixed effects yields a dealer-specific balance sheet cost component of about 10 percentage points. Thus,

[16]Note that we cannot rule out the presence of adverse selection in normal times, as it enters the constant terms in Table 5. Our approach uses cross-sectional variation to identify adverse selection only in the pandemic.

the adverse selection component accounts for a little over half of the observed increase in the 75^{th} percentile of the IRC that occurred during the pandemic.[17] For reference, Glosten and Harris (Table 2, pg 136) estimated that 20-30 percent of the bid-ask spread was due to adverse selection *in normal times*.

4.2.3 Alternative specification of dealer funding cost

In this subsection we add more structure to the dealer variable that represents the balance sheet costs. Dealer balance sheet costs may well vary with their cost of funding, which differs across dealers. To investigate this we interact the dealer ID variable with a dealer-specific Overnight Bank Funding Rate (OBFR) from the New York Federal Reserve Bank.[18]

Secondly, dealer funding costs may vary with the macro economy. We capture this variation with an estimate of the 2-year carry on the Treasury cash-swap basis trade, a measure of the tightness of bank leverage constraints.[19] We interact the time-series with dealer ID dummy variables

[17] As an alternative scaling factor, we ran a quantile regression with the pandemic dummy as the sole independent variable to obtain a similar estimate of about 22 percentage points for the effect of the pandemic on the 75^{th} percentile of the IRC. This alternative approach also suggests that the adverse selection component is roughly half the total effect.

[18] According to the NY Fed: "The overnight bank funding rate is a measure of wholesale, unsecured, overnight bank funding costs. It is calculated using federal funds transactions, certain Eurodollar transactions, and certain domestic deposit transactions, all as reported in the FR 2420 Report of Selected Money Market Rates. [...] The overnight bank funding rate (OBFR) is calculated as a volume-weighted median of overnight federal funds transactions, Eurodollar transactions, and the domestic deposits reported as "Selected Deposits" in the FR 2420 Report."

[19] Thanks to Chase and Sharon Ross for sharing their data.

Table 5: 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 lowest 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. LowPrice_{it} takes the value 1 if the weighted-average price of CLO i on day t is below the median CLO price for that week. The sample in columns 1 through 5 is AAA-rated CLO tranches. The sample in columns 6 through 9 is class E CLO tranches. 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) E	(4) E
[0.25]Covid_t	2*	3.64	10.15***	14.98*
	(1.08)	(9.98)	(2.81)	(8.05)
[0.25]LowPrice_{it}	0.57	0.39	1.74	2.25
	(1.25)	(0.85)	(1.71)	(1.55)
[0.25]$\text{Covid}_t \times \text{LowPrice}_{it}$	0.03	0.63	-2.01	-3.96
	(1.49)	(1.21)	(3.67)	(3.69)
[0.5]Covid_t	4.5***	31.8***	16.5***	26.56***
	(0.98)	(8.7)	(2.85)	(5.05)
[0.5]LowPrice_{it}	1.19	1.5*	2.45	2.37
	(1.15)	(0.8)	(1.8)	(1.61)
[0.5]$\text{Covid}_t \times \text{LowPrice}_{it}$	-0.57	-0.63	-3.58	-4.03
	(1.32)	(1.16)	(3.93)	(3.93)
[0.75]Covid_t	10.33***	67.43***	31.08***	41.45***
	(1.08)	(10.71)	(4.16)	(13.08)
[0.75]LowPrice_{it}	1.59	1.56	3.08	2.67
	(1.19)	(0.97)	(2.15)	(1.85)
[0.75]$\text{Covid}_t \times \text{LowPrice}_{it}$	12.2***	12.64***	5.5	4.53
	(2.25)	(2.01)	(5.47)	(4.8)
CUSIP fixed effects	Y	Y	Y	Y
Additional controls:				
Dealer	Y	Y	Y	Y
COVID×Dealer	N	Y	N	Y
Observations	2,666	2,666	1,903	1,903
H_0: [0.25]$\text{Covid}_t \times \text{LowPrice}_{it}$ = [0.75]$\text{Covid}_t \times \text{LowPrice}_{it}$				
F test	29.44***	42.22***	2.2	6.35**

