

Internet Appendix

Portfolio Dynamics and the Supply of Safe Securities

David Xiaoyu Xu

October, 2022

This Internet Appendix contains the following parts. First, Section [IA.1](#) describes the data and sample. Second, Section [IA.2](#) presents detailed facts on the market structure of nonbank institutions in the leveraged loan market. Third, Section [IA.3](#) shows empirical patterns of transitory price changes for loans of different quality in early 2020. Fourth, Section [IA.4](#) provides analysis for equilibrium with optimal safe debt maturity choices, which is omitted in the paper. Fifth, Section [IA.5](#) analyzes competitive equilibrium and its efficiency when manager types are discrete. Finally, Section [IA.6](#) presents supplementary empirical analyses.

Table of Contents

IA.1 Data and Sample Construction	2
IA.1.1 Data and Sample	2
IA.1.2 Cleaning CLO datasets	3
IA.1.3 Counterfactual portfolios	4
IA.2 Market Structure of Nonbanks: Additional Facts	5
IA.3 CLO Loan Trades and Secondary Market Prices	6
IA.4 Omitted Analysis of Safe Debt Maturity Choice	7
IA.4.1 Manager Choices	7
IA.4.2 Outsider Purchase	8
IA.4.3 Equilibrium	8
IA.5 Equilibrium with Discrete Manager Types	12

IA.6 Supplementary Empirical Analysis	14
IA.6.1 Capital Structure and Portfolio Quality	14
IA.6.2 Estimating the Effect of Risk Retention	15

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 secondary market interactions in response to the arrival of a negative macroeconomic 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 I use the first snapshot available between July 1 – August 15, 2020 for a “post” period.¹ To measure secondary market prices at the trough, I also 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 loans. CLOs in the sample are

¹CLO 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.

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 mutual funds), CLOs do not have regular disclosure dates, and their balance sheets are usually reported prior to the end of a certain period. In the database, 75% of CLO–month pairs have at least one report 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 original and current amount of liability outstanding at the tranche level 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, balance held in the portfolio, 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 issuer 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 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 transactions raw dataset provides information on the direction (buy or sell), loan par amount, transaction price, and 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 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 generate a counterfactual

²When 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.

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

observation for each loan, I begin with a large set of portfolio holdings that consist of every CLO’s first portfolio snapshot reported between July 1 and August 15, 2020 (“post period”). Since there is no loan-level unique identifier available, I identify individual loans by a pair of issuer ID and maturity date.⁴ I then calculate ex-post credit rating (coupon rate) for an ex-ante loan holding as the value-weighted average rating (coupon rate) across all CLOs’ ex-post matched holdings.⁵ Merging ex-post information to the pre 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 non-securitized loan funds. Based on data from regulatory reports, Panel (a) reports leveraged loan holdings for mutual funds and hedge funds, the two largest groups of non-securitized funds in this market. Whereas the holdings by mutual funds have been fluctuating 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.

⁴Occasionally, 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.

⁵A 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 affect 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

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

where the prices are calculated using market values reported in CLO portfolio snapshots in the three periods.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 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 asymmetric price pressure makes maintaining collateral quality costly for CLOs.

⁶I use market values reported in portfolio holdings because these prices are based on dealer quotes and trustee banks’ estimates, which help mitigate the concern of price staleness for infrequently traded debt. See Appendix IA.1.1 for details on price measurement.

IA.4 Omitted Analysis of Safe Debt Maturity Choice

This section provides the steps omitted for brevity in Subsection 3.5 of the paper.

IA.4.1 Manager Choices

I first analyze the manager's secondary market problem at $t = 1$, taking choices at $t = 0$ and loan prices as given. If the public signal is positive, short-term debt rolls over, and trades are trivial. If negative signal arrives, the manager takes prices as given and solves

$$v(x_{i,h}, x_{i,l}, a_i) = \max_{\Delta x_{i,h}, \Delta x_{i,l}, \Delta a_i} \sum_j (x_{i,j} + \Delta x_{i,j}) F_j^- - (a + \Delta a_i), \quad (\text{IA.2})$$

subject to the budget constraint (BC'), maintenance collateral constraint (MCC'), and the short-sale constraints. Similar to the baseline model, this problem can be simplified to

$$\max_{\Delta x_{i,l}, \Delta a_i} \Delta x_{i,l} \left(F_l^- - F_h^- \frac{q_l}{q_h} \right) + \Delta a_i \left(\frac{F_h^-}{q_h} - 1 \right), \quad (\text{P1}')$$

subject to constraints

$$\Delta x_{i,l} f_h^- \frac{q_l}{q_h} + \Delta a_i \left(1 - \frac{f_h^-}{q_h} \right) \leq x_{i,h} f_h^- - a_i, \quad (\text{IA.3})$$

and $\Delta x_{i,l} \geq -x_{i,l}$, $-a_i \leq \Delta a_i \leq 0$.

The manager's optimal choices depend on balance sheet at $t = 0$ and loan prices at $t = 1$. The following observation pins down the sufficient and necessary condition for the manager to prefer early debt repayment ex post.

Lemma IA.1. *Early repayment $\Delta a_i = -a_i$ is ex-post desirable if and only if $q_h > f_h^* := f_h^- + \frac{q_l}{F_l^-} (F_h^- - f_h^-)$.*

Proof. To see that $q_h > f_h^*$ is sufficient, note that it implies $\frac{q_h}{F_h^-} > \frac{q_l}{F_l^-} + \frac{f_h^-}{F_h^-} \left(1 - \frac{q_l}{F_l^-} \right) \geq \frac{q_l}{F_l^-}$, which in turn implies that the objective in problem (P1') is strictly increasing in $\Delta x_{i,l}$. So constraint (IA.3) binds, and the objective reduces to $\Delta a_i \frac{F_l^- (f_h^* - q_h)}{f_h^- q_l}$, which strictly decreases in Δa_i and implies that $\Delta a_i = -a_i$ is optimal.

Conversely, if $\Delta a_i = -a_i$ is desirable, then $\frac{q_l}{F_l^-} < \frac{q_h}{F_h^-}$: otherwise, the objective in problem (P1') would reduce to $\Delta a_i \left(\frac{F_h^-}{q_h} - 1 \right)$, which strictly increases in Δa_i . Hence, the objective

reduces to $\Delta a_i \frac{F_l^-(f_h^* - q_h)}{f_h^- q_l}$, and $q_h > f_h^*$ is also necessary. \square

Intuitively, the manager wants to repay debt early if and only if q_h is sufficiently high. In this case, after the repayment, the manager can hold only low-quality loans and expect a high equity return. By contrast, if $q_h \leq f_h^*$, delaying repayment by holding sufficient high-quality loans is desirable.

