The Dynamics of Adverse Selection in Privately-Produced Safe Debt Markets

Nathan Foley-Fisher, Gary Gorton, and Stéphane Verani

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Abstract

Privately-produced safe debt is designed so that there is no adverse selection in trade. This is because no agent finds it profitable to produce private information about the debt's backing and all agents know this (i.e., it is information-insensitive). But in some macro states, it becomes profitable for some agents to produce private information, and then the debt faces adverse selection when traded (i.e., it becomes information-sensitive). We empirically study these adverse selection dynamics in a very important asset class, collateralized loan obligations, a large symbiotic appendage of the regulated banking system, which finances loans to below investment-grade firms.

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1 Introduction

There is a primitive demand for safe debt, debt that can store value through time safely and can be traded without fear of adverse selection. The government cannot completely meet this demand (see, e.g., Krishnamurthy and Vissing-Jorgensen (2012), Caballero, Farhi and Gourinchas (2017), Gorton, Llewellen and Metrick (2012), and Gorton (2017)). The private sector cannot produce riskless debt, but it can produce a close substitute, debt 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 dynamics of this switch from information-insensitive to information-sensitive in the collateralized loan market and document the resulting adverse selection.

The risk of a switch from information-insensitive to sensitive, and the resulting adverse selection, is a unique risk. Because the security is designed to be information-insensitive, no investor has an incentive to produce

private information about the security's fundamentals. Ex ante investors do not investigate the fundamentals of the bond and accept the debt at par. Investors are uninformed by design. In particular, the risk of a switch to adverse selection is neither investigated nor priced ex ante. Ex post in the case of bad times, they cannot price the security because they have not invested in the technology to do so. See Kaplan (2006), Hanson and Sunderam (2013), and Monnet and Quintin (2017). So, privately-produced safe debt is a double-edged sword: It serves its purpose of avoiding adverse selection until it doesn't.

A collateralized loan obligation (CLO) is a legal entity that buys loans from banks and finances them by issuing debt in the capital market.[1] 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". According to Fed Chair Jerome Powell 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 about 70 percent of U.S. companies, including companies like Burger King, United Airlines, Avis Rent a Car, and Equinox Fitness.

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

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[1]The CLO manager can subsequently buy and sell assets.

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, 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. "Safety" means that it is highly likely to pay off at par at maturity and, if it is sold early, it will sell for (almost) par. It is information-insensitive.

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.

Consistent with the AAA tranches having a convenience yield, these tranches are held by insurance companies, pension funds, U.S. and foreign banks, and U.S. investment banks. The mezzanine tranches in the middle of the CLO capital structure are held by hedge funds and asset managers, among others. The equity part of the capital structure is held by private equity firms, the CLO managers, and CLO sponsors. See Liu and Schmidt-

Eisenlohr (2019) and DeMarco, Liu and Schmidt-Eisenlohr (2020).

CLOs hold very risky loans but still 65 percent of the CLO capital structure is rated AAA, on average. AAA tranches are the most senior and the CLO holds a diversified portfolio of loans. 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 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!

When the COVID-19 pandemic took hold in March 2020, risks to the pools of loans underpinning CLOs rose as the pandemic posed an immediate and prolonged threat to corporate profitability. Facing the prospect of widespread downgrades and possible defaults, we show below that the AAA tranches became information-sensitive. Prior to the pandemic, AAA tranches traded at (almost) par. But in the pandemic the AAA prices fan out below par, despite unprecedented actions by the Federal Reserve to improve financial intermediation.[2]

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[2]In general, all of the Federal Reserve's actions potentially had an indirect effect on CLO markets by improving the conditions for financial intermediation. Indeed, we will show that the Federal Reserve improved market liquidity for CLOs. Nevertheless, secondary market pricing did not return to pre-pandemic levels, suggesting that trading

The increase in AAA price dispersion, reflecting the differential pricing based on information, is shown by the boxplots in Figure 1.

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 ±1.5×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.
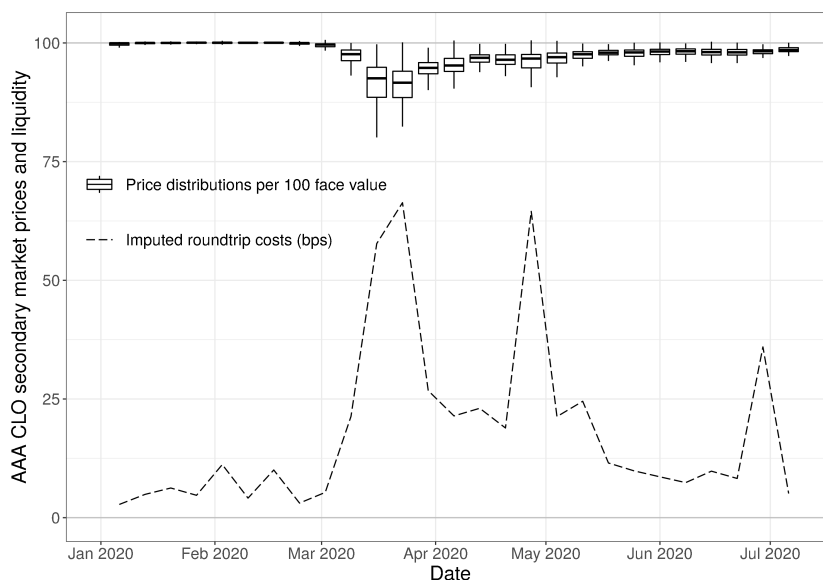
The central boxes show the interquartile range of prices bisected by the median as a horizontal line. The whiskers show the distribution of prices beyond the interquartile range, excluding outliers. The figure summarizes our argument. Prior to the pandemic there was no price dispersion. AAA tranches traded at par of $100, consistent with information-insensitivity. When the pandemic hits, the price distribution widens out below par as

was based on private information about the underlying pool of collateral.

shown by the box plots. 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. The lower dotted line is similar to a bid-ask spread, a measure of averse selection (discussed in detail later). This measure increases considerably when the pandemic hits, due to adverse selection. In the analysis presented below, we will provide formal tests of the information shown in Figure 1.