Table 6: 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 lowest 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. LowPrice_{it} takes the value 1 if the weighted-average price of CLO i on day t is below the median CLO price for that week. The sample in columns 1 through 3 is AAA-rated CLO tranches. The sample in columns 4 through 5 is class E CLO tranches. 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) E	(5) E
[0.25]Covid_t	0.32	-0.42	0.52	7.07***	-0.86
	(0.61)	(1.07)	(5.53)	(2.19)	(5.59)
[0.25]LowPrice_{it}	0.11	0.4	-1.58	1.56	2.15
	(0.65)	(0.92)	(5.21)	(2.18)	(1.54)
[0.25]$\text{Covid}_t \times \text{LowPrice}_{it}$	0.29	0.03	1.62	-1.58	-2.93
	(0.96)	(1.22)	(5.33)	(3.01)	(3.81)
[0.5]Covid_t	0.53	-0.72	-0.58	7.84***	10.55**
	(0.59)	(1.19)	(6.23)	(2.33)	(5.15)
[0.5]LowPrice_{it}	0.03	0.34	-1.58	0.21	2.63*
	(0.65)	(0.95)	(5.52)	(2.32)	(1.59)
[0.5]$\text{Covid}_t \times \text{LowPrice}_{it}$	0.96	0.74	1.65	2.09	-3.26
	(0.96)	(1.22)	(5.6)	(3.16)	(4.07)
[0.75]Covid_t	1.94**	7.4***	27.77***	6.22**	1.46
	(0.78)	(2.42)	(10.12)	(3.11)	(7.84)
[0.75]LowPrice_{it}	-0.69	1.3	-1.04	6.65*	3.53*
	(0.86)	(1.26)	(5.26)	(3.5)	(1.86)
[0.75]$\text{Covid}_t \times \text{LowPrice}_{it}$	8.08***	10.67***	8.97	6.64	1.16
	(1.19)	(1.88)	(5.71)	(4.48)	(4.61)
CUSIP fixed effects	Y	Y	Y	Y	Y
Additional controls:					
Dealer	Y	Y	Y	Y	Y
2yr-Carry rate×Dealer	Y	N	N	Y	N
OBFR×Dealer	N	Y	Y	N	Y
Observations	2,486	2,666	985	1,850	1,903
H_0: [0.25]$\text{Covid}_t \times \text{LowPrice}_{it}$ = [0.75]$\text{Covid}_t \times \text{LowPrice}_{it}$					
F test	58.48***	40.68***	1.87	4.45**	1.75

which allow the aggregate shock to have a different effects across dealers. The cash-swap basis is the return to a trading strategy that is long a Treasury and short the same maturity interest rate swap (i.e. receive LIBOR, pay swap rate), while financing the Treasury at the overnight repo rate, and financing the initial margin and repo haircut with 1-year OIS. We use the absolute value of the 2-year maturity carry to measure bank leverage constraints.

Table 6 shows that our previous findings are robust to specifications that include these alternative measures of balance sheet costs. Columns 1 and 2 show the results with the 2-year carry rate and OBFR, respectively, for the AAA-rated CLO tranches. We again find that the coefficient on the interaction term is economically and statistically significant only for the 75^{th} percentile of the IRC distribution. Columns 4 and 5 show the coefficient on the interaction terms remain insignificant for the sample of E-class CLO tranches.

Lastly, in column 3, we repeat the analysis in column 2 restricting the sample to CLOs that had relatively low exposure–defined as those below the median–to the vulnerable sectors. This sample selection is a further test for the presence of adverse selection as these tranches are *less* likely to experience adverse selection. Consistent with the rest of our findings, the coefficient on the interaction term for the 75^{th} percentile is no longer significant. In summary, our analysis points to the arrival of adverse selection in the market for AAA-rated CLO tranches during the pandemic.

5 The Switch to Information-Sensitive Debt

A consequence of the arrival of adverse selection is that debt securities that were previously information-insensitive become information sensitive. In this section, we study the switch to information-sensitive debt. We first present a set of facts about the price distribution of AAA CLO tranche prices and the underlying loan portfolio. We then formally test for the switch to information sensitivity with a quantile regression framework.

5.1 AAA CLO Price Dispersion During the Pandemic

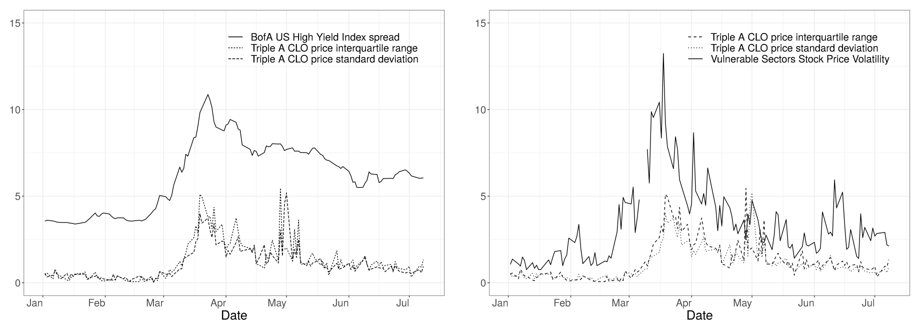
Figure 1 above displayed the fanning out of post-pandemic prices, suggesting that investors were differentially pricing the AAA tranches using information from trustee reports most likely. "Fanning out" corresponds to an increase in measures of prices dispersion.