Whether the desirable actions are feasible is determined by inequality (ICC'). For example, if $q_h > f_h^-$, a manager having short-term safe debt $a_i > (x_{i,h}q_h + x_{i,l}q_l) \frac{q_h}{f_h^-}$ has to repay in bad times even if her ex-post desired action is to rollover debt.

IA.4.2 Outsider Purchase

Given the linear cost structure of the storage technology, outside buyers' demand for loan j in the secondary market is

$$z_j(q_j) = \begin{cases} +\infty, & (1-p)\left(\frac{F_j^-}{q_j} - 1\right) > \kappa \\ \forall z \in \mathbb{R}_+, & (1-p)\left(\frac{F_j^-}{q_j} - 1\right) = \kappa \\ 0, & (1-p)\left(\frac{F_j^-}{q_j} - 1\right) < \kappa \end{cases} \quad (\text{IA.4})$$

The types and quantities of loans bought by outsiders are determined by the levels of prices: they store more when anticipating larger profits from buying loans at a discount in bad times.

IA.4.3 Equilibrium

In equilibrium, the issuance of long-term safe debt, short-term safe debt, and equity are jointly determined with outsider purchases and secondary market prices. The following proposition summarizes the set of competitive equilibria that can arise in this generalized economy.

Proposition IA.1 (Equilibrium with Safe Debt Maturity Choice). *Depending on parameter values, there are four types of competitive equilibrium, each has a different combination of nonbank liabilities:*

- (i) *Long-term safe debt and equity. There exists a unique $\lambda^l \in (0, 1)$ such that managers $[0, \lambda^l]$ issue long-term safe debt, and the rest issue only equity. No risky loan is sold to*

outside buyers.

- (ii) *Short-term safe debt, long-term safe debt, and equity.* There exist a unique pair of $\lambda^{st}, \lambda^{lt}$, where $0 < \lambda^{st} < \lambda^{lt} < 1$, such that managers $[0, \lambda^{st}]$ issue short-term safe debt, $(\lambda^{st}, \lambda^{lt}]$ issue long-term safe debt, and the rest issue only equity. A subset of low-quality loans are sold to outside buyers in bad times.
- (iii) *Short-term safe debt and long-term safe debt.* There exists a unique $\lambda^{st} \in (0, 1)$ such that managers $[0, \lambda^{st}]$ issue short-term safe debt, and the rest issue long-term safe debt. All low-quality loans are sold to outside buyers in bad times.
- (iv) *Only short-term safe debt.* All managers issue short-term safe debt, and all high-quality and low-quality loans are sold to outside buyers in bad times.

Proof. I characterize competitive equilibria by searching over three mutually exclusive cases.

Case 1: $q_h \in (0, f_h^-]$. In this case, short maturity is strictly dominated because long maturity maximizes ex-ante safe debt capacity ($a_i \frac{q_h}{q_l} \leq a_i$), and $\Delta a_i = 0$ is ex-post desirable. The equilibrium has an interior cutoff and is unique with respect to price ratio $\frac{q_l}{q_h} < \frac{F_l^-}{F_h^-}$. Secondary market clearing condition implies that no loan can be sold to outside buyers. So in this case, $q_l \geq \frac{(1-p)F_l^-}{1-p+\kappa}$. The equilibrium exists when κ is relatively large with respect to γ .

Case 2: $q_h \in (f_h^-, f_h^*]$. In this case, short maturity maximizes safe debt capacity (i.e., $a_i \frac{q_h}{q_l} > a_i$), but $\Delta a_i = 0$ is ex-post desirable. Inequality $\frac{q_l}{q_h} \leq \frac{F_l^-}{F_h^-}$ holds, otherwise there is either zero demand for low-quality loans or infinite demand for high-quality loans.⁷ Hence, constraint (IA.3) binds, and optimal secondary market trades can be derived accordingly. There are generally three liability types for managers to choose from.

- (i) If a manager issues only equity, optimal secondary market trades are $\Delta x_{i,h} = -x_{i,h}$, $\Delta x_{i,l} = x_{i,h} \frac{q_h}{q_l}$, and continuation value $v^e = (x_{i,h} \frac{q_h}{q_l} + x_{i,l})F_l^-$. The manager's marginal payoff from lending is $y_i^e := pF_h^+ + (1-p)F_l^- \frac{q_h}{q_l}$, and its payoff is

$$V_i^e = y_i^e c'^{-1}(y_i^e) - c(c'^{-1}(y_i^e)) - x_{i,l} \left(p(F_h^+ - F_l^+) + (y_i^e - pF_h^+) \left(1 - \frac{q_l}{q_h} \right) \right). \quad (\text{IA.5})$$

- (ii) If a manager issues long-term safe debt, optimal secondary market trades are $\Delta x_{i,h} = \frac{a_i}{f_h^-} - x_{i,h}$, $\Delta x_{i,l} = (x_{i,h} - \frac{a_i}{f_h^-}) \frac{q_h}{q_l}$, and continuation value $v^{lt} = (x_{i,h} \frac{q_h}{q_l} + x_{i,l})F_l^- - a_i(1 +$

⁷For different nonban liability types, see below for the corresponding optimal secondary market trades, which are derived from problem (P1').

$\frac{q_h F_l^-}{q_l f_h^-} - \frac{F_h^-}{f_h^-}$). At $t = 0$, the manager faces constraint $a_i \leq (x_{i,h} + x_{i,l} \frac{q_l}{q_h}) f_h^-$, with shadow price $\eta_i^{lt} = \max\{\gamma - \xi_i - (1-p)(\frac{q_h F_l^-}{q_l f_h^-} - \frac{F_h^-}{f_h^-}), 0\}$. When $\eta_i^{lt} > 0$, the marginal payoff from lending is $y_i^{lt} = pF_h^+ + (1-p)F_h^- + (\gamma - \xi_i)f_h^-$, and its payoff is

$$V_i^{lt} = y_i^{lt} c'^{-1}(y_i^{lt}) - c(c'^{-1}(y_i^{lt})) - x_{i,l} \left(p(F_h^+ - F_l^+) + (y_i^{lt} - pF_h^+) \left(1 - \frac{q_l}{q_h} \right) \right). \quad (\text{IA.6})$$