To show that when the pandemic struck, some investors started producing information, we show that there is a structural break in the standard deviation of AAA-rated CLO prices with the onset of the pandemic, confirming what is shown in Figure 1 and suggesting that the prices contain tranche-specific information. We also provide the results of a difference-in-differences quantile regression of secondary market prices of AAA-rated CLO tranches on an index of the stock price volatility of industries (e.g., Oil & Gas, Leisure, Retail) that were identified by Sallerson (2020) as being especially vulnerable to the pandemic. The regression shows that the uncertainty about the vulnerable industries is driving the dispersion in AAA-rated CLO tranche prices.

Where do investors get information on the CLOs' portfolios? We look at AAA-rated CLO tranche price changes just after the release of monthly trustee reports on the CLOs (which occur at different dates during the month) that contain relevant information for investors. Prior to the

pandemic, price changes were consistently near zero around trustee report dates, but not so once the pandemic hits.

Leveraged loans do not trade frequently. And they do not trade in a central location. They trade over-the-counter. Consequently, CLOs buy third-party prices to mark their loans to "market". For example, CLOs are required to mark-to-market riskier loans rated CCC and below that they hold in excess of some predetermined contractual limit. As a result, the amount of loans that CLOs have to mark-to-market increased sharply during the pandemic when the leveraged loan market experienced a massive wave of downgrades. We examine the loan prices supplied by two third-party pricing agencies. A measure of the increase in ignorance of the uninformed is the difference in these prices, for the same loan on the same date, from the two pricing agencies. The difference in the distributions of these two loan prices is significant. In other words, disagreement goes up with the onset of the pandemic.

We then turn to measuring the resulting adverse selection; see Glosten and Milgrom (1985) and Dang et al. (2019). We show that a measure of the bid-ask spread, the imputed roundtrip cost (IRC) of transactions, explained later, increased dramatically, indicating a deterioration in market liquidity. In Figure 1, the dashed line is the IRC in basis points for the AAA-rated CLO tranches from January 1, 2020. The deterioration in secondary market trading conditions began on Monday, March 9. From about 10bps at the

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beginning of the year, the IRC peaked at over 100bps on March 19. This sudden loss of market liquidity coincided with falling prices. By March 18, the average mid price for transacting the most-senior CLO tranches had already fallen below 95 cents.

The literature closest to our work includes Brancati and Macchiavelli (2019), Gallagher, Schmidt, Timmermann and Wermers (2020), Perignon, Thesmar and Vuillemey (2018), and Benmelech and Bergman (2018). Brancati and Macchiavelli (2019) examine the Panic of 2007-2008 and "... provide direct evidence that while in good times bank debt is largely informationally insensitive, it becomes significantly sensitive to information in bad times" (p. 99). Gallagher et al. (2020) study investor information production, money market funds (MMFs) redemptions, and MMF managers' rebalancing decisions during the Eurozone crisis. They find that there was significant selective information acquisition about fund holdings and, although there were redemptions at all funds, the reductions were largest for funds with the most sophisticated investors, who did produce information. "Under these circumstances, MMF shares become information-sensitive because MMFs' risk exposures are suddenly differentiated following the acquisition of information" (p. 1). Perignon et al. (2018) study the wholesale CD market in Europe during 2008-2014. Lenders to banks moved their money from bad banks (those whose future performance decreases) to good banks, apparently on the basis of private

information that they produced. The uninformed faced adverse selection in that they did not move their money. Benmelech and Bergman (2018) study U.S. corporate bonds. They show that when there is a drop in a bond's price, the bond becomes more illiquid, suggesting adverse selection. Other, more distantly, related literature is surveyed in Dang et al. (2019). We differ from this previous research by focusing on privately-produced safe debt. We explicitly show that when AAA-rated debt becomes information-sensitive, it coincides with the arrival of adverse selection, consistent with Dang, Gorton and Holmström (2018).

The paper proceeds as follows. In Section 2 we briefly describe the data, provide some background on CLOs, and some background on the loans in CLO portfolios. Section 3 analyzes the switch from information-insensitive to information-sensitive. When the pandemic hit some agents became informed while others did not. Section 4 studies these two groups: the informed and the uninformed. That this switch coincided with the arrival of adverse selection is studied in Section 5. Section 6 concludes.

2   Background and Data

In this section we first discuss the dataset that we constructed to assess the information sensitivity of CLOs 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.

Then we provide some detail about how CLOs work, and examine the underlying loans in CLO portfolios. Finally, we summarize the loans held by CLOs.

2.1 Data

We identify CLO tranches using Bloomberg's Backoffice data on asset-backed securities and 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

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

time, quantity, price, and counterparty. FINRA made asset-backed security secondary market trading data, including CLO debt, 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 trading during the pandemic to the financial crisis 2007-09. We follow standard procedures for cleaning these data.[4] We use confidential regulatory data with dealer bank identifiers, which allows 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,

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

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: 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 the underlying risks across CLO tranches. We investigate the role of information production below.

Dang et al. (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.