We now show that uncertainty about the vulnerable industries is responsible for differentiation in transaction prices across AAA-rated CLO tranches. The lowest transaction prices for AAA 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.

Panel (a) of figure 9 shows the time series of two measures of the dispersion in the prices of AAA-rated CLO tranches. Also shown is the Bank of America-Merrill Lynch High Yield Index Option-Adjusted Spread. This index is appropriate for comparison because CLOs hold loans to below investment-grade firms. Compared to this index are the two measures of dispersion across CLO tranches: the standard deviation and the interquartile range.[20] The two measures of dispersion are highly correlated and mirror the movements in the High Yield Index.

Figure 9: Dispersion of prices, the high yield spread, and vulnerable sector stock price volatility. This figure compares the time series of dispersion in the prices of AAA-rated CLO tranches to the Bank of America-Merrill Lynch High Yield Index Option-Adjusted Spread (left-hand panel) and the volatility of the stock prices of firms in the sectors identified by Moody's as vulnerable to the pandemic shock (right-hand panel). We calculate two measures of dispersion across CLO prices: the standard deviation and the interquartile range. Source: Authors' calculations from data provided by TRACE, FRED, Bloomberg LP, Moody's Analytics, S&P, and Fitch.

(a) High yield spread **(b)** Vulnerable stock price volatility



As a complement to panel (a), we replaced the high-yield spread with the stock price volatility in the industries that Moody's identified as being

[20]To calculate the dispersion measures we first calculate a daily weighted-average price, where the weights are transaction volumes.

most vulnerable to the pandemic shock. The solid line in panel (b) of figure 9 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. Bank loans and bonds are alternative sources of funding for firms. Based on the time-series of data since January 1, 2020, the correlation between the high-yield spread and the volatility index is 0.61.

Figure 10 shows the AAA tranche prices by the top and bottom quartiles, with one standard deviation bounds. This graphically shows the differentiation between CLO tranches. That investors are distinguishing between different CLO tranches means that they are distinguishing between different loans. We can also look at the loans in CLO portfolios.

Panel (a) of Figure 11 shows loan prices by quartile. It is clear that, indeed, investors were differentiating been good and bad loans. And this was at the root of differential AAA tranche pricing. But note that it is *not* the case that the price dispersion is simply due to the pandemic shock to the vulnerable industries. Panel (b) of Figure 11 shows vulnerable loan prices by quartile. A common or sector-specific risk premium arising when the pandemic hits cannot explain this differentiation in loan pricing. In other words, our results are not compatible with an alternative scenario in which risk just 'went up', more so for industries affected by the pandemic. Underscoring this point, at no point during the pandemic did any AAA-

Figure 10: AAA CLO tranche prices by quartile. The figure shows the median AAA-rated tranche price ± one standard deviation for the tranches that are traded in the top and bottom quartiles of the price distributions. Source: Authors' calculations from data provided by TRACE, Bloomberg LP, Moody's Analytics, S&P, and Fitch.