(iii) If a manager issues short-term safe debt, in bad times it optimally repays $\Delta a_i = -\frac{a_i q_h - (x_{i,h} q_h + x_{i,l} q_l) f_h^-}{q_h - f_h^-}$ and trades $\Delta x_{i,h} = \frac{x_{i,h} f_h^- + x_{i,l} q_l - a_i}{q_h - f_h^-}$, $\Delta x_{i,l} = -x_{i,l}$. These actions lead to continuation value $v^{st} = \frac{F_h^- - f_h^-}{q_h - f_h^-} (x_{i,h} q_h + x_{i,l} q_l - a_i)$. At $t = 0$, the manager faces constraints $a_i \leq x_{i,h} q_h + x_{i,l} q_l$, $(x_{i,h} + x_{i,l} \frac{q_l}{q_h}) f_h^- \leq a_i$, with shadow prices $\eta_i^{st} = \max\{\gamma - \xi_i - (1-p)\frac{F_h^- - f_h^-}{q_h - f_h^-}, 0\}$ and $\varphi_i^{st} = \max\{(1-p)\frac{F_h^- - f_h^-}{q_h - f_h^-} - (\gamma - \xi_i), 0\}$, respectively. When $\eta_i^{st} > 0$, the marginal payoff from lending is $y_i^{st} = pF_h^+ + (1-p + \gamma - \xi_i)q_h$, and its payoff is

$$V_i^{st} = y_i^{st} c'^{-1}(y_i^{st}) - c(c'^{-1}(y_i^{st})) - x_{i,l} \left(p(F_h^+ - F_l^+) + (y_i^{st} - pF_h^+) \left(1 - \frac{q_l}{q_h} \right) \right). \quad (\text{IA.7})$$

The following observations suggest a pecking order among these liability choices. First, $q_h \in (f_h^-, f_h^*]$ implies $\frac{F_h^- - f_h^-}{q_h - f_h^-} - (\frac{q_h F_l^-}{q_l f_h^-} - \frac{F_h^-}{f_h^-}) = -\frac{q_h(q_h - f_h^*)}{(q_h - f_h^-)q_l f_h^-} \geq 0$, which further implies $\eta_i^{lt} \geq \eta_i^{st}$. Second, $y_i^{lt} = y_i^e + \eta_i^{lt} f_h$ when $\eta_i^{lt} > 0$, and $y_i^{st} = y_i^{lt} + \eta_i^{st}(q_h - f_h^-)$ when $\eta_i^{st} > 0$, so $y_i^e < y_i^{lt} < y_i^{st}$. Third, manager payoff strictly increases in y_i : $\frac{\partial V_i}{\partial y_i} = c'^{-1}(y_i) - x_{i,l}(1 - \frac{q_l}{q_h}) > c'^{-1}(pF_h^+ + (1-p)F_h^-) - x_{i,l} > 0$. Hence, others equal, a manager issues short-term safe debt if $\eta_i^{st} > 0$, issues long-term safe debt if $\eta_i^{lt} > \eta_i^{st} = 0$, and issues only equity if $\eta_i^{lt} = 0$.

By monotonicity of η_i^{lt} and η_i^{st} in i , liability choices in equilibrium are characterized by cutoffs. The uniqueness of these cutoffs are guaranteed by the monotonicity of secondary market aggregate excess demand. Clearly, η_i^{lt} cannot be zero for all i , otherwise $\Delta x_{i,l} > 0$ for all i and market does not clear unless $\frac{q_l}{F_l^-} = \frac{q_h}{F_h^-}$, but this equation contradicts $\eta_i^{lt} = 0$. Market-clearing condition (12) indicates that in equilibrium, outsiders only buy loans that have a (weakly) higher expected return. Equilibrium outcomes depend parameter values:

1. $\eta_i^{st} = 0$ for all i , and there exists $\lambda^{lt} \in (0, 1)$ such that $\eta_i^{lt} > 0$ if and only if $i \in [0, \lambda^{lt}]$.

Equilibrium loan prices satisfy $q_h \leq f_h^- + \frac{1}{\gamma}(1-p)(F_h^- - f_h^-)$, $q_l \geq \frac{(1-p)F_l^-}{1-p+\kappa}$, and $\frac{q_l}{q_h} = \frac{(1-p)F_l^-}{(1-p)F_h^- + (\gamma - \xi_{\lambda^{lt}})f_h^-}$. No loan is sold to outsiders.

2. There exist $\lambda^{st}, \lambda^{lt}$ such that $0 < \lambda^{st} < \lambda^{lt} < 1$, $\eta_i^{st} > 0$ if and only if $i \in [0, \lambda^{st}]$,

and $\eta_i^{lt} > \eta_i^{st} = 0$ if and only if $i \in (\lambda^{st}, \lambda^{lt}]$. Equilibrium loan prices satisfy $q_h = f_h^- + \frac{(1-p)(F_h^- - f_h^-)}{\gamma - \xi_{\lambda^{st}}}$, $q_l = \frac{(1-p)F_l^-}{1-p+\kappa}$, and $\frac{q_l}{q_h} = \frac{(1-p)F_l^-}{(1-p)F_h^- + (\gamma - \xi_{\lambda^{lt}})f_h^-}$. In the secondary market, managers with long-term safe debt buy all high-quality loans sold by managers with short-term safe debt and managers with only equity. Low-quality loans are bought by managers with only equity as well as outsiders.

3. $\eta_i^{lt} > 0$ for all i , and there exists $\lambda^{st} \in (0, 1)$ such that $\eta_i^{st} > 0$ if and only if $i \in [0, \lambda^{st}]$. Equilibrium loan prices satisfy $q_h = f_h^- + \frac{(1-p)(F_h^- - f_h^-)}{\gamma - \xi_{\lambda^{st}}}$, $q_l = \frac{(1-p)F_l^-}{1-p+\kappa}$, and $\frac{q_l}{q_h} > \frac{(1-p)F_l^-}{(1-p)F_h^- + (\gamma - 2\xi)f_h^-}$. In the secondary market, managers with long-term safe debt buy all high-quality loans sold by managers with short-term safe debt. All low-quality loans are bought by outsiders.
4. $\eta_i^{st} > 0$ for all i . Equilibrium loan prices are $q_j = \frac{(1-p)F_j^-}{1-p+\kappa}$, $j = h, l$. In the secondary market, all loans are sold to outsiders.

Case 3: $q_h \in (f_h^*, F_h^-]$. In this case, long maturity is strictly dominated because short-term debt maximizes ex-ante safe debt capacity ($a_i \frac{q_h}{q_l} > a_i$), and $\Delta a_i = -a_i$ is ex-post desirable. Since all managers issuing safe debt will choose short maturity and that $q_h > f_h^*$ implies $\frac{q_l}{F_l^-} < \frac{q_h}{F_h^-}$, optimal trades $\Delta x_{i,h} = -x_{i,h}$ for all $i \in \mathcal{I}$. If outsiders buy loan h , their demand for loan l , which has a higher return, will be infinity. This contradicts with market clearing condition (12). So this case cannot be an equilibrium. \square

Type-i equilibrium arises when outsiders' cost of buying loans is high relative to the non-pecuniary benefit of safe debt. In this case, short maturity either fails to maximize safe debt capacity, or its capacity advantage is overwhelmed by the cost of early liquidation. Hence, long maturity is preferred, and managers substitute portfolios rather than liquidate loans in the secondary market.

