Internet Appendix

"Portfolio Dynamics and the Supply of Safe Securities"

This Internet Appendix contains the following parts. Section IA.1 describes data and sample. Section IA.2 presents facts on nonbank institutions in the leveraged loan market. Section IA.3 shows empirical patterns of transitory loan price changes in early 2020. Finally, Section IA.4 provides supplementary empirical analyses.

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IA.1. Data and Sample Construction

IA.1.1. Data and Sample

The main data used in this study come from Acuris Creditflux CLO-i, a database compiled from CLO trustee bank reports. This database provides information on CLO tranches, portfolio holdings, loan trades, and collateral test results. To examine CLOs' balance sheets, I construct a quarterly panel sample based on the most recent reports of a CLO by the end of each quarter. I include a CLO–quarter pair if information on the CLO's liabilities is available and its portfolio includes at least 50 loans and has at least $50 million total par value. This filter leads to 13,825 quarterly observations for US CLOs between 2010–2019.

To investigate loan trades upon the the arrival of a negative systemic shock, I construct a cross-sectional sample that tracks the changes in CLO loan portfolios between February 15 – June 30 of 2020. This sample includes all US CLOs that are issued before year 2020. For each CLO, I use the last portfolio snapshot available between January 1 – February 14, 2020 as the observation for a "pre" period and the first snapshot available between July 1 – August 15, 2020 for a "post" period.[1] To measure secondary market prices at the trough, I use the last snapshot between March 15–April 15, 2020 as the observation for the "mid" period. To alleviate measurement errors, I winsorize prices at the 1% and 99% percentiles.

Other databases used in this paper include CRSP mutual fund portfolio holdings, Mergent Fixed Income Securities Database (FISD), Morningstar, and the SEC's Form ADV. Panel A of Table IA.3 provides summary statistics of the panel sample. On average, a CLO has $435 million principal outstanding and a portfolio consisting of 222 pieces of loan shares. CLOs in the sample are overall young with an average age of 4.2 years. For most CLOs, 60% to 75% of liabilities are AAA-rated tranches.

IA.1.2. Cleaning CLO datasets

Creditflux CLO-i database collects information about individual CLOs from trustee reports. In this database, each CLO is identified by a unique deal ID, and each of the CLO's liability tranches is uniquely identified by a tranche ID. Unlike regulated institutions (e.g., banks and

[1] CLO trustee reports do not have any uniform report dates, and the time windows are used to select snapshots that are informative about CLO portfolios before and after the shock. My findings are insensitive to different choices of time windows.

mutual funds), CLOs do not have regular disclosure dates, and their balance sheets are rarely reported exactly at the end of a certain calender period. In the database, 75% of CLO–month pairs have at least one reported snapshot available.

Liabilities. I begin with all US CLO deals that are issued in US dollars and have a nonmissing closing date (i.e., the date when a CLO comes into legal existence) between 2000–2020. There are 2,306 unique CLOs, 21,970 unique tranches, and 82,447 deal-level reports, and 612,689 tranche-level reports in total. These reports provide information on the original and current sizes of individual tranches and the legal identity of the asset manager. To determine the seniority of a tranche, I use variable Seniority Name and rely on original credit rating whenever this variable is missing. I hand match CLO manager company names to the filing number in the SEC's Form ADV database and use this number as a unique manager identifier.

Portfolio Holdings. The holdings dataset provides information on the borrower, loan facility type, interest rate, amount of holding, credit rating, maturity date, and Moody's industry classification for each loan in a CLO's portfolio snapshot. For years after 2017, a trustee-reported market price for each holding is also available. An important data limitation is that there is no loan-level unique identifier. While the dataset provides issuer names and issuer IDs, a substantial fraction of these two variables are incorrectly assigned. Moreover, as different CLO managers prepare reports independently and most borrowers are private companies, a borrower might appear with different names in different reports. To mitigate the impact of data inaccuracy on inferences based on the COVID-19 cross-sectional sample, I carefully compare the name of every leverage loan borrower between 2016—2019 with the isssuer names in CLO holdings data and manually correct 1,297 issuers that have mismatched names or (and) IDs.[2] I also replace a loan's interest rate to be missing if the reported value

[2]When different names of the same firm are reported, I check each borrower's historical names, business names, nicknames, acquisition target names, and wholly-owned financing subsidiary names, and ensure that the same issuer ID is applied.

is zero. After correcting these data errors, I eliminate duplicate records at the deal ID–report date–borrower–maturity date–balance amount level and aggregate balance amount to the deal ID–report date–borrower–maturity date level.[3] After this cleaning procedure, the dataset includes 22.3 million holding records.

Loan Trades. For each loan trade, the raw transactions dataset provides information on the direction (buy or sell), loan par amount, transaction price, and the date of the trade. After removing duplicate records, I map loan trade records to CLOs using deal report ID.

Collateral Tests. The raw dataset for collateral tests provides information on the name, current score, threshold score, and the date of a test. I determine a test record as an over-collateralization test if the test name includes keywords "OC", "O/C", or "overcollateral". Among OC tests, I further determine a record as a test for a senior tranche if the test name contains keywords "Class A", "Senior", "A ", "A/B OC", or "AB OC". This procedure selects all senior OC thresholds and test scores, but cannot accurately identify the thresholds for the most senior (AAA) tranches. Any zero-valued threshold or test score is treated as missing. If the current threshold is missing or zero, I use original threshold score instead. For a few cases where a deal has multiple test scores for senior tranches, I use the lowest nonmissing score to mitigate the impact of data errors.

Currency Conversion. CLO tranches and portfolio loan holdings denominated in Euro are converted into US dollar based on the current USD-EUR exchange rate.

