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. Section IA.4 analyzes competitive equilibrium and its efficiency properties when institutions' debt issuance costs are discrete. Section IA.5 analyzes equilibria with optimal safe debt maturity choices. Section IA.6 discusses imperfectly contractible loan types. Finally, Section IA.7 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.

[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.

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 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 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

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

[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.

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.

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

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

[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.

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 asymmetric price pressure makes maintaining portfolio quality costly for CLOs.

IA.4 Discrete Debt Issuance Cost Types

Consider the simplest case with heterogeneous debt issuance costs: institutions 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 institutions 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 results 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 $(\underline{x}^{SP}, \bar{x}^{SP}, \underline{a}_i^{SP}, \bar{a}_i^{SP})$

[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.

to denote respectively competitive and the planner's allocations.[7]

Proposition IA.1. *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 institutions underinvest, and the market underproduces safe debt: $\bar{x}^{CE} < \bar{x}^{SP}$, and $A^{CE} < A^{SP}$.*

Proof. In both competitive and the 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 (12)–(14) and (22)–(24) 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 convenience, I define $(\underline{x}, \bar{x}) := \Big(c'^{-1}(pR + 1 - p + \gamma - \underline{\xi}), c'^{-1}(pR + 1 - p + \gamma - \bar{\xi})\Big)$, which are the two types' lending choices in static securitization.

Both types bind: For the competitive market, this implies $\frac{(1-p)\pi}{1-p+\gamma-\underline{\xi}} < \frac{q_l}{q_h} < \frac{(1-p)\pi}{1-p+\gamma-\bar{\xi}}$, $(\underline{x}^{CE}, \bar{x}^{CE}) = \Big(\underline{x}, c'^{-1}(pR + (1-p)\pi\frac{q_h}{q_l})\Big)$, 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 $\underline{\alpha}^{CE} := (\bar{x} - x_L)\Big(\bar{x} - (1 - \frac{(1-p)\pi}{1-p+\gamma-\bar{\xi}} x_L)\Big)^{-1}$ and $\bar{\alpha}^{CE} := (\underline{x} - x_L)\Big(\underline{x} - (1 - \frac{(1-p)\pi}{1-p+\gamma-\underline{\xi}} x_L)\Big)^{-1}$. For the planner, both types facing binding collateral constraints implies $(\underline{x}^{SP}, \bar{x}^{SP}) = \Big(\underline{x}, c'^{-1}(pR + 1 - p + \psi^{SP})\Big)$ 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 $(1-\alpha)(\bar{x} - x_L) - \int_\alpha^1 \bar{a}_i^{CE}\, \mathrm{d}i$. 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 $\underline{\xi}$ 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 $\int_0^\alpha \underline{a}_i^{CE}\, \mathrm{d}i - \alpha(\underline{x} - x_L)$ and $(1-\alpha)(\underline{x} - x_L)$. Market clearing requires the demand to be no

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

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 $\bar{\xi}$ 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 (15).[8] 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. □

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

The intuition of this underproduction result is the same as that in Proposition 2. 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 institutions for whom issuing safe debt is privately optimal but socially inefficient.

IA.5 Analysis of Safe Debt Maturity Choice

This section provides the analysis omitted for brevity in Subsection 3.5 of the paper. I extend the model in two ways. First, I generalize risky loans' payoff distributions. This is needed because, as will be clear shortly, the distribution in Section 2 mechanically makes short-term debt an inferior choice. Second, I introduce outside loan buyers, as the absence of net cash trades in the secondary market makes early repayment impossible in equilibrium.

The generalized payoff distribution is as follows. I denote type $j \in \{h, l\}$ loans' fundamental value conditional on $t = 1$ signal $s \in \{+, -\}$ by $F_j^s := \mathbb{E}[R_j|s]$ and let f_j^s be the

[8] The intuition for this result is similar to that of Corollary 2.3: when constraints are slack for both individual institutions and the planner, the pecuniary externality does not affect the efficiency of allocation.

lower bound of the support of the conditional distribution.[9] The support of the conditional distribution can be any compact subset of $\mathbb{R}_+$ such that $f_h^+, f_h^- > 0$. To simplify the analysis, I assume $f_j^+ > F_j^-$ for $j \in \{h, l\}$ and $f_l^- = 0$, which preserves the intuition.[10]