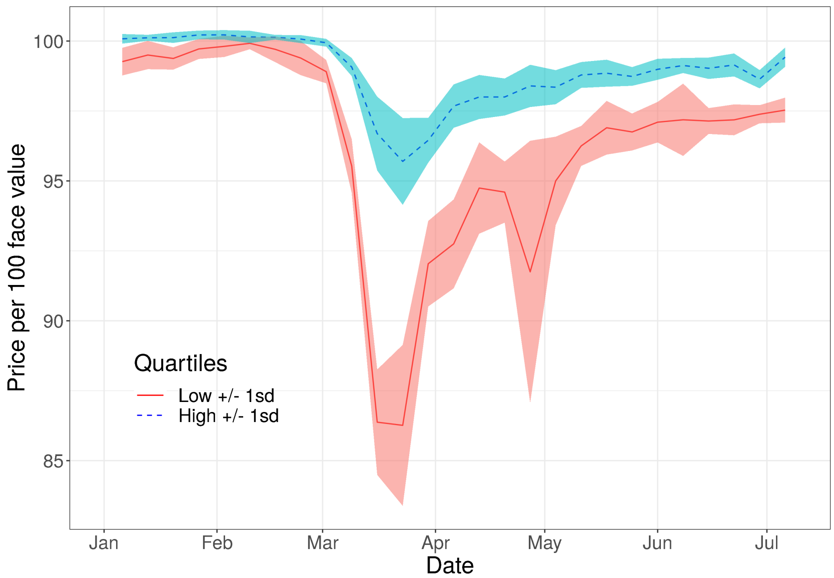
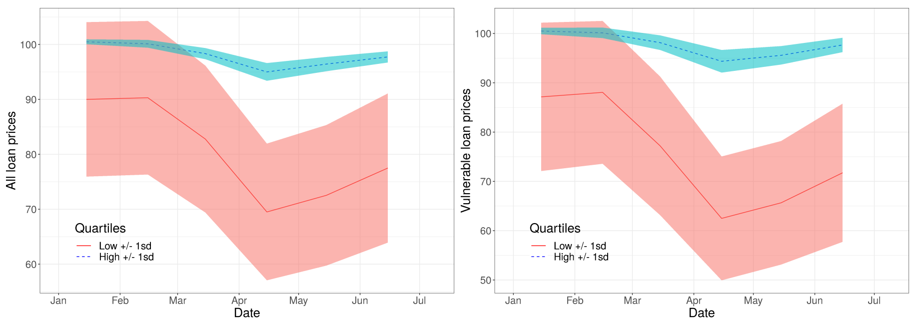


Figure 11: Loan prices by quartile. The figure shows the median loan price ± one standard deviation for the leveraged loans in the top (high) and bottom (low) quartiles of their price distributions. The left panel shows the prices for all leveraged loans and the right panel shows the prices for loans to firms in industries identified by Moody's as vulnerable to the pandemic shock. Source: Authors' calculations from data provided by Moody's Analytics.

(a) All loans **(b)** Loans to vulnerable firms



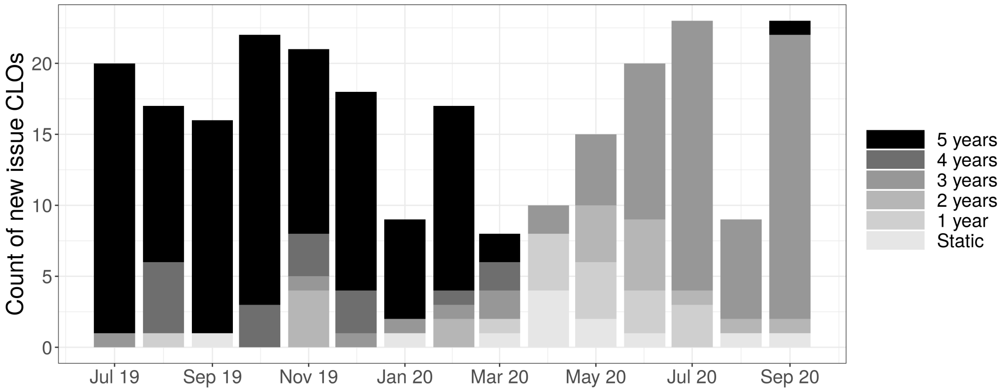
rated CLO tranche experience a credit rating downgrade, or even a negative outlook.

In online appendix 9.2, 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 adverse selection hypothesis, the lower part of the distribution of AAA tranche price is sensitive to new information about the vulnerable industries because investors are distinguishing those AAA CLO tranche that became information sensitive.

6 CLOs during the Pandemic

During the pandemic, CLOs have continued to be issued. But their structure has been altered significantly to avoid adverse selection. A key issue is how much discretion the portfolio manager has to trade the portfolio, meaning that loans go in and out (see Table 3). More trading would require constant monitoring of new loans. As reported by Millar (2020) "New issues were largely either static or had one-year reinvestment periods in April..." In other words, the managerial discretion to alter the portfolio has been significantly reduced. This shift is shown in Figure 12.

Figure 12: US CLO count by reinvestment period. The bar chart shows the monthly count of newly-issued CLOs by the period over which managers have reinvestment discretion. Source: Authors' calculations from data provided by S&P Global Market Intelligence.



The dark shaded part of a bar is the number of CLOs that had a five-year reinvestment period, i.e., the manager could trade the portfolio during the first five years.

Another key issue is how incentive compatible the manager's stake is in the CLO. Deals have been restructured to decrease managerial discretion and also to increase the incentives of managers not to engage in insider trading of the sort J.P. Morgan warned about. Also, new deals are being driven by affiliated equity (equity from elsewhere in the firm that is not consolidated with the CLO managers). Small CLO managers do not have access to affiliated equity and so cannot issue new CLOs. Only those with reputation risk are able to issue, using affiliated equity.