IA.1.3. Counterfactual portfolios

I construct counterfactual static CLO portfolios by tracking loan holdings before the COVID-19 shock hits the US market. The static portfolio is based on the last portfolio snapshot reported between January 1 and February 15, 2020 ("pre period"). To track quality changes of each loan, I begin with a large set of portfolio holdings that consist of every CLO's first

[3] These duplicates were generated when the database scraped data from original trustee reports.

portfolio snapshot reported between July 1 and August 15, 2020 ("post period"). Since there is no unique loan identifier, I identify individual loans by a pair of issuer ID and maturity date.[4] I then determine ex-post credit rating (or coupon rate) of a loan as the value-weighted average rating (or coupon rate) of that particular loan across all CLOs' ex-post holdings.[5] Merging ex-post observations with ex-ante snapshots allows me to track changes in credit ratings and coupon rates for more than 94% of ex-ante loan holdings. To mitigate data errors introduced in this procedure, I use only portfolios for which at least 90% of pre-period holdings are tracked in counterfactual static portfolios (97% of the sample).

IA.2. Market Structure of Nonbanks: Additional Facts

Figure IA.1 summarizes annual CLO issuance. The pre-crisis issuance volume dropped to almost zero in 2009 and bounced back in 2012. In each of recent years, roughly 100 unique managers issued a total of 200–300 new CLOs, whose aggregate size is around $150 billion.

Figure IA.2 presents detailed information on loan funds. Based on data from regulatory reports, Panel (a) reports leveraged loan holdings by mutual funds and hedge funds, the two largest groups of loan funds in this market. Whereas the holdings of mutual funds fluctuate between $100–200 billion in recent years, the amount of loans held by hedge funds has grown substantially. As of 2021, these two groups hold similar amounts of leveraged loans.

Panel (b) decomposes the size and number of public loan funds into three groups: open-end mutual funds, close-end mutual funds, and exchange-traded funds (ETFs). Open-end funds clearly dominate in terms of assets under management, despite a comparable number of close-end funds and the entry of ETFs in the last decade.

[4] Occasionally, for the same loan, there is moderate variation in reported maturity dates across different CLOs. To address this, I use the quarter of reported maturity date.

[5] A limitation of this approach is that two loans issued by the same borrower and have the same maturity date would not be distinguished.

IA.3. CLO Loan Trades and Secondary Market Prices

When more than a thousand CLOs are forced to trade in the same direction, their trades are likely to exert pressure on secondary market loan prices. This subsection examines the cross section of leveraged loan price drops in late March of 2020 ("mid" period), the epicenter of the COVID-19 shock. For each loan, I measure its transitory price drop as

$$Drop_j = \frac{Price_j^{mid}}{\frac{1}{2} \times (Price_j^{pre} + Price_j^{post})} - 1, \tag{IA.1}$$

where the prices in each of the three periods are calculated as weighted average market values reported in CLO portfolio snapshots.[6] This measure captures the magnitude of a loan's price drop relative to a hypothetical linearly-extrapolated price level. My goal is to detect price pressures of CLO trades by comparing price drops across loans of different quality. To do so, I group individual loans based on post-period credit rating and calculate an average drop magnitude for each group.

Empirically isolating loan price changes caused by CLO trades is challenging. To alleviate the concern that observed price changes might be merely driven by changes in perceived fundamentals, I apply the same exercise above to high-yield bonds, which are not traded by CLOs, using similar data from mutual fund portfolio snapshots.

Figure IA.3 presents the results. Although these corporate debt generally experienced sizable transitory price drops, leveraged loans and high-yield bonds exhibited different cross-sectional patterns. In Panel (a), the magnitude of loan price drops is monotonic in credit rating, ranging from nearly 15% for the "B-" group to only 5% for the "BB+" group. By contrast, in Panel (b), the magnitudes of bond price drops are mostly around 15% across rating groups. These price patterns provide suggestive evidence that CLOs' purchases (sales) of high-quality (low-quality) loans increase (decrease) secondary market loan prices. Such

[6] I use market values reported in portfolio holdings because these prices are based on current dealer quotes or trustee bank estimates, which helps mitigate the concern of price staleness for infrequently traded loans.

asymmetric price pressure makes maintaining portfolio quality costly for CLOs.

IA.4. Supplementary Empirical Analysis

IA.4.1. Capital Structure and Portfolio Quality

In my model, institutions' lending and financing choices generate a cross-sectional relationship between capital structure and the quality of loan portfolio. It is trivial that better quality loans can back more safe debt; However, as CLOs optimally exhaust safe debt capacity, the model predicts a strong positive correlation between portfolio quality and safe debt outstanding. This endogenous relationship arises from the joint choices of portfolio and safe debt financing, which are both driven by unobserved securitization costs. I examine this relationship by estimating panel regression

$$Quality_{it} = \beta AAA\%_i + \Gamma' Control_{it} + \delta_t + \epsilon_{it}, \tag{IA.2}$$

where the dependent variable is collateral quality measured using either portfolio value-weighted average loan rating or coupon rate. The variable of interest, $AAA\%_i$, is a CLO's AAA-rated tranche size as a fraction of total size of the deal. All specifications include year-quarter fixed effects δ_t, thereby estimating β using only cross-sectional variation. This addresses the impact of time-varying market conditions on overall leveraged loan quality.

Panel B of Table IA.3 presents summary statistics, and Table IA.4 reports the estimation results. Across specifications, point estimates $\hat{\beta}$ are both statistically and economically significant. Column (1) indicates that a CLO with a 10% larger AAA tranche on average holds a loan portfolio with 0.17 notch higher credit rating. Controlling for CLO size and age, as in column (2), the estimate becomes moderately larger. In column (3), I also include CLO cohort fixed effects that absorb any persistent balance sheet heterogeneity induced by different timings of CLO issuance.[7] The point estimate remains similar, suggesting that the

[7] CLO age is absorbed by the two groups of fixed effects in columns (3) and (6).

result is not driven by unobserved shocks during the quarter of CLO issuance.

Columns (4)–(6) replace the dependent variable with portfolio value-weighted average coupon rate, which measures loan quality based on market risk pricing rather than rating agencies' models. Since leveraged loan coupons are quarterly updated based on a floating benchmark rate (typically 3-month LIBOR), in the cross section, a higher coupon implies a riskier portfolio. For both measures, an interquartile variation in $AAA\%$ is associated with roughly 0.5 standard deviation higher collateral quality, suggesting a strong positive relationship between portfolio quality and safe debt outstanding.[8]

IA.4.2. Credit Risk Retention Regulation

The regulation, generally referred to as Credit Risk Retention Rule, was initially proposed by 6 federal agencies in 2011 to implement the credit risk retention requirements of the Dodd-Frank Act. The rule requires securitizers to retain at least 5% of un-hedged credit risk of collateral assets for any asset-backed securities (ABS).[9] The final rule became effective for residential mortgage-backed securities (RMBS) in December 2015 and for other ABS, including CLOs, in December 2016.