Type-ii and type-iii equilibria feature a "pecking order" in maturity choices. While short maturity maximizes ex-ante safe debt capacity, ex post it is more costly to liquidate loans than to substitute portfolios. A greater safe debt capacity is more valuable for managers facing lower costs of securitization. So in equilibrium, only managers with sufficiently low issuance costs choose short maturity, and other managers issue long-term safe debt or only equity. In bad times, the first group of managers liquidate all loans, whereas the second and

third groups substitute portfolios. Outside buyers absorb low-quality loans, which provide a higher return to them. High-quality loans change hands among managers.

Type-iv equilibrium arises when outsiders' funding cost is sufficiently low. In this case, the cost of early liquidation is smaller than the benefit of greater safe debt capacity. Hence, all managers optimally issue short-term safe debt to exploit cheap financing and liquidate their entire portfolios when negative news arrives. Unlike equilibrium types i–iii, no manager's safe debt relies on loans originated by others.

IA.5 Equilibrium with Discrete Manager Types

Consider the simplest case with heterogeneity: managers have two types $\xi_i \in \{\underline{\xi}, \bar{\xi}\}$, where $0 \leq \underline{\xi} < \bar{\xi} < \gamma$. The two types have exogenous population mass $\alpha \in (0, 1)$ and $1 - \alpha$, respectively. In this case, initial collateral constraints must bind for at least one type because managers face the same profit from liquidity provision but enjoy different private benefits from safe debt issuance. Market-clearing prices, and hence allocations, depend on fraction α . To illustrate the inefficiency in this two-type case, the proposition below focuses on a subset of α values, and the complete analysis can be found in the proof. For notational convenience, I use $(\underline{x}^{CE}, \bar{x}^{CE}, \underline{a}_i^{CE}, \bar{a}_i^{CE})$ and $(\underline{x}^{SP}, \bar{x}^{SP}, \underline{a}_i^{SP}, \bar{a}_i^{SP})$ to denote respectively the competitive and planner's allocations for the two types.⁸

Proposition IA.2. *Suppose $\xi_i \in \{\underline{\xi}, \bar{\xi}\}$. When $\alpha \in (\underline{\alpha}^{CE}, \bar{\alpha}^{SP})$ for endogenous cutoffs $0 < \underline{\alpha}^{CE} < \bar{\alpha}^{SP} < 1$, the equilibrium is constrained inefficient. In particular, high-cost managers underinvest, and the market underproduces safe debt: $\bar{x}^{CE} < \bar{x}^{SP}$, and $A^{CE} < A^{SP}$.*

Proof. In both the competitive and planner's allocations, the exogenous fraction $\alpha \in (0, 1)$ determines which type(s) face a binding constraint on the choice of a_i . There are three possibilities. For each of them, allocation results follow from Kuhn-Tucker conditions (4)–(6) and (14)–(16) and the market clearing condition. Figure IA.6 summarizes the results. There are four endogenous cutoffs, $0 < \underline{\alpha}^{SP} < \underline{\alpha}^{CE} < \bar{\alpha}^{SP} < \bar{\alpha}^{CE} < 1$, that divide $(0, 1)$ into five mutually exclusive regions. Prices and allocations are different across regions. For notational

⁸I include subscript i for choices of a_i because these choices depend on idiosyncratic quality shocks $\tilde{x}_{i,l}$.

convenience, I define $(\underline{x}, \bar{x}) := (c'^{-1}(pR + 1 - p + \gamma - \underline{\xi}), c'^{-1}(pR + 1 - p + \gamma - \bar{\xi}))$, which are the two types' lending choices in static securitization.

Both types bind: For the competitive market, this implies $\frac{(1-p)\pi}{1-p+\gamma-\underline{\xi}} < \frac{q_l}{q_h} < \frac{(1-p)\pi}{1-p+\gamma-\bar{\xi}}$, $(\underline{x}^{CE}, \bar{x}^{CE}) = (\underline{x}, c'^{-1}(pR + (1-p)\pi\frac{q_h}{q_l}))$, and $(\underline{a}_i^{CE}, \bar{a}_i^{CE}) = (x_{i,h} + x_{i,l}\frac{q_l}{q_h}, 0)$. Secondary market demand and supply for h are $\alpha x_L \frac{q_l}{q_h}$ and $(1-\alpha)(\bar{x} - x_L)$. Market clearing requires $\alpha \in (\underline{\alpha}^{CE}, \bar{\alpha}^{CE})$, where $\underline{\alpha}^{CE} := (\bar{x} - x_L)\left(\bar{x} - (1 - \frac{(1-p)\pi}{1-p+\gamma-\bar{\xi}}x_L)\right)^{-1}$ and $\bar{\alpha}^{CE} := (\underline{x} - x_L)\left(\underline{x} - (1 - \frac{(1-p)\pi}{1-p+\gamma-\underline{\xi}}x_L)\right)^{-1}$. For the planner, both types facing binding collateral constraints implies $(\underline{x}^{SP}, \bar{x}^{SP}) = (\underline{x}, c'^{-1}(pR + 1 - p + \psi^{SP}))$ and $(\underline{a}_i^{SP}, \bar{a}_i^{SP}) = (x_{i,h} + x_{i,l}\pi, 0)$. Note that $\gamma - \bar{\xi} < \psi^{SP} < \gamma - \underline{\xi}$, so market clearing requires $\alpha \in (\underline{\alpha}^{SP}, \bar{\alpha}^{SP})$, where $\underline{\alpha}^{SP} := (\bar{x} - x_L)(\bar{x} - (1 - \pi)x_L)^{-1}$ and $\bar{\alpha}^{SP} := (\underline{x} - x_L)(\underline{x} - (1 - \pi)x_L)^{-1}$.