Table 1: Summary statistics This table reports summary statistics for the CLO tranche secondary market trading data used in the analysis. The unit of observation is CLO tranche i on day t, conditional on at least one transaction occurring. 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. The columns labelled "*p-value*" report the p-values from testing the equality of the statistics in the pre-pandemic and pandemic subsamples. Source: Authors' calculations from data provided by 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	

2.2   CLO Background

CLOs are securitization vehicles created typically by large asset managers to finance pools of leveraged loans extended to below investment grade firms. These loans are predominantly originated by banks as part of a syndication (Bruche, Malherbe and Meisenzahl, 2020). A CLO manager first buys a pool of leveraged loans on the secondary market. The initial pool of loans may remain unchanged in a "static" CLO. More often, the loans are actively traded by the CLO manager in accordance with the terms of the prospectus, which specifies *inter alia* the currency, maturity,

industry, and rating of the loans that may enter the pool. The cash flows from the pool of loans are used to pay the interest and principal on a set of securities (tranches) issued by the CLO vehicle, which are structured as a hierarchy of claims on the underlying collateral. Each security has a priority claim on the capital structure.

CLOs allocate the effects of default risk in the underlying pool of loans in three 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 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]

2.3   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

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

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: Author's calculations from data provided by Standard & Poor's and Moody's Analytics.
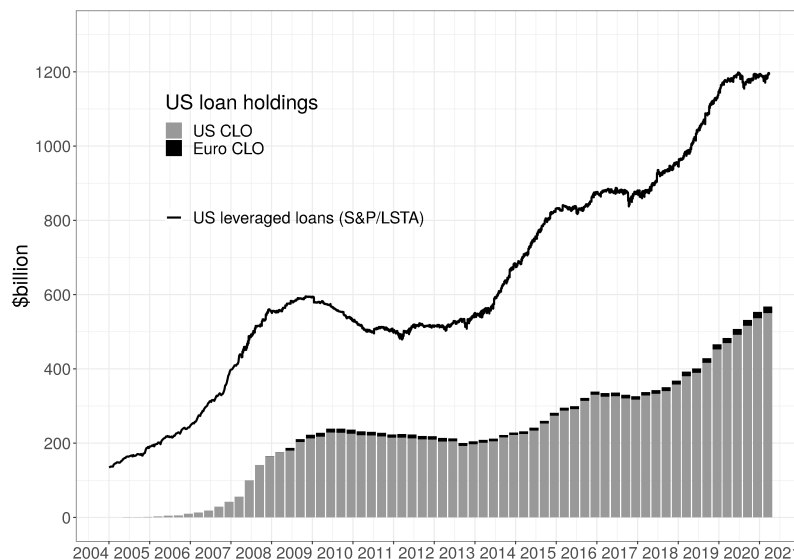
show that variation in the distributions of loan prices depend on whether the firms belonged to industries that were more vulnerable to the pandemic shock.

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

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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.

Table 2: Summary statistics of CLO loan portfolios. The table shows the mean, median, and standard deviation of characteristics of CLO loan portfolios before and after the declaration of the pandemic. 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.

Characteristic	Pre-pandemic, 1,627 CLOs			Pandemic, 1,599 CLOs		
	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
CLO market value (loans, $mn)	421.4	408.9	175.7	367.7	353.7	157.7
Mean loan value ($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

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,

Transportation: Cargo, and Transportation: Consumer. Appendix 7 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 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 8 in appendix 8.

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

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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). The statistics are provided for all leveraged loans and separately for the sectors that Moody's identified as vulnerable to the pandemic shock. Source: Authors' calculations from data provided by Moody's Analytics.

Variable (units)	Statistic	All transactions			Vulnerable sector			Non-vulnerable sector		
		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	

of the leveraged loans in their portfolios.[6] We use these data to construct 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.

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[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 report market values identical to Markit bid prices.

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: Automotive; Consumer goods: Durable; Energy: Oil & Gas; Hotel, Gaming & Leisure; Retail; Transportation: Cargo; Transportation: Consumer. The unshaded boxplots contain loans to firms in all other industries. We obtain a monthly price for each loan by averaging its daily prices. Source: Authors' calculations from data provided by Moody's Analytics.
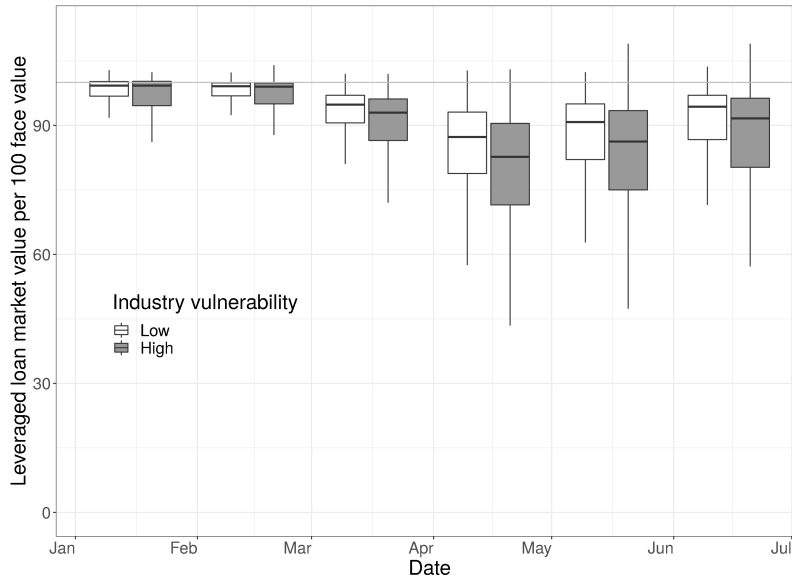
2.4 Trading CLO Tranches and Loans

The trading of CLO tranches and the underlying loans occurs in the over-the-counter market. There is no central location for trade; it is bilateral, though intermediated by dealer banks. The intermediation can occur when a dealer bank buys a tranche, holds it in inventory, and sells it later (a principal trade). Or the dealer bank matches a seller with a buyer (an agency trade). Other than the parties to the trade, no agent sees the price until it is reported on TRACE later. So, in these over-the-counter markets there is no price aggregation. And by the the time a price is reported

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on TRACE, in the case of a CLO tranche, it is stale, because the CLO manager could have changed the loans in the portfolio. Trading is similar in the loan market. Loan prices are not reported on TRACE because loans are not bonds and as such are not covered.