The regulation's inclusion of CLOs was resisted practitioners. The main complaint was that the rule imposes large operational and capital costs on the portfolio managers, rather than the owners ("securitizers", defined by the Dodd-Frank Act), of the underlying loans and might drive managers out of the CLO business. In November 2014, the Loan Syndications and Trading Association (LSTA), representing CLO managers, filed a lawsuit against the Federal Reserve and the SEC. In February 2018, the US Court of Appeals for the D.C. Circuit concluded that managers of open-market CLOs are not "securitizers" under the Dodd-Frank Act and are not subject to the requirements of the Risk Retention Rule. Consequently, CLO

[8] After partialling out time fixed effects, the standard deviation of coupon rate is 0.48%.

[9] Securitizers can choose to retain 5% of every tranche ("vertical retention"), the bottom tranche with a fair value of 5% of all tranches ("horizontal retention"), or any convex combination of these two. See SEC Final Rules 34-73407 for more details.

managers became exempted from the rule in May 2018.

Figure IA.5 presents the timing of the regulatory events and annual CLO entry rate in the US and European markets between 2000–2019. Before 2008, CLO entry rates in the US and Europe had similar time trends. Probably because a similar risk retention rule was introduced in Europe in 2010, the European CLO market recovered slowly compared to the US market. However, after the finalization of the US risk retention rule in late 2014, there was a salient drop in CLO entry. This drop quickly reversed when the policy got revoked in early 2018.

IA.4.3. Estimating the Effect of Risk Retention

This subsection further examines the regulation's effect on CLO entry, which was predicted to be devastating by the LSTA and CLO managers. The Credit Risk Retention Rule's inclusion of CLOs received considerable resistance from practitioners. Panel (a) of Figure IA.6 shows that the LSTA more than doubled its lobbying spending in 2014, the year when the rule was finalized. Panel (b) presents the results of LSTA's 2013 survey on CLO managers' expectation of the rule's impact on their business, which appears devastating. This subsection investigates the realized impact of the policy.

Identifying and estimating the US Credit Risk Retention Rule's effect on CLO entry is challenging. First, the policy was imposed on the entirety of CLOs issued during its effective period, making it difficult to find a control group. Second, the policy was introduced soon after the crisis and then revoked shortly, leaving us with very limited time-series variations for statistical inference. As an attempt to quantify the effect, I exploit the fact that virtually the same policy was imposed on the European CLO market before the US market and estimate panel regression

$$Entry_{imt} = \beta_0 + \beta_1 USmkt_{im} \times CRR_t + \beta_2 USmkt_{im} + \beta_3 CRR_t + \Gamma' Control_{m,t-1} + \epsilon_{imt}, \quad \text{(IA.3)}$$

where every observation is a manager–market–year during 2013—2019. $USmkt_{im}$ is an indicator variable that equals one (zero) for any manager i if market m is US (Europe). CRR_t is an indicator variable that equals one for 2015–2017, during which the Credit Risk Retention Rule affects the US market. I control for lagged growth rates of government debt and total bank deposits in either market as proxies for the major supply of safe debt. The identification of parameter β_1 is based on an assumption that the entry rate in the US market would have evolved similarly as in the European market in the absence of the policy.

Panel B of Table IA.3 presents summary statistics for this sample, and Table IA.5 reports the estimation results. Columns (1) and (4) indicate that the policy reduces the number and size of CLO entry by 0.3 and $130 million, respectively. In column (2), the magnitude is similar for entry count after controlling for safe debt supply, and the magnitude becomes greater for the size of entry in column (5). In columns (3) and (6), I further include interaction terms with an indicator variable that equals one if the asset manager's CLO AUM in year 2014 is above median. The triple-interacted term's coefficient is statistically indistinguishable from zero, suggesting that the absolute effect of regulation has similar magnitudes on smaller and larger managers. As smaller managers' pre-treatment levels of outcome variables are substantially smaller larger managers', this indicates a greater relative impact on smaller managers' business. Overall, the regulation causes an economically large reduction in CLO entry: the magnitudes are roughly 40% of unconditional averages.