Investors have access to a costly storage technology between $t = 0$ and $t = 1$, a process that I interpret as the formation of specialized capital for buying liquidated assets, such as distressed debt strategy funds. Storing every unit of consumption goods incurs a constant cost $\kappa > 0$, which captures the difficulty of participating in the secondary market. Let such outsider buyers' demand for loan j be z_j. The market clearing condition in period $t = 1$ thus becomes

$$\int_i \Delta x_{i,j} \,\mathrm{d}i + \frac{z_j}{q_j} = 0 \quad \text{for } j \in \{h, l\}. \tag{IA.2}$$

In period $t = 0$, institutions can issue both short-term and long-term safe debt, so the initial collateral constraint becomes

$$\min\left\{a_i \frac{q_h}{f_h^-}, a_i\right\} \leq \sum\nolimits_j x_{i,j} q_j. \tag{IA.3}$$

This constraint requires the portfolio value to be enough for the institution to keep debt safe through either portfolio substitution or early repayment. Which of these two allows for a larger safe tranche depends on loan prices: Long-term contract maximizes safe debt capacity if $q_h \leq f_h^-$, and vice versa.

Now the institution's decision problem in period $t = 1$ includes debt repayment. Since institutions can prepay long-term debt or roll over short-term debt, maturity choice is effectively a repayment choice. Let Δa_i be the net change in safe debt (i.e., $\Delta a_i < 0$ is a repayment). The institution chooses $\Delta x_{i,h}, \Delta x_{i,l}, \Delta a_i$ to maximize equity payoff subject to budget constraint

$$\sum\nolimits_j (x_{i,j} + \Delta x_{i,j}) q_j \leq \sum\nolimits_j x_{i,j} q_j + \Delta a_i, \tag{IA.4}$$

maintenance collateral constraint

$$a_i + \Delta a_i \leq (x_{i,h} + \Delta x_{i,h}) f_h^-, \tag{IA.5}$$

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

[9] Accordingly, Assumption 1 is generalized to $c'(\bar{x}_l) < pF_h^+ + (1-p)F_h^-$.

[10] As long as f_l^- is sufficiently lower than f_h^-, replacing bad loans with good loans improves the worst-possible portfolio payoff, and dynamic portfolios can increase long-term safe debt capacity.

IA.5.1 The Institution's Choices

I first analyze the institution'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 institution takes prices as given and solves

$$v(x_{i,h}, x_{i,l}, a_i) = \max_{\Delta x_{i,h}, \Delta x_{i,l}, \Delta a_i} \quad \textstyle\sum_j (x_{i,j} + \Delta x_{i,j}) F_j^- - (a + \Delta a_i), \tag{IA.6}$$

subject to the budget constraint (IA.4), maintenance collateral constraint (IA.5), and the short-sale constraints. Similar to the baseline model, this problem can be simplified to

$$\max_{\Delta x_{i,l}, \Delta a_i} \quad \Delta x_{i,l} \Big(F_l^- - F_h^- \frac{q_l}{q_h} \Big) + \Delta a_i \Big(\frac{F_h^-}{q_h} - 1 \Big), \tag{IA.7}$$

subject to constraints

$$\Delta x_{i,l} f_h^- \frac{q_l}{q_h} + \Delta a_i \Big(1 - \frac{f_h^-}{q_h} \Big) \leq x_{i,h} f_h^- - a_i, \tag{IA.8}$$

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

The institution's optimal choices depend on balance sheet at $t = 0$ and loan prices at $t = 1$. The following lemma pins down a sufficient and necessary condition for the institution 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 $q_h > f_h^\star := f_h^- + \frac{q_l}{F_l^-}(F_h^- - f_h^-)$.*

Proof. To see that $q_h > f_h^\star$ is sufficient, note that this inequality implies $\frac{q_h}{F_h^-} > \frac{q_l}{F_l^-} + \frac{f_h^-}{F_h^-}\Big(1 - \frac{q_l}{F_l^-}\Big) \geq \frac{q_l}{F_l^-}$, which in turn implies that the objective in problem (IA.7) is strictly increasing in $\Delta x_{i,l}$. So constraint (IA.8) binds, and the objective reduces to $\Delta a_i \frac{F_l^-(f_h^\star - q_h)}{f_h^- q_l}$, which strictly decreases in Δa_i. Therefore $\Delta a_i = -a_i$ 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 (IA.7) would reduce to $\Delta a_i \Big(\frac{F_h^-}{q_h} - 1\Big)$, which strictly increases in Δa_i. Hence, the objective reduces to $\Delta a_i \frac{F_l^-(f_h^\star - q_h)}{f_h^- q_l}$, and $q_h > f_h^\star$ is also necessary. □