# 3   The Switch to Information-Sensitive Debt

In this section we study the switch from information-insensitive debt to information-sensitive debt. First, we show that the onset of the pandemic coincided with a regime switch in the standard deviation of AAA tranche prices. Then we adopt a quantile regression approach to 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.

3.1   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.

Panel (a) of figure 4 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.[7] The two measures of dispersion are highly correlated and mirror the movements in the High Yield Index.

Figure 4: 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. The solid line in the left-hand panel is the high yield spread and in the right-hand panel 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. In both panels, the short-dashed line is the interquartile range of daily prices and the long-dashed line is the standard deviation of daily prices. 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

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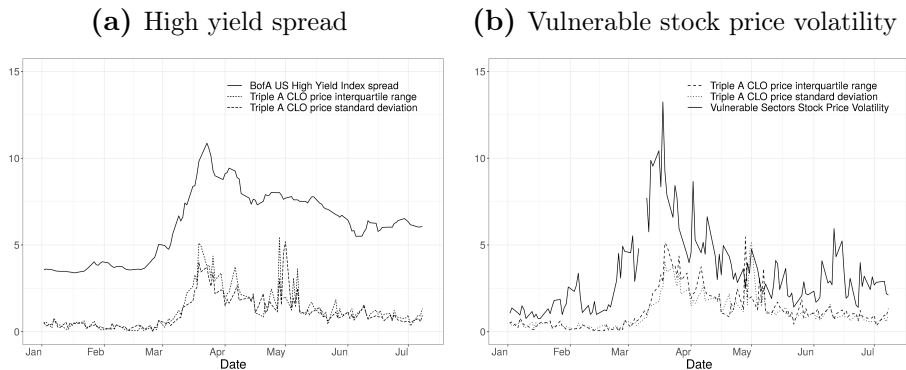
[7]To calculate the dispersion measures we first calculate a daily weighted-average price, where the weights are transaction volumes.

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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 most vulnerable to the pandemic shock. The solid line in panel (b) of figure 4 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.

We can further formalize this increase in dispersion by estimating structural breaks in the standard deviation of AAA-rated CLO prices. We do this by 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.

Figure 5 shows the results. The shaded regions show 95 percent confidence intervals for the location of the structural breaks. AAA-rated tranche prices show little dispersion prior to the pandemic, consistent with the AAA-rated tranches being information-insensitive. From mid-March until early May the dispersion is high and variable, before settling down

somewhat, but still above the pre-pandemic levels.

Figure 5: Structural breaks in the standard deviation of AAA-rated 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. 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, Bloomberg LP, Moody's Analytics, S&P, and Fitch.
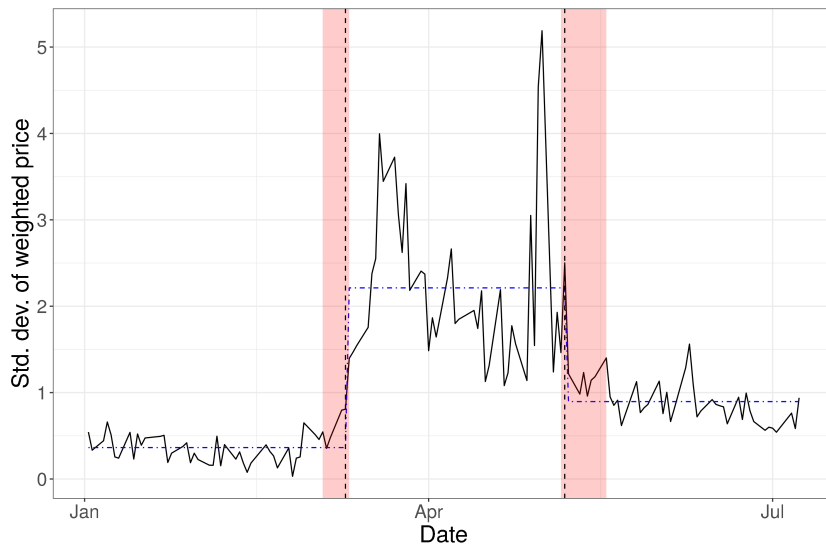
The first structural break is estimated to have occurred between March 4 and March 11, 2020, when the World Health Organization declared the novel coronavirus outbreak a pandemic.[8] The timing of this structural break coincides with disruptions to a wide range of financial markets, including Treasuries (Logan, 2020) and corporate debt (Kargar, Lester, Lindsay, Liu, Weill and Zuniga, 2020; Haddad, Moreira and Muir, 2020).

The second structural break is estimated to have occurred between May 6 and May 18, with a point estimate of May 7. The window of

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[8]https://www.who.int/news-room/detail/27-04-2020-who-timeline---Covid-19

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the break is wider than the first, and is likely a response to the combined impact of several announcements by the Federal Reserve. In particular, on May 4, the Board of Governors announced that the Primary Market Corporate Credit Facility (PMCCF) and Secondary Market Corporate Credit Facility (SMCCF) would begin purchasing corporate bonds in "early May". The SMCCF is the only emergency facility with the authority to purchase corporate debt below investment grade. Following through, the New York Fed announced on May 11 that the SMCCF would begin purchasing exchange traded funds on May 12. Also on May 12, the Board of Governors announced that the Term Asset-Backed Securities Loan Facility (TALF) would accept a narrowly-defined set of highly-rated CLO tranches.[9] All of these announcements had the potential to directly improve conditions in the CLO market. In addition, several further announcements in the time window indirectly affected conditions by modifying the liquidity coverage ratio (May 5) and the supplementary leverage ratio (May 15). These modifications were intended to ease banks' ability to provide credit and financial intermediation services. As such, they had a potentially indirect effect on conditions in the CLO market.