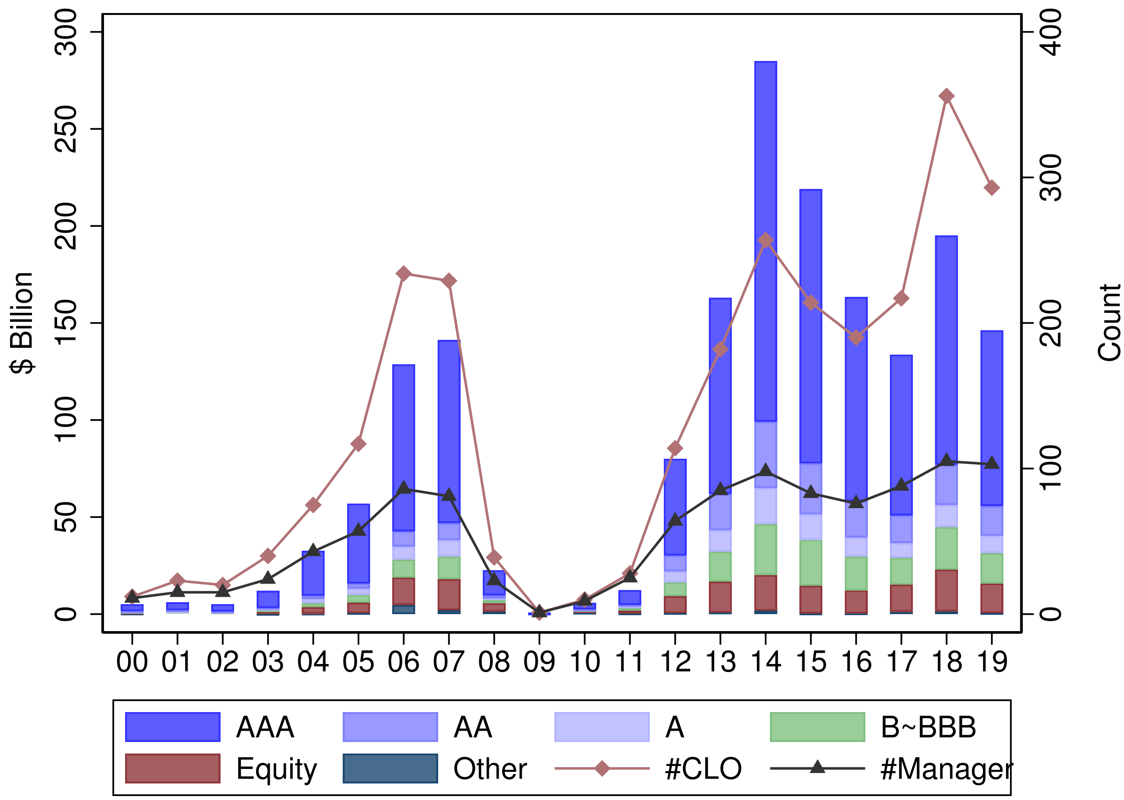
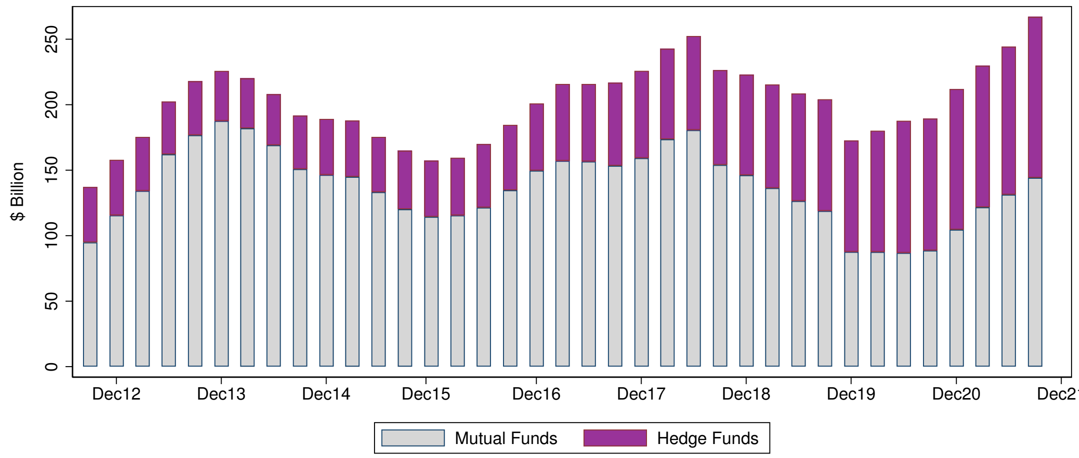
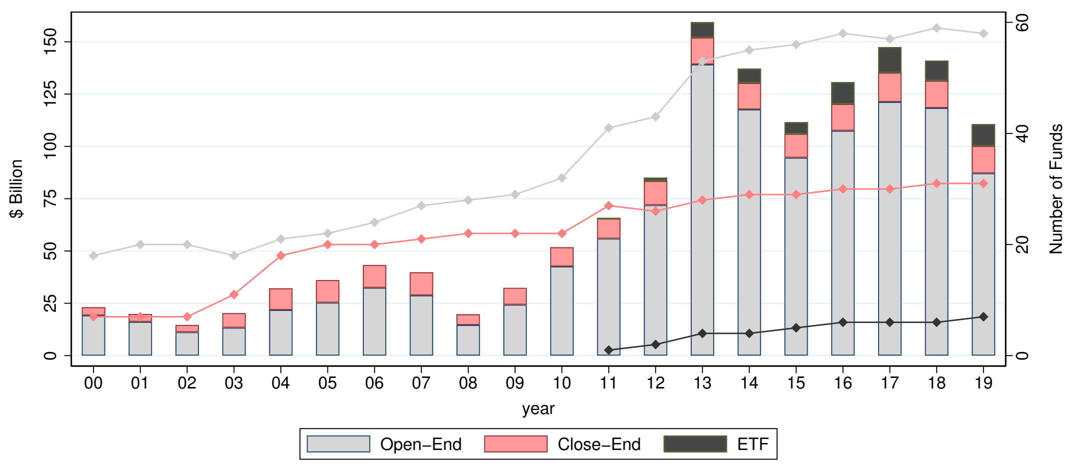


Figure IA.1: **CLO Issuance.**
This figure plots annual issuance of open-market CLOs in the US and Europe between 2000–2019. The issuance amount is by CLO tranche, identified based on initial credit ratings. Tranche size denominated in Euros are converted to USD using the exchange rate at issuance date. The connected lines indicate the numbers of deals and asset managers in each year. "Others" include mixed tranches and other non-rated tranches. Data come from Creditflux CLO-i databse.