Type $\bar{\xi}$ slack: For the competitive market, this implies $\frac{q_l}{q_h} = \frac{(1-p)\pi}{1-p+\gamma-\bar{\xi}}$, $(\underline{x}^{CE}, \bar{x}^{CE}) = (\underline{x}, \bar{x})$, and $\underline{a}_i^{CE} = x_{i,h} + x_{i,l}\frac{q_l}{q_h}$, $\bar{a}_i^{CE} \in [0, x_{i,h} + x_{i,l}\frac{q_l}{q_h}]$. Secondary market demand and supply for h are $\alpha x_L \frac{q_l}{q_h}$ and $(1-\alpha)(\bar{x} - x_L) - \int_{\alpha}^1 \bar{a}_i^{CE} di$. Market clearing requires the demand to be no less than the supply when $\bar{a}_i^{CE} = 0, \forall i \in [\alpha, 1]$, which is equivalent to $\alpha \leq \underline{\alpha}^{CE}$. For the planner, type $\bar{\xi}$ facing slack collateral constraints implies $(\underline{x}^{SP}, \bar{x}^{SP}) = (\underline{x}, \bar{x})$, and $\underline{a}_i^{SP} = x_{i,h} + x_{i,l}\pi$, $\bar{a}_i^{SP} \in [0, x_{i,h} + x_{i,l}\pi]$. Similarly, market clearing requires $\alpha \leq \underline{\alpha}^{SP}$.

Type $\underline{\xi}$ slack: For the competitive market, this implies $\frac{q_l}{q_h} = \frac{(1-p)\pi}{1-p+\gamma-\underline{\xi}}$, $(\underline{x}^{CE}, \bar{x}^{CE}) = (\underline{x}, \underline{x})$, and $\underline{a}_i^{CE} \in [0, x_{i,h} + x_{i,l}\frac{q_l}{q_h}]$, $\bar{a}_i^{CE} = 0$. Secondary market demand and supply for h are $\int_0^{\alpha} \underline{a}_i^{CE} di - \alpha(\underline{x} - x_L)$ and $(1-\alpha)(\underline{x} - x_L)$. Market clearing requires the demand to be no less than the supply when $\underline{a}_i^{CE} = x_{i,h} + x_{i,l}\frac{q_l}{q_h}, \forall i \in [\alpha, 1]$, which is equivalent to $\alpha \geq \bar{\alpha}^{CE}$. For the planner, type $\underline{\xi}$ facing slack collateral constraints implies $(\underline{x}^{SP}, \bar{x}^{SP}) = (\underline{x}, \underline{x})$, and $\underline{a}_i^{SP} \in [0, x_{i,h} + x_{i,l}\pi]$, $\bar{a}_i^{SP} = 0$. Similarly, market clearing requires $\alpha \geq \bar{\alpha}^{SP}$.

Clearly, $\underline{x}^{CE} = \underline{x}^{SP} = \underline{x}$ for any α . When $\alpha \leq \underline{\alpha}^{SP}$ or $\alpha \geq \bar{\alpha}^{CE}$, lending choices are identical in the competitive and planner's allocations, so $A^{CE} = A^{SP}$ by Equation (7).⁹ The result that $\bar{x}^{CE} < \bar{x}^{SP}$ and $A^{CE} < A^{SP}$ when $\alpha \in (\underline{\alpha}^{SP}, \underline{\alpha}^{CE})$ follows from the following observations. When $\underline{\alpha}^{SP} < \alpha \leq \underline{\alpha}^{CE}$, $\psi^{SP} > \gamma - \bar{\xi}$ implies $\bar{x}^{CE} < \bar{x}^{SP}$; When $\underline{\alpha}^{CE} < \alpha \leq \bar{\alpha}^{SP}$, $\underline{a}_i^{CE} < \underline{a}_i^{SP}$ and $\bar{a}_i^{CE} = \bar{a}_i^{SP}$; When $\bar{\alpha}^{SP} < \alpha \leq \bar{\alpha}^{SP}$, $(1-p)\pi\frac{q_h}{q_l} < 1 - p + \gamma - \underline{\xi}$ implies $\bar{x}^{CE} < \bar{x}^{SP}$. This completes the proof. \square

⁹The intuition for this result is similar to that of Corollary 4.3: when constraints are slack for both individual managers and the planner, the pecuniary externality does not affect the efficiency of allocation.

When α is in a medium region, the equilibrium price ratio tightens the low-cost type’s binding collateral constraints, preventing them from issuing efficient quantities of safe debt. While the low-cost type’s lending is efficient, high-cost managers underinvest as they do not fully internalize the collateral value of loans. Consequently, the market underproduces safe debt because of a deficiency of aggregate collateral.

The intuition of this underproduction result is the same as that in Proposition 4. Note that in this two-type case, there is no excessive entry into safe debt creation. However, with more than two types, in equilibrium there can be a nonempty subset of managers for whom issuing safe debt is privately optimal but socially inefficient.

IA.6 Supplementary Empirical Analysis

IA.6.1 Capital Structure and Portfolio Quality

In my model, managers’ balance sheet choices generate a cross-sectional relationship between a nonbank’s capital structure and the quality of its loan portfolio. It is trivial that better quality loans can back more safe debt; However, as CLO managers 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 commonly driven by unobserved securitization costs. I examine this relationship by estimating panel regression

$$Quality_{it} = \beta AAA\%_i + \Gamma' Control_{it} + \delta_t + \epsilon_{it}, \quad (IA.8)$$

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 accounts for 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.¹⁰ The point estimate remains similar, suggesting that the 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.¹¹

IA.6.2 Estimating the Effect of Risk Retention

The Credit Risk Retention Rule’s inclusion of CLOs received considerable resistance from practitioners. Panel (a) of Figure IA.5 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 policy’s realized impact.

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

¹⁰CLO age is absorbed by the two groups of fixed effects in columns (3) and (6).

¹¹After partialling out time fixed effects, the standard deviation of coupon rate is 0.48%.

panel regression

$$Entry_{imt} = \beta_0 + \beta_1 USmkt_{im} \times CRR_t + \beta_2 USmkt_{im} + \beta_3 CRR_t + \Gamma' Control_{m,t-1} + \epsilon_{imt}, \quad (IA.9)$$

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.

References

Foley-Fisher, N., G. B. Gorton, and S. Verani (2020). Adverse selection dynamics in privately-produced safe debt markets. Technical report, National Bureau of Economic Research.