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[9]See   https://www.federalreserve.gov/newsevents/pressreleases/files/monetary20200512a1.pdf

3.2 Quantile Regression

We delved deeper into the relationship between the dispersion of AAA CLO tranche prices and uncertainty about vulnerable industries using quantile regression with CUSIP fixed effects. The dependent variable 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). We estimate the conditional quantile functions $Q_{\text{Trading price}_{it}}(\tau|\text{Covid}_t, \text{Volatility}_t)$ of the response of the t-th observation on the i-th CLO tranche's Trading price$_{it}$ given by

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

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 4 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 (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 25th and 75th 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. The variation is strongest for the tranches that were information insensitive in the pre-pandemic period. Before the pandemic, the distribution of

Table 4: 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)
$[0.25]Covid_t \times Volatility_t$	-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)
$[0.5]Covid_t \times Volatility_t$	-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)
$[0.75]Covid_t \times Volatility_t$	-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: $[0.25]Covid_t \times Volatility_t = [0.75]Covid_t \times Volatility_t$						
χ^2_1 test statistic	76.78***	77.67***	18.89***	13.59***	16.54***	5.04**

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 25th and the 75th percentile is economically meaningful. The counterfactual price of a AAA CLO tranche that moved from the 75th percentile to the 25th 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.

Figure 6 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 7 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.

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Figure 6: AAA CLO tranche prices by quartile. The figure shows the median AAA-rated tranche price $\pm$ 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.
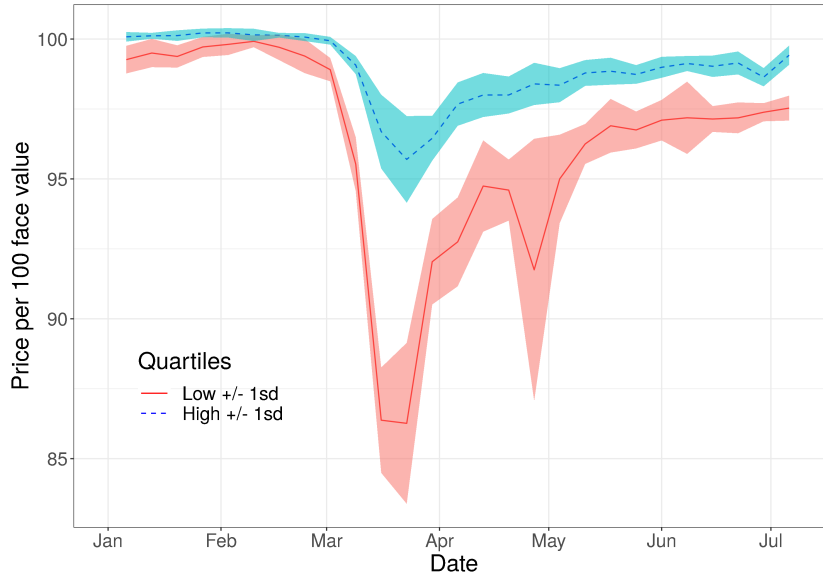
But note that it is *not* the case that the price dispersion is simply due to the pandemic shock to the vulnerable industries. Panel (b) of Figure 7 shows vulnerable loan prices by quartile.

4   The Informed and the Uninformed

According to a Bloomberg article, on May 20, 2020, J.P. Morgan sent an extraordinary email to its clients warning them of "information asymmetries" in the fast-moving CLO market.[10] The cited cause for concern was originators, sponsors, and even managers that were interested

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

Figure 7: 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
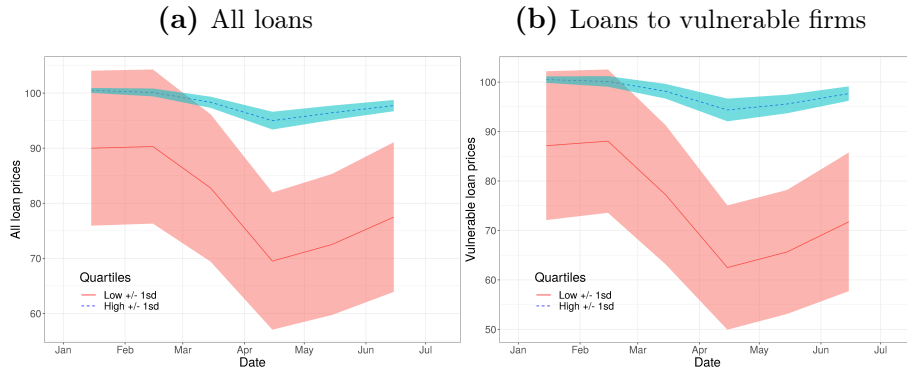
in *buying* their own CLO tranches based on nonpublic information about "the potential effects of Covid-19 on the portfolio" that "may constitute insider information". In this section we examine the risk to investors from such information asymmetries.

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. In the first subsection, we ask whether the information in those reports was used once the pandemic started. Then we look at a measure of disagreement between third-party loan price suppliers. These agents see 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".[11] 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.[12]

4.1   The Informed

Production of information about CLOs starts with studying trustee reports, which are published monthly for each CLO. Each CLO has a trustee, a

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

[12]See https://www.baincapitalcredit.com/approach.

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 and is responsible for paying funds to investors on coupon dates. The trustee's report comes out monthly, but there is no set date.