Intuitively, the institution wants to repay debt early if and only if q_h is sufficiently high. In this case, after the repayment, the institution can hold only low-quality loans and expect a high equity return. By contrast, if $q_h \leq f_h^\star$, delaying repayment by holding sufficient high-quality loans is desirable. Whether the desirable actions are feasible is determined by inequality (IA.3). For example, an institution with short-term safe debt may have to repay in bad times even if its ex-post desired action is to rollover.

The institution's maturity choice at $t = 0$ is thus based on a tradeoff between ex-ante safe debt capacity and the payoff of ex-post actions. Under the distribution in Section 2, $q_h \leq f_h^-$, and short maturity is strictly dominated because early repayment maximizes neither ex-ante safe debt nor the institution's ex-post payoff. Therefore, it was without loss of generality to restrict attention to long-term safe debt.

IA.5.2 Outsider Purchase

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

$$z_j(q_j) = \begin{cases} +\infty, & (1-p)\left(\frac{F_j^-}{q_j} - 1\right) > \kappa \\ \forall z \in \mathbb{R}_+, & (1-p)\left(\frac{F_j^-}{q_j} - 1\right) = \kappa \\ 0, & (1-p)\left(\frac{F_j^-}{q_j} - 1\right) < \kappa \end{cases}. \tag{IA.9}$$

Since storage is costly, the type(s) 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.5.3 Equilibrium

Similar as before, the institution's financing is constrained by price-dependent collateral constraints (IA.3). The difference is that now prices are affected by both institutions and investors. Hence, 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.

Proposition IA.2 (Equilibrium with Maturity Choice)**.** *Depending on parameter values, there are four types of equilibrium, each featuring a different mix of institution liabilities:*

(i) Long-term debt and equity. There exists a unique $\lambda^{lt} \in (0, 1)$ *such that institutions* $[0, \lambda^{lt}]$ *issue long-term safe debt, and the rest issue only equity. In bad times, institutions*

trade with each other, and no loan is sold to outside buyers.

(ii) Short-term debt, long-term debt, and equity. There exist a unique pair of $\lambda^{st}, \lambda^{lt}$, where $0 < \lambda^{st} < \lambda^{lt} < 1$, such that institutions $[0, \lambda^{st}]$ 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 debt and long-term debt. There exists a unique $\lambda^{st} \in (0, 1)$ such that institutions $[0, \lambda^{st}]$ 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 debt. All institutions issue short-term safe debt, and all 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 ($a_i \frac{q_h}{q_l} \le a_i$), and $\Delta a_i = 0$ is ex-post desirable. The equilibrium has an interior cutoff and is unique with respective 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, $q_l \ge \frac{(1-p)F_l^-}{1-p+\kappa}$. The equilibrium exists when κ is relatively large with respect to γ.

Case 2: $q_h \in (f_h^-, f_h^\star]$. 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 $\frac{q_l}{q_h} \le \frac{F_l^-}{F_h^-}$ holds, otherwise there is either zero demand for low-quality loans or infinite demand for high-quality loans.[11] Hence, constraint (IA.8) binds, and optimal secondary market trades can be derived accordingly. There are generally three types of liabilities for institutions to choose from.

(i) If an institution 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 institution's marginal payoff from lending is $y_i^e := pF_h^+ + (1-p) F_l^- \frac{q_h}{q_l}$, and its payoff is

$$V_i^e = y_i^e c'^{-1}(y_i^e) - c(c'^{-1}(y_i^e)) - x_{i,l}\Big(p(F_h^+ - F_l^+) + (y_i^e - pF_h^+)\Big(1 - \frac{q_l}{q_h}\Big)\Big). \quad \text{(IA.10)}$$

(ii) If an institution 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 $v^{lt} = (x_{i,h} \frac{q_h}{q_l} + x_{i,l}) F_l^- -$