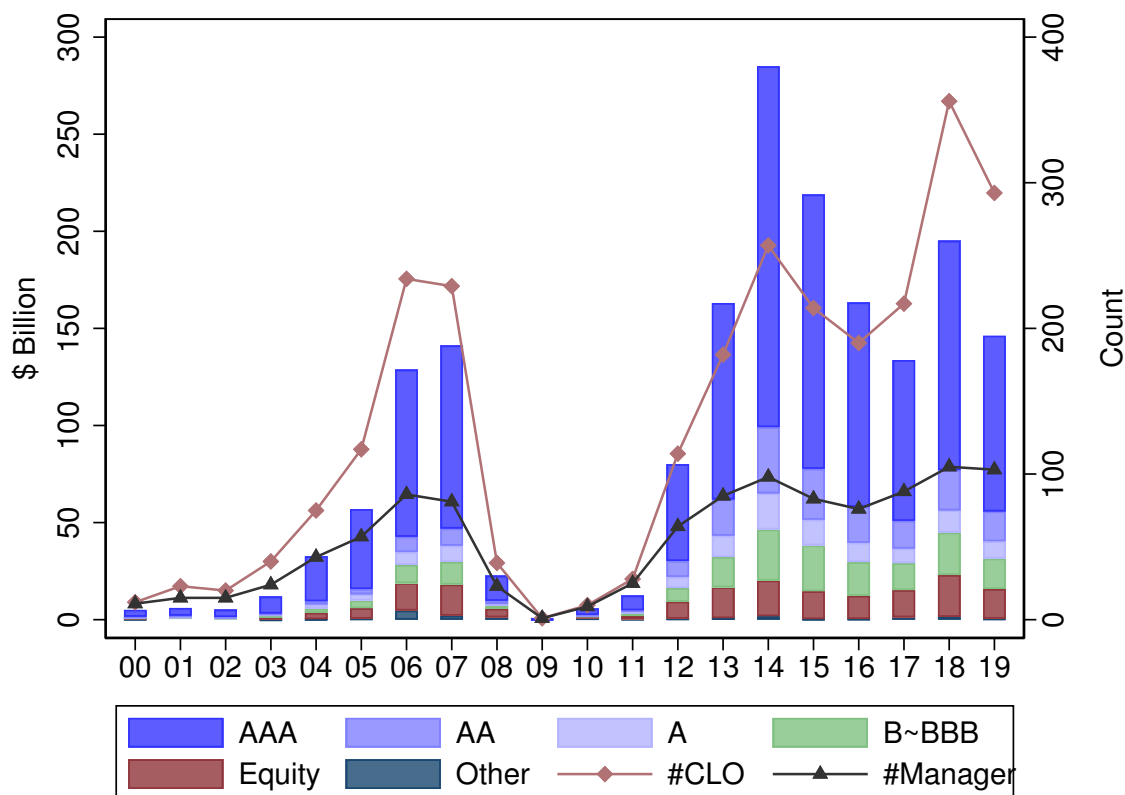
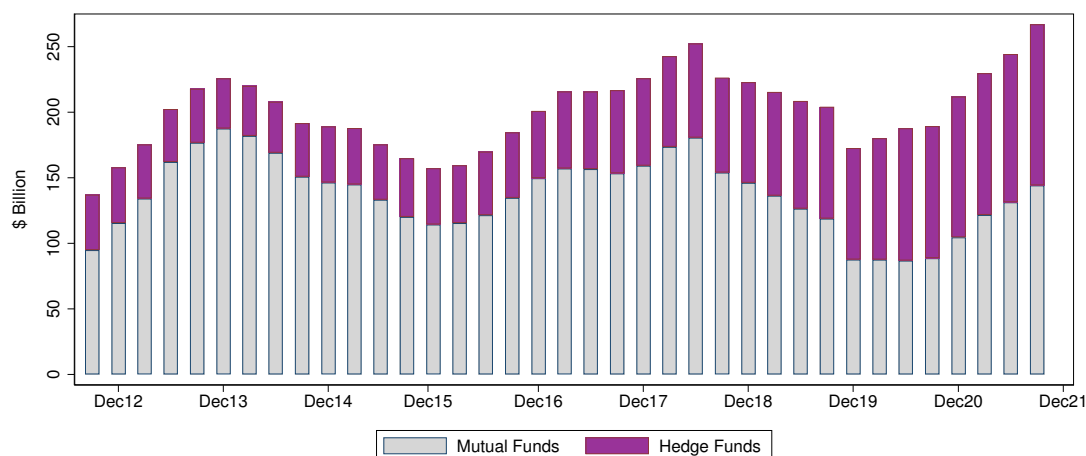
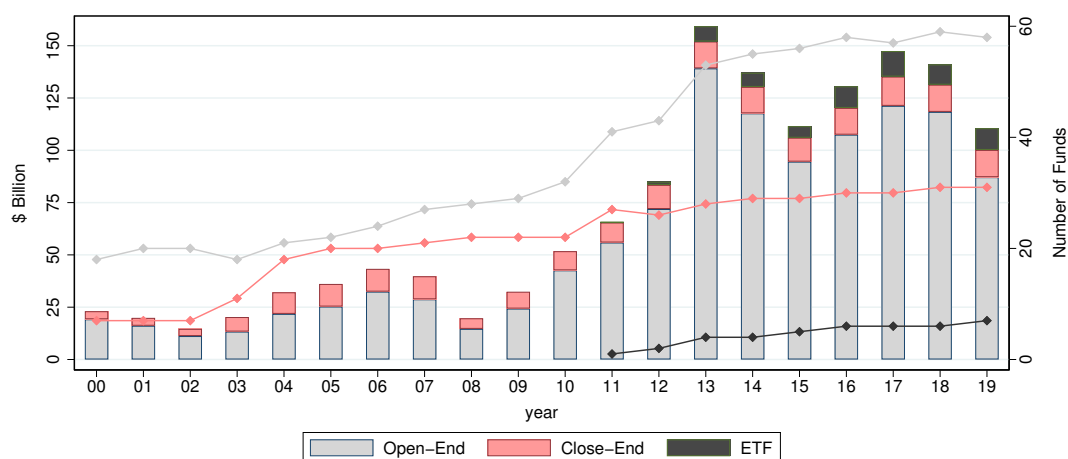


Figure IA.1: **CLO Issuance.**

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 database.