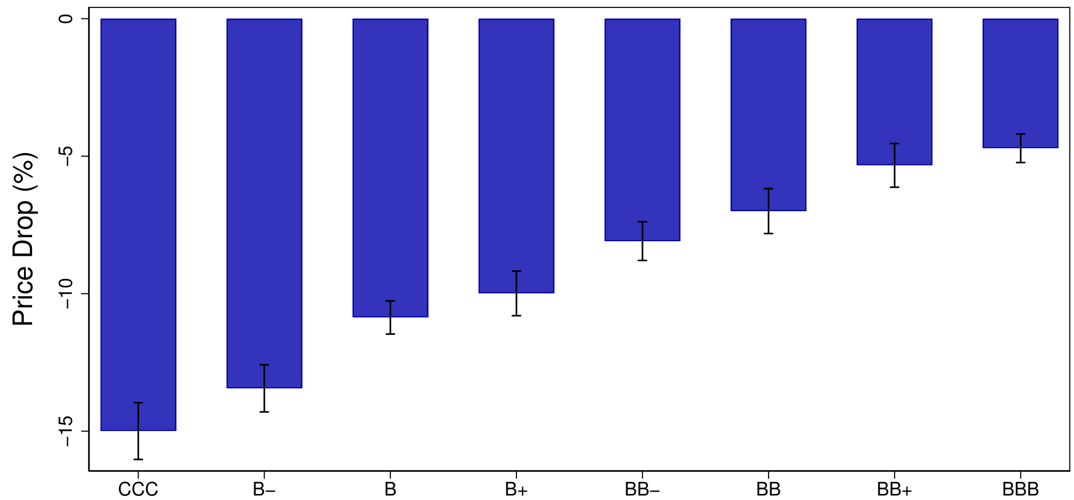


(a) Leveraged Loans Held by Mutual Funds and Hedge Funds

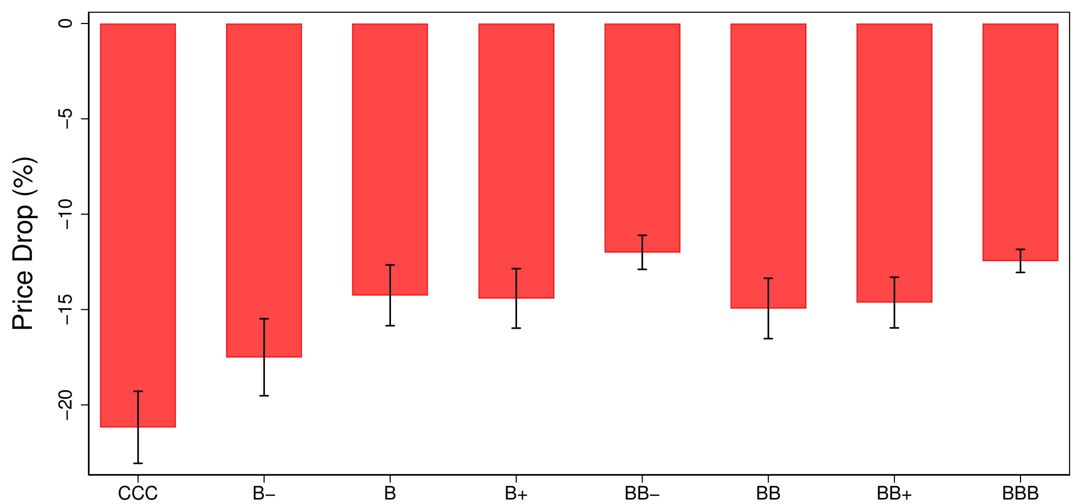


(b) Composition of Public Loan Funds

Figure IA.2: **Non-Securitized Loan Funds.**
Panel (a) of this figure shows the amount of leveraged loans held by mutual funds (reported in the Shared National Credit Program) and hedge funds (reported in SEC Form PF) between 2012–2021. Data are from FRED, Federal Reserve Bank of St. Louis. Panel (b) decomposes public loan funds into open-end mutual funds, close-end mutual funds, and exchange-traded funds between 2000–2019. The stacked bars plot total assets under management, and the connected lines show the number of funds. Data for public loan funds are from Morningstar.



(a) Leveraged Loans



(b) High-Yield Bonds

Figure IA.3: **Secondary Market Prices in the COVID-19 Crisis.**
This figure plots average transitory secondary market price drop in March 2020 for corporate debts within each credit rating group. In Panel (a), leveraged loan prices are based on reported market values in CLO portfolio holdings. In Panel (b), high yield corporate bond prices are based on reported market values in corporate bond mutual fund portfolio holdings. Price drop is measured as the decrease in secondary market price in March 2020 relative to the average price before and after the COVID-19 shock. The vertical lines indicate 95% confidence intervals for group means.

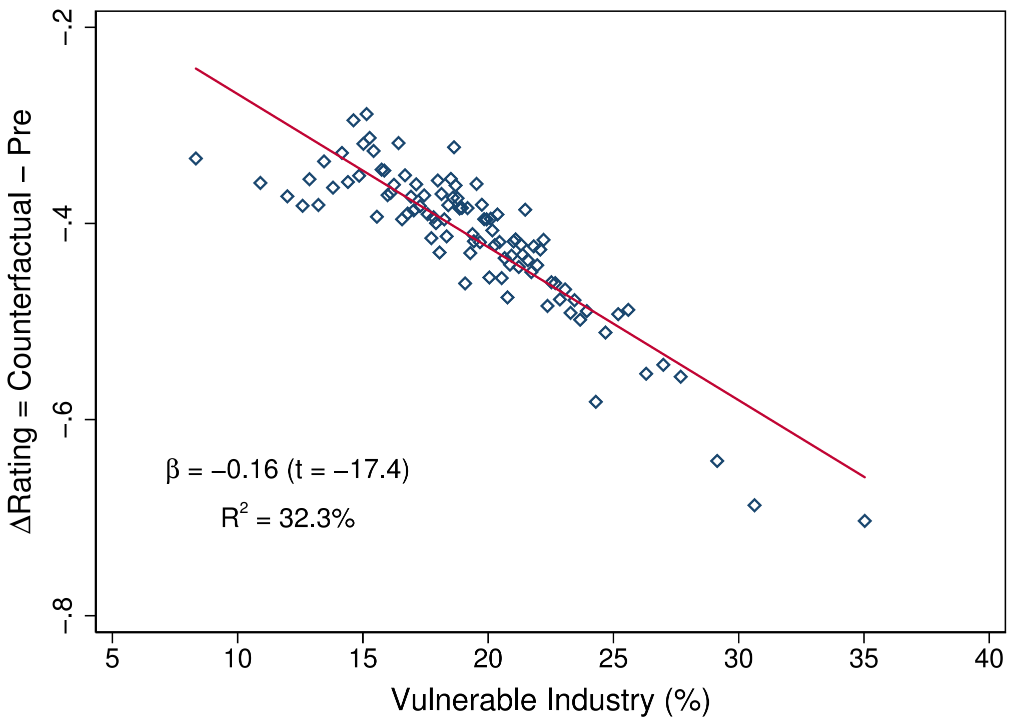


Figure IA.4: **Exposure to Vulnerable Industries and Counterfactual Quality Deterioration.**

This figure is a scatter plot that groups CLOs into 100 bins by portfolio weight in industries vulnerable to the COVID-19 pandemic before February 15, 2020 and depict the average counterfactual portfolio value-weighted average credit rating change between February 15 and June 30, 2020 within each bin.