The trustee reports are informative but, as mentioned above, they are only the starting point. Credit analysts are necessary to take the information in the trustee reports and make it meaningful. For example, suppose the CLO manager has sold a loan and bought another loan, in a different industry. This information would be revealed by the trustee report. But then the new loan's firm would have to be studied. We do not observe this last 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 8 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

Figure 8: 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. The dark gray bars show the distribution of price changes in the pre-pandemic period, defined as any date between January 1 and March 1, 2020. The light gray bars show the distribution in the pandemic period from March 1 to June 1, 2020. The data include all trustee reports released in 2020. Source: Authors' calculations from data provided by TRACE, Moody's Analytics, Bloomberg LP, Moody's Analytics, S&P, and Fitch.
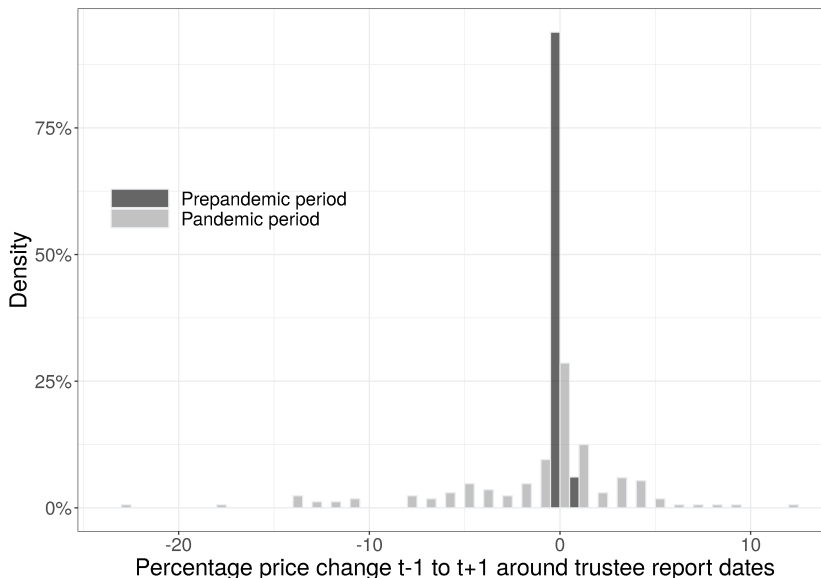
the CLO manager took positive trading actions or a loan improved.

4.2   The Uninformed

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 on communication

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

This difficulty has been shown by Cici, Gibson and Merrick (2011) who study 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.

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 or 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 9 shows that disagreement increased significantly once the pandemic started. But there is no statistical difference between the

disagreement about vulnerable and non-vulnerable industries.

Figure 9: 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. The leveraged loans are separated into two groups. We define a loan as having high vulnerability if it is to a firm in any of the seven industries identified by Moody's as being most at risk from the pandemic. Source: Authors' calculations from data provided by Moody's Analytics.
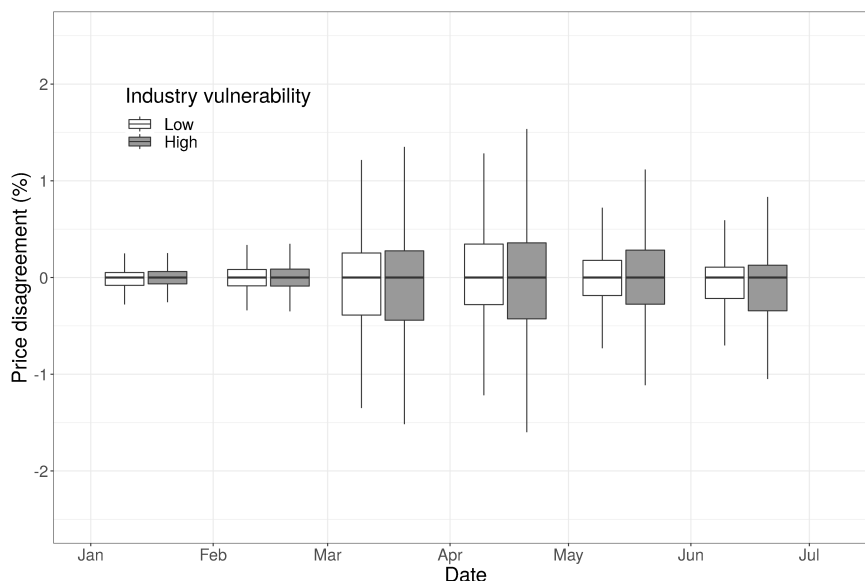
5   Information-Sensitivity, Adverse Selection

The preceding analysis showed that AAA CLO tranches became information-sensitive. In this section we argue that the switch from insensitive to sensitive coincided with the arrival of adverse selection or the fear of adverse selection. Prior to the pandemic, investors had not been producing information. There was no need to and it would not pay to produce information. In fact, they may not know how to produce information. It is not sufficient even just look at the portfolio. An investor must understand

how the loans to different industries are correlated and understand the internal workings of the CLO. Without this the investor risks facing a better informed trader.

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. Glosten and Milgrom (1985) show that the bid-ask spread widens when there is an increase in adverse selection.[13]

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

5.1 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.[14] Measuring the time between

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[13]There are also interest costs and regulatory costs associated with holding an inventory. But agency trades are intraday. And, in any case, these did not change over our sample period.

[14]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

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. 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.[15] We identify agency trades as those with two or three trades in a given CLO tranche with the same trade size that take place within a calendar day.[16]

To calculate the 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 a dealer, potentially with inter-dealer trades. Following Dick-Nielsen et al. (2012), if we observe two or three 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. For each such trade, we calculate the IRC as the percentage difference between the maximum and minimum prices contained in this roundtrip trade. We then calculate a daily weighted-average IRC over all roundtrip trades, where the weights are the volume of each trade.