7 Concluding remarks

We measured the lemons premium on AAA CLO tranches that had low prices when the pandemic hit. The lemons premium is associated with the arrival of adverse selection in the CLO market. When securities are information-insensitive, it is not profitable to produce private information about their fundamentals ex ante and everyone knows this. AAA CLO tranches trade at par with a narrow bid-ask spread. Adverse selection is avoided. When AAA-rated CLO tranches become information-sensitive, as they did in the pandemic, uninformed traders are not prepared to produce information (see Hanson and Sunderam (2013)). They had not invested in the technology to do so (e.g., buying data, hiring analysts). The bid-ask spread of some AAA CLO tranches increased more for those securities with relatively low prices in part because uninformed investors do not know what the price should be. They face adverse selection. In this paper we documented these dynamics of adverse selection in the CLO market when the pandemic hit. We decomposed bid-ask spreads in a quantile fixed effects regression framework into a component reflecting dealer bank balance sheet costs and the adverse selection component. We find that those CLOs with a lemons premium experienced, on average, 12 percentage points higher bid-ask spread accounting for about half of the total increase during the pandemic.

Note that if it were an economy-wide shock that introduced a risk premium for AAA-rated CLOs, then their bid-ask spreads would widen uniformly. The information about each CLO's exposure to vulnerable industries in the trustee reports is not sufficient to explain the wider bid-ask spreads. Importantly, it is one thing to know the exposure and another thing to know how loans/industries will perform. We showed in Figure 11 that there is dispersion in loan prices within the vulnerable/not industries and we showed in Figure 5 that there is price disagreement within the vulnerable/not industries. These empirical facts are not compatible with an alternative scenario in which risk simply 'went up', more so for firms or industries affected by the pandemic. For these reasons, the evidence suggests that investors are producing private information about the loans held by CLOs. In normal times, investors don't produce this private information.

When adverse selection sets in, the market becomes less liquid in the precise sense that the securities are information-sensitive; there is adverse selection. Some price drops have often been referred to as "fire sales" or "selling pressure". These notions seem to imply that there are no buyers with available cash to invest, though no evidence has been shown that this is the case. It would also seem to imply there would be no correlation between low prices and higher bid-ask spreads, after controlling for dealer bank balance sheet costs. We showed, contrary to these ideas, that there was a relationship between the bid-ask spread and price dispersion due to adverse selection.

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8 Data appendix – For Online Publication

This appendix provides the details on data construction to replicate the analysis in the paper.

8.1 Bloomberg

We begin our data construction using the asset-backed security Backoffice data from Bloomberg. We identify the universe of collateralized loan obligations (CLOs) using the identifier "`mtg_deal_typ`" column in the Backoffice data. Bloomberg provides cross-sectional information for every tranche issed by each CLO, including CUSIP identifiers.

8.2 Regulatory TRACE

We use the CUSIP variable from the Bloomberg data to identify individual transactions on CLO tranches in the Trade Reporting and Compliance Engine (TRACE), created by the Financial Regulatory Authority (FINRA).

8.3 Ratings

We also use the CUSIP variable from the Bloomberg data to identify ratings actions by Moody's, S&P, and Fitch. Our rating information comes from direct daily feed from Moody's, S&P, and Fitch that are added to the initial historical baseline refresh that cover every security in our sample. The rating actions include when an agency places a tranche on watch to forewarn investors of a potential change in rating.

8.4 Moody's loan-level data

We combine loan-level information about the CLOs in our analysis from Moody's. The majority of this information is obtained from monthly trustee reports prepared by each CLO and processed by Moody's. In addition, Moody's provides further information from pricing specialists (e.g. Loanx and Reuters) and in-house assessments.

We link the loan-level data to the other datasets using a cross-walk provided by Moody's to the Bloomberg identifier "`mtg_deal_name`".