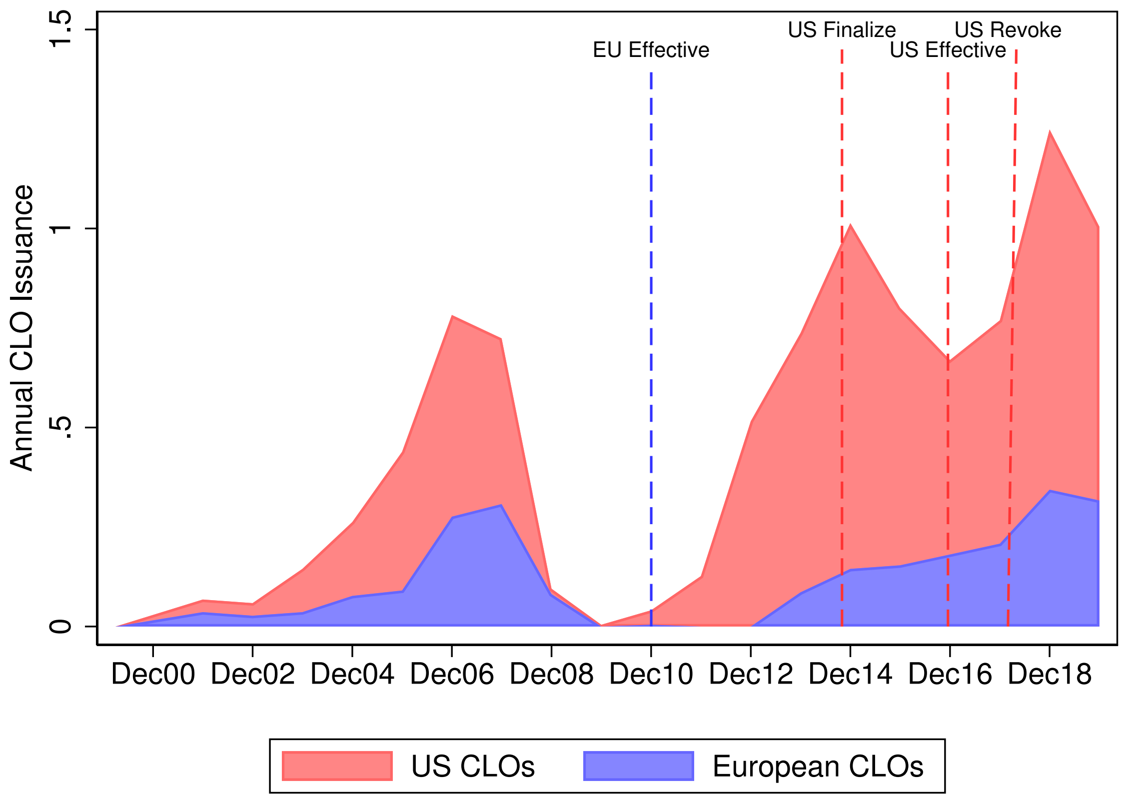
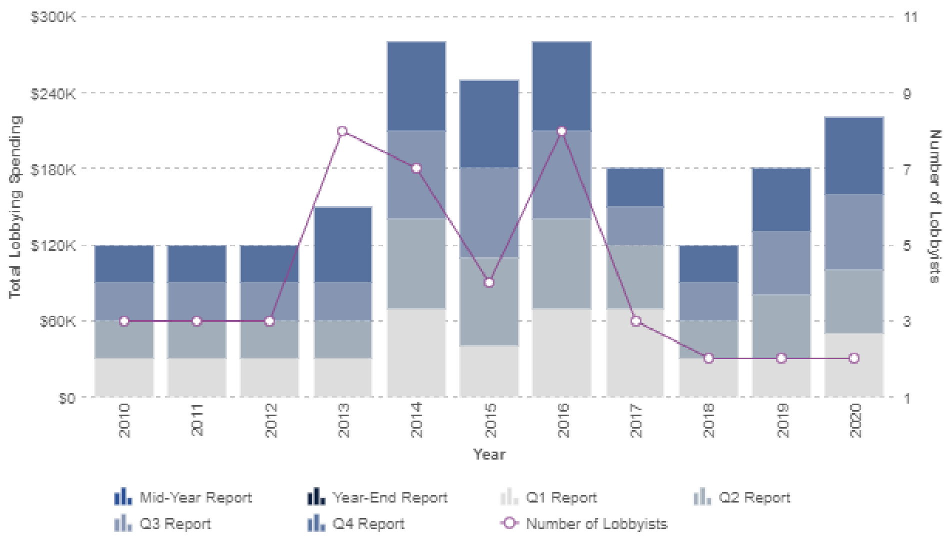
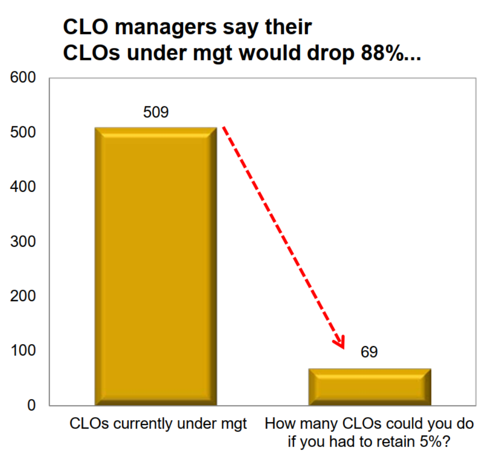
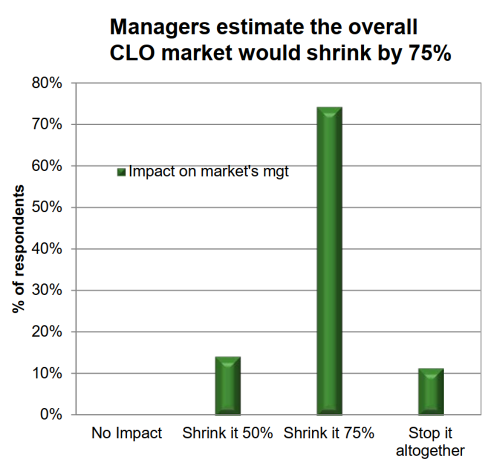