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

$a_i(1+\frac{q_h F_l^-}{q_l f_h^-}-\frac{F_h^-}{f_h^-})$. At $t=0$, the institution faces constraint $a_i \le (x_{i,h}+x_{i,l}\frac{q_l}{q_h})f_h^-$, 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

$$V_i^{lt}=y_i^{lt}c'^{-1}(y_i^{lt})-c(c'^{-1}(y_i^{lt}))-x_{i,l}\Big(p(F_h^+-F_l^+)+(y_i^{lt}-pF_h^+)\Big(1-\frac{q_l}{q_h}\Big)\Big). \quad \text{(IA.11)}$$

(iii) If an institution 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 $\Delta x_{i,h}=\frac{x_{i,h}f_h^-+x_{i,l}q_l-a_i}{q_h-f_h^-}, \Delta x_{i,l}=-x_l$. 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 institution faces constraints $a_i\le x_{i,h}q_h+x_{i,l}q_l, (x_{i,h}+x_{i,l}\frac{q_l}{q_h})f_h^- \le a_i$, 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

$$V_i^{st}=y_i^{st}c'^{-1}(y_i^{st})-c(c'^{-1}(y_i^{st}))-x_{i,l}\Big(p(F_h^+-F_l^+)+(y_i^{st}-pF_h^+)\Big(1-\frac{q_l}{q_h}\Big)\Big). \quad \text{(IA.12)}$$

The following observations suggest a pecking order among these liability choices. First, $q_h\in(f_h^-,f_h^\star]$ implies $\frac{F_h^- - f_h^-}{q_h-f_h^-}-(\frac{q_h F_l^-}{q_l f_h^-}-\frac{F_h^-}{f_h^-})=-\frac{q_h(q_h-f_h^\star)}{(q_h-f_h^-)q_l f_h^-}\ge 0$, which further implies $\eta_i^{lt}\ge\eta_i^{st}$. 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, institution 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, an institution 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 (IA.2) 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 $q_h\le f_h^-+\frac{1}{\gamma}(1-p)(F_h^- - f_h^-)$, $q_l\ge\frac{(1-p)F_l^-}{1-p+\kappa}$, 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, institutions with long-term safe debt buy all high-quality loans sold by institutions with short-term safe debt and institutions with only equity. Low-quality loans are bought by institutions 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, institutions with long-term safe debt buy all high-quality loans sold by institutions 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: $q_h \in (f_h^\star, F_h^-]$. 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 institutions issuing safe debt will choose short maturity and that $q_h > f_h^\star$ 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 (IA.2). So this case cannot be an equilibrium. □

Type-i equilibrium arises when the cost of storage, κ, is relatively high. In this case, short maturity either fails to maximize debt capacity, or its capacity advantage is overwhelmed by the cost of early liquidation. Hence, long maturity is preferred, and institutions 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 safe debt capacity, ex post it is more costly to liquidate loans than to substitute portfolios. A greater debt capacity is more valuable for institutions facing lower costs of debt issuance. So in equilibrium, only institutions with sufficiently low issuance costs choose short maturity, and other institutions issue long-term safe debt or only equity. In bad times, the first group of institutions liquidate loans, whereas the second and third groups substitute portfolios. Outside buyers absorb low-quality loans, which provide a higher return. High-quality loans change hands among institutions.

Type-iv equilibrium arises when outsiders' storage cost is sufficiently low. In this case, the cost of early liquidation is smaller than the benefit of greater debt capacity. Hence, all institutions optimally issue short-term safe debt to exploit cheap financing and liquidate their entire portfolios when negative news arrives.

IA.6 Imperfectly Contractible Loan Types

To allow for imperfectly contractible loan types, I consider that unlike in (4), a contract asking the institution to hold at least m_i units of eligible loans at $t = 1$ can only enforce

$$m_i \leq x_{i,h} + \Delta x_{i,h} + \rho(x_{i,l} + \Delta x_{i,l}). \tag{IA.13}$$

The right hand side of (IA.13) is the quantity of eligible loans after the institution chooses trades $\Delta x_{i,h}, \Delta x_{i,l}$. From the institution's perspective, every unit of high-quality loans will be eligible with certainty, but only a $\rho \in (0, 1)$ fraction of low-quality loans that are currently eligible will continue to be eligible post trade. Thus, parameter ρ captures credit ratings' inaccurate and slow reaction to changes in loan quality: The greater ρ is, the more low-quality loans can be mixed into the required eligible holdings. The value of ρ is common knowledge at $t = 0$, but the quality of loans is only observed by institutions at $t = 1$.