8.5 Barchart data

Download the seven sectors listed in the table below from the website (`https://www.barchart.com/stocks/sectors/rankings`) 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 7: 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

9 Additional results – For Online Publication

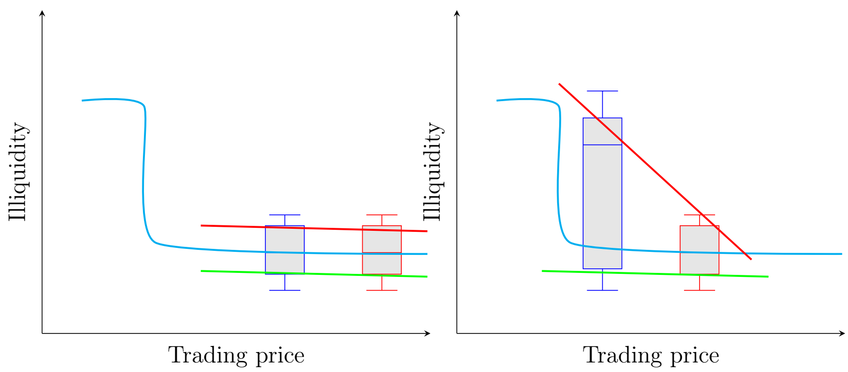
9.1 Alternative specification with continuous price variable

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 13 adapts Figure 8 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 8. 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 8, the relationship between IRC and prices is likely to be nonlinear.

Figure 13: Schematic linear relationship between imputed roundtrip costs and prices. The figure adapts Figure 8 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 8: 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

9.2 Quantile regression 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 adverse selection hypothesis, 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).[21] We estimate the conditional quantile functions $Q_{\text{Trading price}_{it}}(\tau|\text{Covid}_t, \text{Volatility}_t)$ of the response of the t-

[21] Appendix 9.3 reports a robustness check where we replace our measure of realized volatility with a measure of forward volatility.

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

$$\begin{aligned} Q_{\text{Trading price}_{it}}(\tau|\text{Covid}_t, \text{Volatility}_t) = \alpha^i &+ \beta_1(\tau)\text{Covid}_t \\ &+ \beta_2(\tau)\text{Volatility}_t \\ &+ \beta_3(\tau)\text{Covid}_t \times \text{Volatility}_t \;, \end{aligned} \quad (2)$$

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 9 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 9: 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***	-0.59***	-1.23**	-3.72***	-12.54***	-22.09***
	(0.21)	(0.22)	(0.58)	(0.89)	(1.33)	(1.89)
[0.25]Volatility_t	-2.41	-4.97**	-24.88***	-53.56***	0	-69.14**
	(1.94)	(2.25)	(7.64)	(13.32)	(12.01)	(31.54)
[0.25]$\text{Covid}_t \times \text{Volatility}_t$	-79.04***	-83.59***	-150.69***	-181.15***	-232.75***	-197.09***
	(8.03)	(8.48)	(23.16)	(31.24)	(37.71)	(61.1)
[0.5]Covid_t	-1.23***	-1.23***	-2.1***	-3.83***	-10.97***	-18.75***
	(0.18)	(0.17)	(0.34)	(0.6)	(1.14)	(1.88)
[0.5]Volatility_t	-1.35	-1.58	-15.87***	-23.11**	1.53	-49.01*
	(1.03)	(1.45)	(6.07)	(11.44)	(7.14)	(25.69)
[0.5]$\text{Covid}_t \times \text{Volatility}_t$	-36.24***	-40.42***	-78.8***	-106.52***	-149.41***	-100.54*
	(6.29)	(6.26)	(13.54)	(22.88)	(32.74)	(58.66)
[0.75]Covid_t	-1.55***	-1.54***	-2.15***	-3.7***	-8.91***	-13.58***
	(0.16)	(0.15)	(0.33)	(0.5)	(0.85)	(1.82)
[0.75]Volatility_t	1.3	0.22	-11.13*	-7.74	0.41	-26.57
	(2.19)	(1.58)	(5.96)	(9.71)	(7.82)	(25.3)
[0.75]$\text{Covid}_t \times \text{Volatility}_t$	-12.46**	-16.05***	-44.23***	-54.05***	-81.18***	-51.83
	(5.47)	(5.04)	(12.02)	(18.41)	(20.82)	(48.65)
CUSIP FE	Y	Y	Y	Y	Y	Y
Observations	16,417	18,208	5,899	6,734	8,386	6,017
	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	76.78***	77.67***	18.89***	13.59***	16.54***	5.04**

(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 9.4 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 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 8 bps.