Figure IA.5: **Risk Retention and CLO Entry in the US and European Markets.** This figure plots the timing of regulatory events and annual average number of an asset manager's CLO deals issued in the US and European markets. The Capital Requirements Directive II introduced in Europe requires 5% risk retention for all new securitization deals issued after January 2011. These provisions were superseded by an equivalent requirement in Capital Requirements Regulation in January 2014. In the US, the Credit Risk Retention Rule, finalized in October 2014 to require a 5% risk retention, became effective for CLOs in December 2016 and got revoked in February 2018.



(a) LSTA Lobbying by Year





(b) Asset Manager Survey, 2013

Figure IA.6: **Industry Response to CLO Risk Retention.**
Panel IA.6a of this figure shows the Loan Syndication and Trading Association's (LSTA) annual lobbying spending (Source: Center for Responsive Politics). Panel IA.6b shows the result of LSTA 2013 survey on asset managers' expected impact of US CLO Credit Risk Retention on the market.

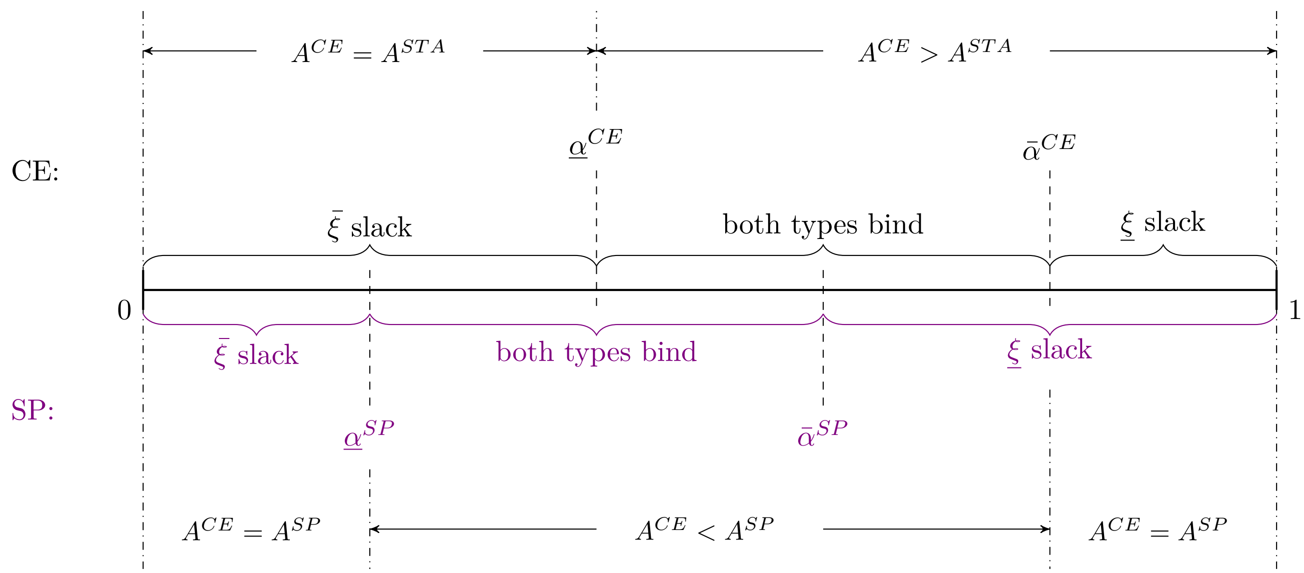


Figure IA.7: **Two-Type Case: Competitive and Planner's Allocations.**
This figure illustrates how the competitive and planned allocations in the two-type case depend on $\alpha \in (0, 1)$, the fraction of low-cost type institutions.

Table IA.1: **CLO Debt Maturity**

This table presents empirical distributions of CLO debt tranche maturity, measured in number of years. The sample includes US CLOs issued between 2010 and 2020.

Seniority	Mean	SD	p10	p25	p50	p75	p90	N
AAA	9.1	2.6	6	8	9	11	12	2,928
AA	9.8	2.4	7	9	10	12	13	2,238
A	10.2	2.5	7	9	10	12	13	2,194
BBB	11.1	2.7	8	10	12	12	14	2,051
BB	11.8	2.9	9	11	12	13	15	1,917
B	11.9	3.2	8	11	12	13	16	676
Total	10.4	2.9	7	9	11	12	13	12,004

Table IA.2: **Conversion from Letter Rating and Numerical Rating**

This table presents the conversion from letter ratings to numerical ratings, for credit ratings by Moody's and S&P. If only one rating agency's letter rating is available for a debt, the numerical rating is based on the available rating. If the two rating agencies' letter ratings convert to different numbers, the numerical rating is calculated as the average of the two converted numbers.