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highly correlated.

[15]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.

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

5.2 Adverse Selection

Figure 10 shows the estimated structural breaks in the 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 intervals.

Figure 10: 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. The solid line is the IRC. 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, Bloomberg LP, Moody's Analytics, S&P, and Fitch.
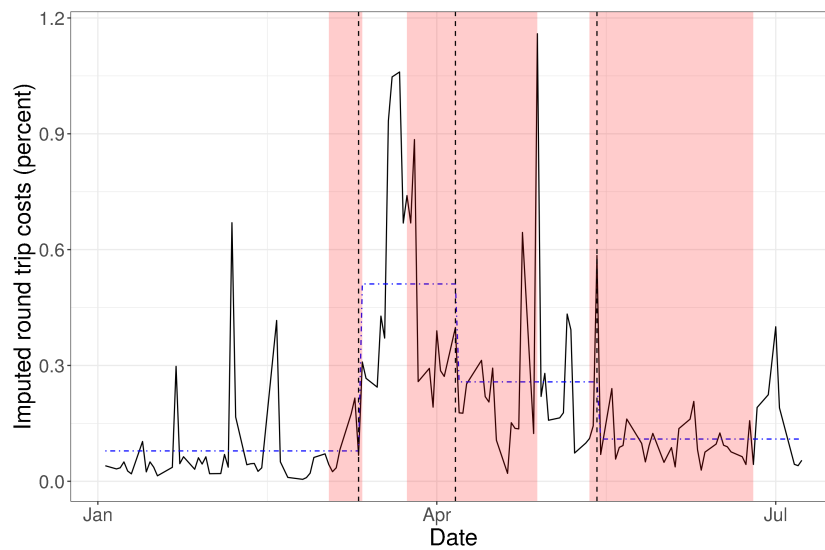
The first structural break is estimated to have occurred between March 3 and March 12, 2020, overlapping with the first break in the standard deviation of trading prices (Figure 12) and coinciding with the March 11 declaration by the World Health Organization of the pandemic.

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 TALF, PMCCF, and 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 11 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 11: 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. We define a CLO's industry vulnerability as the proportion of its loans in the seven industries identified by Moody's as being most at risk from the pandemic. We calculate the exposure from the last trustee report prior to the pandemic. We split CLOs into those above and those below the median vulnerability. Source: Authors' calculations from data provided by TRACE, Moody's Analytics, Bloomberg LP, S&P, and Fitch.
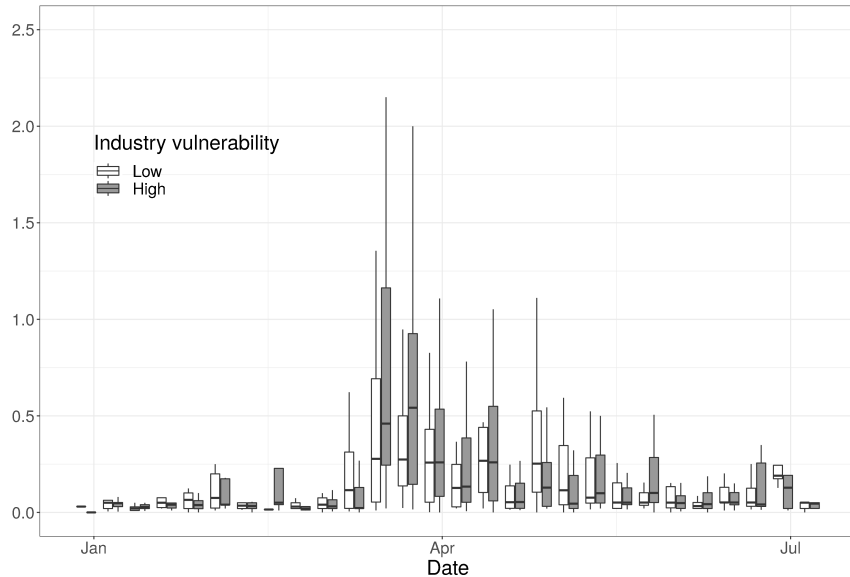
We find generally higher and more variable imputed roundtrip costs

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

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 8.

We provide further evidence consistent with an increase in adverse selection during the pandemic using quantile regressions of IRC on transaction prices (see Benmelech and Bergman (2018)). The dependent variable IRC_{it} is the imputed roundtrip cost of trading CLO tranche i on day t, conditional on a trade taking place. Trading price$_{it}$ is the weighted-average price of the 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. The specification is given by:

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

with quantile $\tau \in \{0.25, 0.5, 0.75\}$ and where α^i is the CUSIP fixed effect. Table 5 shows the results.

Table 5: Adverse selection in AAA-rated CLOs during the pandemic – quantile fixed effect regression. This table shows there was an increase in the negative correlation between the imputed roundtrip cost (IRC) and the price of AAA-rated CLOs 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. 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, Bloomberg LP., Moody's Analytics, S&P, and Fitch. *** p<0.01, ** p<0.05, * p<0.1

	(1) AAA	(2) E
[0.25]Covid_t	-120.56	-1.33
	(147.47)	(44.9)
[0.25]Traded price$_{it}$	-3.26***	-0.68
	(1.43)	(0.45)
[0.25]$\text{Covid}_t \times$ Traded price$_{it}$	1.18	-0.03
	(1.48)	(0.46)
[0.5]Covid_t	38.67	62.82
	(161.16)	(49.86)
[0.5]Traded price$_{it}$	-3.92***	-0.72
	(1.62)	(0.48)
[0.5]$\text{Covid}_t \times$ Traded price$_{it}$	-0.42	-0.75
	(1.61)	(0.52)
[0.75]Covid_t	319.23*	29.99
	(183.09)	(70.74)
[0.75]Traded price$_{it}$	-4.94***	-2.03***
	(1.78)	(0.7)
[0.75]$\text{Covid}_t \times$ Traded price$_{it}$	-3.22*	-0.46
	(1.83)	(0.72)
CUSIP FE	Y	Y
Observations	4,551	3,013
χ^2_1 test statistic[†]	13.22***	0.44