9.3 Robustness: Table 9 with forward volatility

In this subsection, we check whether the results of our quantile fixed effect regression used in section 5 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 10 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 10: Information sensitivity of CLO debt tranches – robustness test with forward volatility. This specifications report in this table replicate those of Table 10, 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. 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$_t$	-0.14	-0.18	0.06	-1.61**	-9.84***	-15.6***
	(0.17)	(0.16)	(0.42)	(0.67)	(1.1)	(1.39)
[0.25]Volatility_1wk_lag$_t$	4.84**	4.3**	10.47	-4.12	-6.82	-57.49**
	(1.92)	(2.16)	(6.93)	(14.99)	(15.22)	(25.63)
[0.25]Covid$_t$×Volatility_1wk_lag$_t$	-90.24***	-93.3***	-195.02***	-236.47***	-276.12***	-311.89***
	(6.28)	(6.31)	(15.62)	(24.03)	(30.3)	(42.31)
[0.5]Covid$_t$	-0.69***	-0.73***	-0.5	-1.34***	-8.09***	-11.72***
	(0.13)	(0.12)	(0.37)	(0.5)	(0.97)	(1.45)
[0.5]Volatility_1wk_lag$_t$	2.35*	2.95**	4.98	-3.65	-20.1**	-62.78***
	(1.21)	(1.27)	(3.05)	(6.71)	(9.79)	(16.71)
[0.5]Covid$_t$×Volatility_1wk_lag$_t$	-52.95***	-56.91***	-136.34***	-182.65***	-203.37***	-271.75***
	(4.08)	(3.9)	(12.4)	(15.19)	(27.72)	(37.7)
[0.75]Covid$_t$	-0.79***	-0.92***	-1.2***	-0.97	-5.01***	-6.59***
	(0.11)	(0.11)	(0.45)	(0.6)	(1.07)	(1.65)
[0.75]Volatility_1wk_lag$_t$	2.43	0.95	1.62	-6.23	2.68	-59.44***
	(2.4)	(1.93)	(3.33)	(6.9)	(10.56)	(18.08)
[0.75]Covid$_t$×Volatility_1wk_lag$_t$	-35.37***	-34.38***	-78.63***	-133.79***	-191.05***	-241.35***
	(3.66)	(3.38)	(15.09)	(17.15)	(30.24)	(38.1)
CUSIP FE	Y	Y	Y	Y	Y	Y
Observations	15,667	17,354	5,512	6,279	7,964	5,760
	H_0: [0.25]Covid$_t$×Volatility_1wk_lag$_t$ = [0.75]Covid$_t$×Volatility_1wk_lag$_t$					
χ^2_1 test statistic	76.81***	90.02***	42.81***	13.62***	5.61**	1.75

9.4 Robustness: Table 9 with other sectors' volatility

In this subsection, we check whether the results of our quantile fixed effect regression used in section 5 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 11 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 11: 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 9 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)
$[0.25]\text{Covid}_t$	-0.58***	-0.59***	-1.23**	-3.77***	-12.55***	-22.62***
	(0.2)	(0.21)	(0.63)	(0.96)	(1.3)	(2.12)
$[0.25]\text{Vul\_Volatility}_t$	6.06	8.21*	18.15***	28.08	44.72***	28.97
	(3.93)	(4.27)	(6.83)	(17.98)	(15.91)	(32.68)
$[0.25]\text{Other\_Volatility}_t$	-10.98**	-16.1***	-53.21***	-109.81***	-82.23***	-145.35***
	(4.89)	(5.59)	(12.02)	(25.08)	(26.61)	(48.67)
$[0.25]\text{Covid}_t\times\text{Vul\_Volatility}_t$	-51.26***	-53.19***	-183.62***	-241.45***	-355.49***	-358.93***
	(10.86)	(13.75)	(29.38)	(47.12)	(75.01)	(97.11)
$[0.25]\text{Covid}_t\times\text{Other\_Volatility}_t$	-37.21***	-39.01**	39.28	77.58	171.61**	240.08*
	(14.3)	(16.33)	(45.36)	(66.51)	(80.44)	(136.17)
$[0.5]\text{Covid}_t$	-1.23***	-1.2***	-2.24***	-4.7***	-11.49***	-20.49***
	(0.18)	(0.18)	(0.35)	(0.63)	(1.11)	(1.52)
$[0.5]\text{Vul\_Volatility}_t$	1.92	4.21*	5.43	10.45	20.63**	31.9
	(2)	(2.51)	(4.72)	(11.03)	(10.03)	(22.66)
$[0.5]\text{Other\_Volatility}_t$	-4.68*	-7.6**	-34.71***	-50.13***	-34.13**	-123.75***
	(2.64)	(3.39)	(10.28)	(17.9)	(14.95)	(38.01)
$[0.5]\text{Covid}_t\times\text{Vul\_Volatility}_t$	-34.22***	-36.16***	-158.37***	-215.43***	-227.01***	-378.15***
	(10.31)	(12.38)	(23.11)	(29.57)	(63.48)	(84.3)
$[0.5]\text{Covid}_t\times\text{Other\_Volatility}_t$	-2.81	-7.13	116.11***	185.97***	124.25	441.64***
	(11.85)	(14.3)	(33.98)	(53.88)	(78.12)	(104.29)
$[0.75]\text{Covid}_t$	-1.58***	-1.55***	-2.56***	-3.85***	-8.86***	-13.61***
	(0.14)	(0.13)	(0.34)	(0.45)	(0.92)	(1.69)
$[0.75]\text{Vul\_Volatility}_t$	5.3*	4.32*	0.06	6.17	11.73	8.59
	(2.9)	(2.53)	(5.04)	(9.32)	(12.51)	(25.99)
$[0.75]\text{Other\_Volatility}_t$	-6.26*	-5.74*	-20.23**	-23.13	-21.32	-78.72*
	(3.52)	(3.22)	(10.15)	(17.01)	(17.48)	(41.97)
$[0.75]\text{Covid}_t\times\text{Vul\_Volatility}_t$	-17.92	-18.83	-110.39***	-189.02***	-161.53***	-193.42
	(12.1)	(12.71)	(25.24)	(24.73)	(61.28)	(136.21)
$[0.75]\text{Covid}_t\times\text{Other\_Volatility}_t$	8.15	3.83	100.78***	180.33***	108.1	198.51
	(13.1)	(13.8)	(34.88)	(35.99)	(68.83)	(147.25)
CUSIP FE	Y	Y	Y	Y	Y	Y
Observations	16,417	18,208	5,899	6,734	8,386	6,017
	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	8.02***	7.55***	4.55**	1	6.42**	1.67