Letter Rating		Numeric Rating
Moody's	S&P	
Aaa–A3	AAA–A-	14
Baa1	BBB+	13
Baa2	BBB	12
Baa3	BBB-	11
Ba1	BB+	10
Ba2	BB	9
Ba3	BB-	8
B1	B+	7
B2	B	6
B3	B-	5
Caa1	CCC+	4
Caa2	CCC	3
Caa3	CCC-	2
Ca	CC, C	1
C	SD, D	0

Table IA.3: **Summary Statistics**

Panel A of this table presents summary statistics of the quarterly panel dataset for 2010–2019, where every observation is a US CLO's most recent information reported by the end of a quarter. The size of a CLO is measured with the total par value of loan holdings (in USD million). *AAA%* is a CLO's most senior debt tranche size divided by total liabilities as observed at its issuance. *Rating* and *Coupon* are par value-weighted averages of a CLO's portfolio loan holdings' current credit ratings and coupon rates (i.e., the sum of a floating benchmark rate and a fixed spread). Panel B presents summary statistics for an annual panel dataset that includes CLOs in both the US and European markets, where every observation is an asset manager–market–year between 2013–2019. *GovDebtGrwoth* and *DepositGrowth* are respectively the growth rates of total government debt and bank deposits in either market. Details on sample construction and the conversion of letter ratings are provided in Appendix IA.1.

	mean	sd	min	p10	p25	p50	p75	p90	max
Panel A: CLO–quarter panel, 2010-2019									
Observations: 13,825									
Size ($mm)	435.4	194.2	50.1	213.4	334.1	417.7	508.3	623.8	3,067.4
Loans (count)	222.3	103.2	51	94	147	217	282	344	815
Age (year)	4.23	2.56	0.00	0.75	2.00	4.00	6.25	8.00	15.50
AAA%	0.68	0.07	0.44	0.61	0.64	0.67	0.74	0.76	0.83
Rating	6.77	0.38	2.51	6.37	6.61	6.79	6.97	7.17	8.39
Coupon (%)	4.91	0.84	0.04	3.80	4.23	4.92	5.60	5.92	8.91
Panel B: asset manager–market–year panel, 2013–2019									
Observations: 2,044									
Entry (count)	0.75	1.3	0	0	0	0	1	3	9
Entry ($ mm)	586.7	1146.8	0.0	0.0	0.0	0.0	787.3	2,006.1	9,544.8
GovDebtGrowth (%)	3.9	2.0	1.4	1.9	2.1	3.6	5.6	7.2	8.0
DepositGrowth (%)	5.1	2.5	1.2	3.0	3.7	4.1	6.2	8.5	11.1

Table IA.4: **Safe Debt Financing and Portfolio Quality**

This table reports results from estimating panel regression

$$Quality_{it} = \beta AAA\%_i + \Gamma' Control_{it} + \delta_t + \epsilon_{it},$$

where every observation is a CLO-quarter pair measured based on the last portfolio snapshot available by the end of a quarter during 2010-2019. The dependent variable is a collateral quality measure. Regressor $AAA\%_i$ is original size of CLO i's AAA-rated debt tranche size divided by total size of the deal. In columns (1)–(3), collateral quality is measured with portfolio value-weighted average loan rating. The measure in columns (4)-(6) is value-weighted average loan interest rate (the sum of a fixed spread and a floating benchmark rate). Control variables, including natural logarithm of total par value of loan holdings and CLO age (in year), are measured at the date when portfolios are reported. Standard errors are clustered at the CLO deal level, and the t-statistics are reported in parentheses. *, **, *** represent 10%, 5%, and 1% levels of statistical significance.

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Var.		*Rating*			*Coupon*	
$AAA\%$	1.68***	1.88***	1.76***	−2.94***	−2.25***	−2.25***
	(6.39)	(6.66)	(6.43)	(-8.06)	(-6.21)	(-6.10)
ln(Size)		0.07**	0.06**		0.14***	0.01
		(2.62)	(2.85)		(2.37)	(0.28)
Age		-0.01			−0.03***	
		(-1.25)			(-4.74)	
Year-Quarter FEs	Y	Y	Y	Y	Y	Y
CLO Cohort FEs	N	N	Y	N	N	Y
Observations	13,825	13,825	13,823	13,825	13,825	13,823
R-squared	0.11	0.12	0.17	0.70	0.71	0.74

Table IA.5: **Credit Risk Retention and CLO Entry**

This table reports results from estimating panel regression

$$Entry_{imt} = \beta_0 + \beta_1 USmkt_{im} \times CRR_t + \beta_2 USmkt_{im} + \beta_3 CRR_t + \Gamma' Control_{m,t-1} + \epsilon_{imt},$$

where every observation is an asset manager–market–year between 2013–2019. $USmkt_{im}$ is an indicator variable that equals one (zero) if market m is the US (Europe). CRR_t is an indicator variable that equals one for years that Credit Risk Retention Rule affects the US market. Control variables are lagged growth rates of total government debt and total deposit in market m. The dependent variable in columns (1)–(3) is manager i's number of CLO issuance in market m and year t. In columns (4)–(6), the dependent variable is the total size (in $ million) of manager i's CLO issuance in market m and year t. In columns (3) and (6), $LargeMgr$ is an indicator variable that equals one if the manager's total size of CLOs measured in year 2014 is above median. Standard errors are clustered at the manager-by-market level, and the t-statistics are reported in parentheses. *, **, *** represent 10%, 5%, and 1% levels of statistical significance.

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Var.	Entry Count			Entry Size ($ mm)		
USmkt×CRR	-0.28^{***}	-0.31^{***}	-0.23^{***}	-130.58^{***}	-218.29^{***}	-184.19^{***}
	(-5.01)	(-4.42)	(-3.53)	(-2.58)	(-3.28)	(-3.84)
USmkt×CRR×LargeMgr			-0.16			-68.20
			(-1.40)			(-0.68)
USmkt	1.07^{***}	1.37^{***}	0.77^{***}	829.96^{***}	952.91^{***}	414.14^{***}
	(8.32)	(8.54)	(6.70)	(7.55)	(7.30)	(5.73)
CRR	-0.06^{***}	-0.03	-0.01	-14.27	-2.25	3.10
	(-2.61)	(-1.56)	(-0.29)	(-1.16)	(-0.18)	(0.26)
LargeMgr			0.49^{***}			353.61^{***}
			(5.40)			(4.83)
USmkt×LargeMgr			1.19^{***}			$1,077.55^{***}$
			(5.63)			(6.00)
CRR×LargeMgr			-0.06			-18.11
			(-1.28)			(-0.52)
Controls	N	Y	Y	N	Y	Y
Observations	2,044	2,044	2,044	2,044	2,044	2,044
R-squared	0.14	0.15	0.35	0.12	0.12	0.32