[†]H_0: [0.25]$\text{Covid}_t \times$Traded price$_{it}$ = [0.75]$\text{Covid}_t \times$Traded price$_{it}$

Column 1 of table 5 shows that the negative correlation between the IRC and the transaction price for AAA-rated CLOs is consistent with adverse selection and the quantile regression reveals that the negative correlation is stronger for more illiquid (higher IRC quantile) CLOs. Moreover, the χ^2 test of the null hypothesis of equality between the 25th and 75th percentile coefficients on the interaction terms $(\text{Covid}_t \times \text{Trading price}_{it})$ indicates that the negative correlation became stronger for those illiquid CLOs during the pandemic. By contrast, column 2 of the same table shows that the information sensitive E-class tranches did not experience the same shift. Of course, these results cannot be interpreted causally because the pandemic likely affected the liquidity of CLOs through several channels, not only through the decline in prices. Nevertheless, the findings are consistent with AAA-rated CLOs becoming information-sensitive during the pandemic.

6   Concluding remarks

We traced the adverse selection dynamics in the CLO market, focusing on AAA tranches, before and after the pandemic. 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. 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 price of the security plummeted in part because uninformed investors do not know what the price should be. They face adverse selection. But informed investors do know what the price should be. The price goes down but the dispersion of prices goes up because of the informed traders. In this paper we documented these dynamics of adverse selection in the CLO market when the pandemic hit.

Note that 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 dispersion across CLOs. The information about each CLO's exposure to vulnerable industries in the trustee reports is not sufficient to explain the dispersion in prices. Importantly, it is one thing to know the exposure and another thing to know how loans/industries will perform. We showed in Figure 7 that there is dispersion in loan prices within the vulnerable/not industries and we showed in Figure 9 that there is price disagreement within the vulnerable/not industries. For these reasons, we believe that investors are producing private information about the loans held by CLOs. In normal times, investors don't produce this private information.

We used the variation in vulnerable/not industries to tease out further evidence for adverse selection. The quantile regression (Table 4) showed

that only the lowest transaction prices for AAA-rated CLOs became correlated with uncertainty about the vulnerable industries during the pandemic. At the same time, the IRC increased *more* for those CLOs that were heavily exposed to vulnerable industries. The combination of these results is difficult to rationalize outside an environment where investors are producing 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. Such 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 that all the prices should drop more or less uniformly. We showed, contrary to these ideas, that the prices drop and become more dispersed due to adverse selection.

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7 Data appendix – For Online Publication

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

7.1 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.

7.2 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).

7.3 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.

7.4   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`".

7.5   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 6: 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

8 Additional results – For Online Publication

8.1 Testing the difference between IRC distributions

Figure 11 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 7 reports that there were roughly equal number of observations in the two samples.

The left-hand panel and right-hand panels of Table 7 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 7: 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	Number of samples: 2
Sample sizes: 314, 395	Sample sizes: 314, 395
Number of simulations: 10,000	Number of simulations: 10,000

	AD	T.AD	asympt. p-value	sim. test p-value	statistic	asympt. p-value	sim. p-value
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			

8.2 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.[17]

8.3 Structural breaks in Class E CLO tranches

Figure 12 presents the structural breaks in both the AAA rated CLO tranches (Panel A) and the Class E CLO tranches (Panel B). These results complement the presentation of Panel A only in Figure 5. 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 4 showed that Class E tranches were information-sensitive prior to the pandemic.

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

Table 8: Loan transactions summary statistics. The table shows summary statistics for leverage loan transactions per CLO in the pre-pandemic period (January 1, 2020—March 1, 2020) and the pandemic period (March 2, 2020—June 30, 2020). These summary statistics exclude transactions in a CLO's ramp-up period by removing transactions in the two months immediately after a CLO's closing date. The statistics are provided for all leveraged loans and separately for the sectors that Moody's identified as vulnerable to the pandemic shock. Source: Moody's Analytics.

Variable (units)	Statistic	All transactions			Vulnerable sector			Non-vulnerable sector		
		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 12: 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.
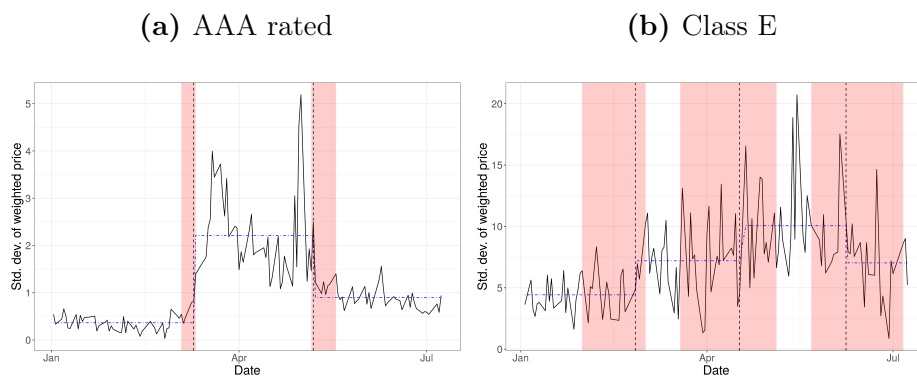
(a) AAA rated
(b) Class E

8.4 Attachment points

Figure 13: **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.