9.5 Testing the difference between IRC distributions

Figure 7 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 12 reports that there were roughly equal number of observations in the two samples.

The left-hand panel and right-hand panels of Table 12 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. In all cases, we can reject the null hypothesis that the two samples are drawn from a common distribution at less than 5 percent.

Table 12: 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. Source: Authors' calculations from data provided by TRACE, Bloomberg LP, and Moody's.

(a) Anderson-Darling Test					(b) Kruskal-Wallis Test		
Number of samples: 2 Sample sizes: 314, 395 Number of simulations: 10,000					Number of samples: 2 Sample sizes: 314, 395 Number of simulations: 10,000		
	AD	T.AD	asympt. p-val.	sim. p-val.	test stat.	asympt. p-val.	sim. p-val.
version 1:	3.967	3.908	0.009	0.0086	5.101	0.0239	0.0243
version 2:	3.980	3.931	0.009	0.0087			

9.6 Loan transaction summary statistics without ramp-up period

This table repeats the analysis in Table 3 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.[22]

9.7 Structural breaks in Class E CLO tranches

Figure 14 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 9 showed that Class E tranches were information-sensitive prior to the pandemic.

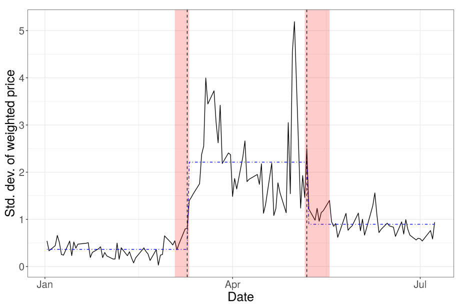
[22] https://www.pinebridge.com/insights/investing/2019/09/clo-beyond-the-complexity

Table 13: 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.

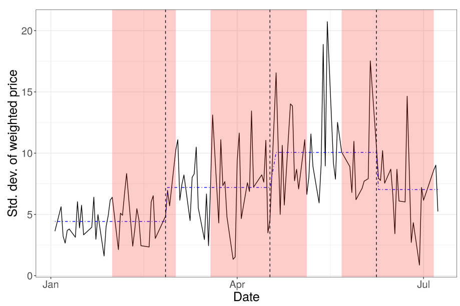
Variable	Statistic	All transactions			Vulnerable sector			Non-vulnerable sector		
(units)		Pre	Post	*p-value*	Pre	Post	*p-value*	Pre	Post	*p-value*
Number of sales	Mean	47.16	82.79	0	6.83	10.99	0	45.09	78.77	0
(per CLO)	SD	59.33	136.29	0	16.41	23.03	0	53.49	127.75	0
	N	1,581	1,625		493	603		1,579	1,624	
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 14: 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



9.8 Attachment points

Figure 15: 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 CLO population is traded in 2020 (779 cusip out of 1684 triple A are traded in 2020). Source: Authors' calculations from data provided by Bloomberg LP, Fitch, Standard & Poor's and Moody's.