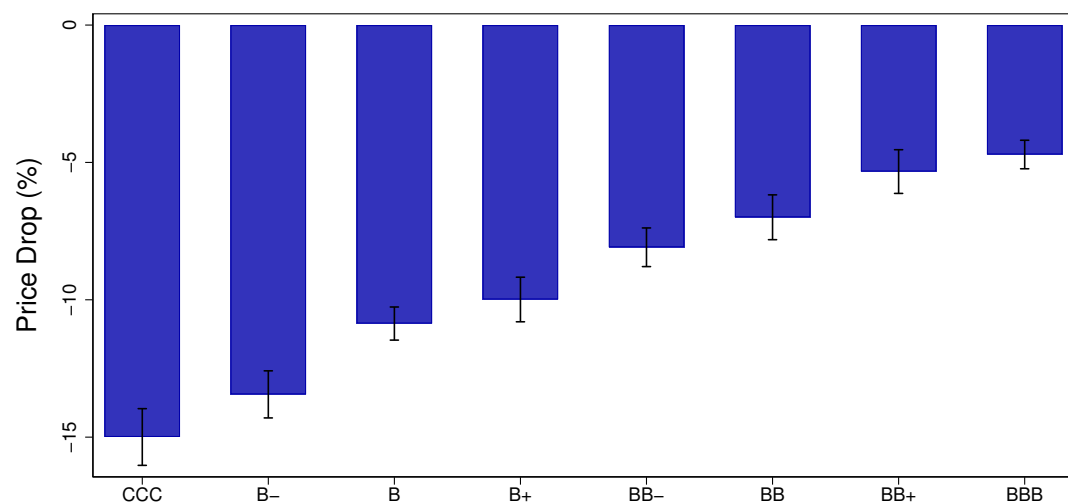
(a) Leveraged Loans Held by Mutual Funds and Hedge Funds



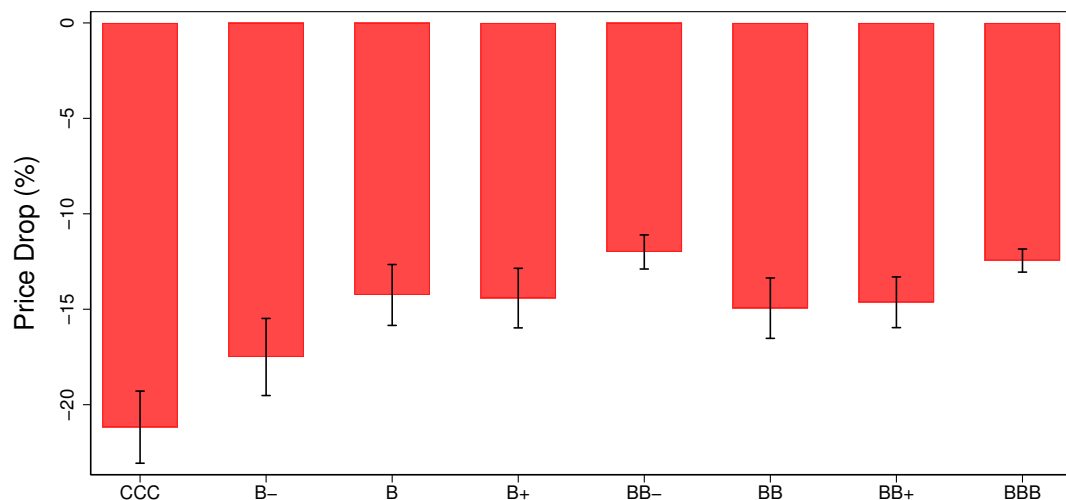
(b) Composition of Public Loan Funds

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.

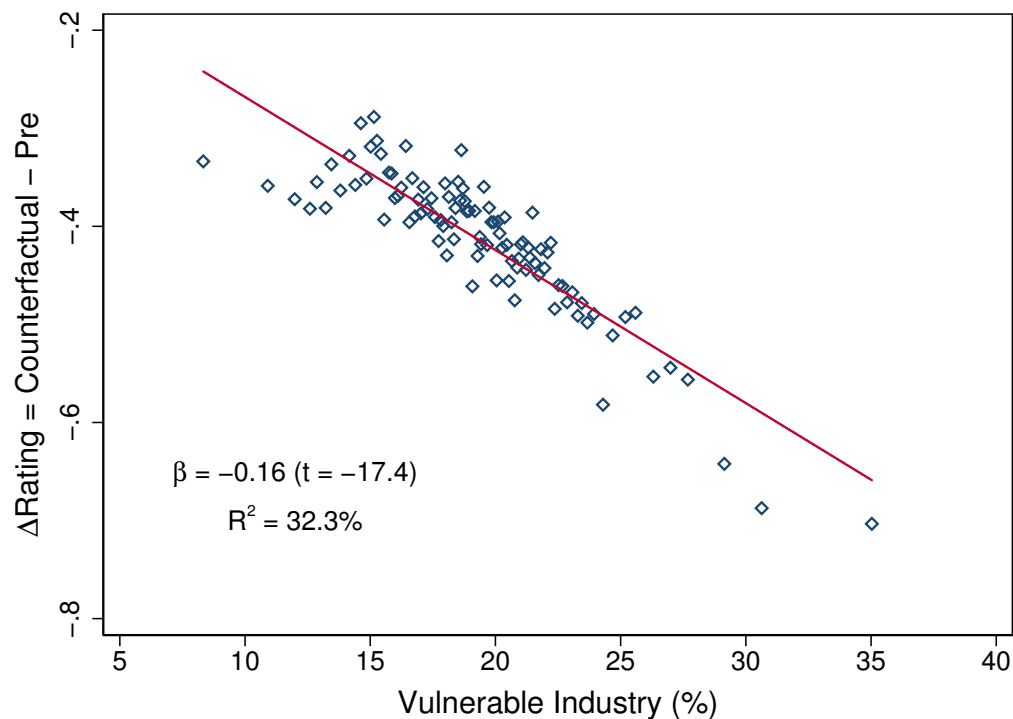
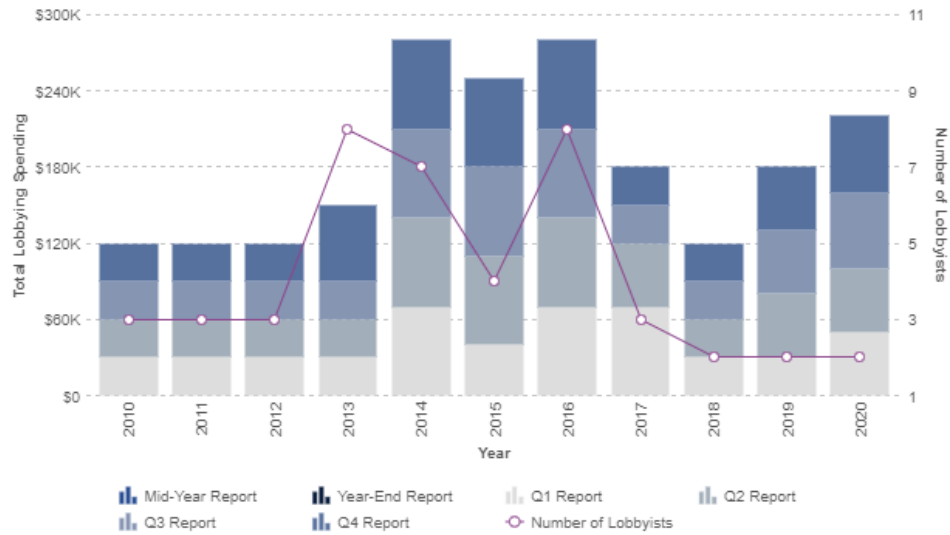
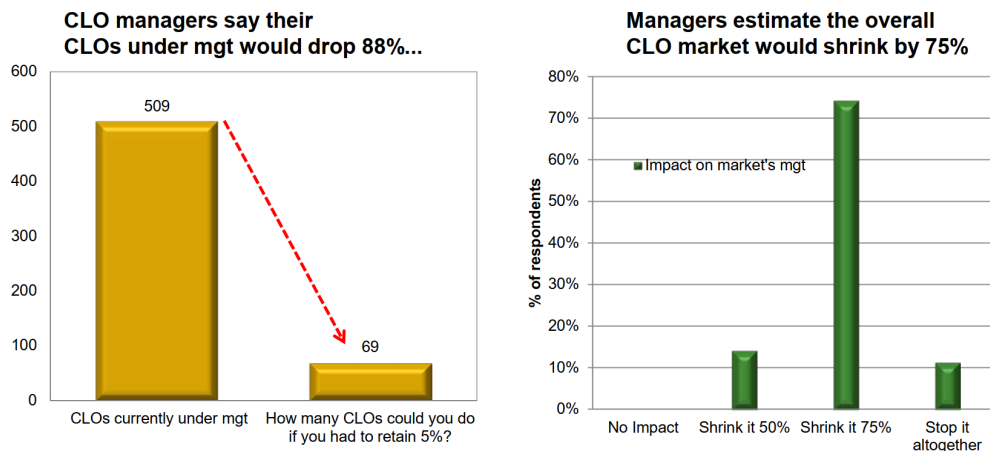


Figure IA.4: **Exposure to Vulnerable Industries and Counterfactual Quality Deterioration.**

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. The definition of vulnerable industries follows [Foley-Fisher, Gorton, and Verani \(2020\)](#): Automotive, Consumer goods: Durable, Energy: Oil & Gas, Hotel, Gaming & Leisure, Retail, Transportation: Cargo, and Transportation: Consumer.



(a) LSTA Lobbying by Year



(b) Asset Manager Survey, 2013

Figure IA.5: Industry Response to CLO Risk Retention.

Panel IA.5a of this figure shows the Loan Syndication and Trading Association's (LSTA) annual lobbying spending (Source: Center for Responsive Politics). Panel IA.5b shows the result of LSTA 2013 survey on asset managers' expected impact of US CLO Credit Risk Retention on the market.

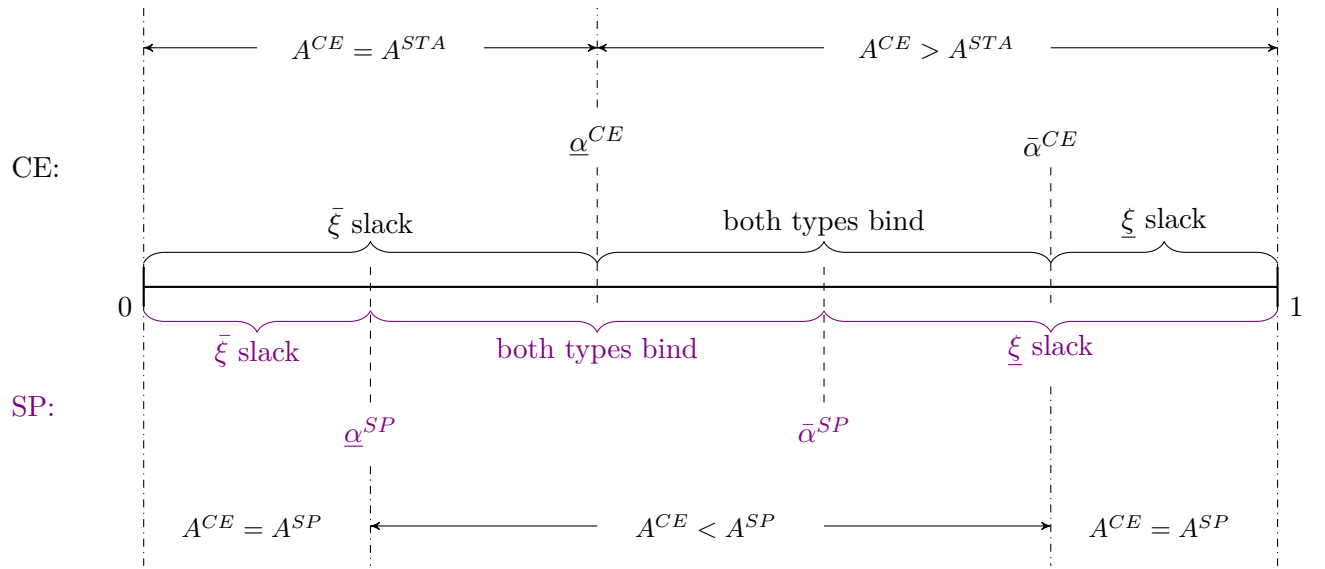


Figure IA.6: **Two-Type Case: Competitive and Planner's Allocations.**

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 managers.

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. *GovDebtGrowth* 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.	<i>Rating</i>			<i>Coupon</i>		
<i>AAA%</i>	1.68*** (6.39)	1.88*** (6.66)	1.76*** (6.43)	−2.94*** (−8.06)	−2.25*** (−6.21)	−2.25*** (−6.10)
ln(Size)		0.07** (2.62)	0.06** (2.85)		0.14*** (2.37)	0.01 (0.28)
Age		−0.01 (−1.25)			−0.03*** (−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.

Dep. Var.	(1)	(2)	(3)	(4)	(5)	(6)
	Entry Count			Entry Size (\$ mm)		
USmkt×CRR	−0.28*** (−5.01)	−0.31*** (−4.42)	−0.23*** (−3.53)	−130.58*** (−2.58)	−218.29*** (−3.28)	−184.19*** (−3.84)
USmkt×CRR×LargeMgr			−0.16 (−1.40)			−68.20 (−0.68)
USmkt	1.07*** (8.32)	1.37*** (8.54)	0.77*** (6.70)	829.96*** (7.55)	952.91*** (7.30)	414.14*** (5.73)
CRR	−0.06*** (−2.61)	−0.03 (−1.56)	−0.01 (−0.29)	−14.27 (−1.16)	−2.25 (−0.18)	3.10 (0.26)
LargeMgr			0.49*** (5.40)			353.61*** (4.83)
USmkt×LargeMgr			1.19*** (5.63)			1,077.55*** (6.00)
CRR×LargeMgr			−0.06 (−1.28)			−18.11 (−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