When a negative signal reveals, institutions with debt outstanding may attempt to "reach for yield" by choosing a portfolio with $x_{i,h} + \Delta x_{i,h} < a_i$, which provides a higher expected equity payoff and makes debt default with a positive probability. From an ex-ante perspective, if the contract cannot effectively prevent institutions from doing this in bad times, the debt tranche is not safe.

In this setting, contracts based on noisy risk measures (i.e., $\rho > 0$) may still make debt safe. Given budget constraint (3), the institution must give up q_l/q_h units of high-quality loans when adding one unit of low-quality loans into its portfolio. This unit fulfills only $\rho < 1$ units of eligible loans because $1 - \rho$ of low-quality loans will become ineligible (e.g., downgraded). If ρ is small, adding low-quality loans into the portfolio decreases eligible holdings. In this case, the institution is constrained by the quantity of low-quality loans that can be possibly held without violating constraint (IA.13). Hence, by setting a sufficiently large m_i, the contract can still force the institution to hold enough high-quality loans and thereby make debt safe.

By contrast, when ρ is large, the right hand side of (IA.13) would be increasing in $\Delta x_{i,l}$, so the contract cannot prevent the institution from adding low-quality loans into the portfolio. The following proposition provides the condition under which the contract can make debt safe.

Proposition IA.3 (Contracting on Noisy Risk Measures)**.** *When contractible risk measures are sufficiently informative about loan quality ($\rho < q_l/q_h$), safe debt capacity is the not affected by the possibility of ex-post risk shifting. If $\rho > q_l/q_h$, institutions cannot create any safe debt backed by dynamic portfolios.*

Proof. When the public signal at $t = 1$ is negative, the institution maximizes the same objective as in problem (8). If $\rho < q_l/q_h$, constraint (IA.13) implies that the constrained optimal trading choice is

$$\Delta x_{i,l} = \max\left\{\frac{x_{i,h} + \rho x_{i,l} - m_i}{\frac{q_l}{q_h} - \rho}, -x_{i,l}\right\}, \tag{IA.14}$$

where m_i is the eligible holding required by the contract. If the contract specifies $m_i = a_i = x_{i,h} + x_{i,l}\frac{q_l}{q_h}$ at $t = 0$, the institution would choose $\Delta x_{i,l} = -x_{i,l}$, which leads to $x_{i,h} + \Delta x_{i,h} = a_i$. So the contract creates the same amount of safe debt as in the case where $\rho = 0$.

Instead, if $\rho > q_l/q_h$, the institution would choose $\Delta x_{i,l} = x_{i,h}\frac{q_h}{q_l}$ as long as m_i is not too large (otherwise the constraint can never be satisfied). This leads to $x_{i,h} + \Delta x_{i,h} = 0$, and no safe debt can be created at $t = 0$. □

Proposition IA.3 shows that perfectly contractible loan types are not a necessary condition for creating safe debt backed by dynamic portfolios. Perhaps surprisingly, as long as contractible risk measures are sufficiently informative, the noises in these measures have no influence on the size of safe tranches: Although ex post, the collateral constraint can be possibly satisfied without keeping debt safe, an institution who has fully used debt capacity ex ante will be forced to replace the entirety of low-quality loans in bad times, which keeps debt safe.

This result reveals an economic link between secondary market prices and the effectiveness of enforceable contracts: If loan prices are severely distorted away from the fundamentals, the contract would not be able to constrain the institution's risk shifting, and it would be impossible to create safe debt backed by dynamic portfolios.

IA.7 Supplementary Empirical Analysis

IA.7.1 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

$$Quality_{it} = \beta AAA\%_i + \Gamma' Control_{it} + \delta_t + \epsilon_{it}, \tag{IA.15}$$

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.[12] 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

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

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.[13]

IA.7.2 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 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

$$Entry_{imt} = \beta_0 + \beta_1 USmkt_{im} \times CRR_t + \beta_2 USmkt_{im} + \beta_3 CRR_t + \Gamma' Control_{m,t-1} + \epsilon_{imt}, \quad \text{(IA.16)}$$

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.

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

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

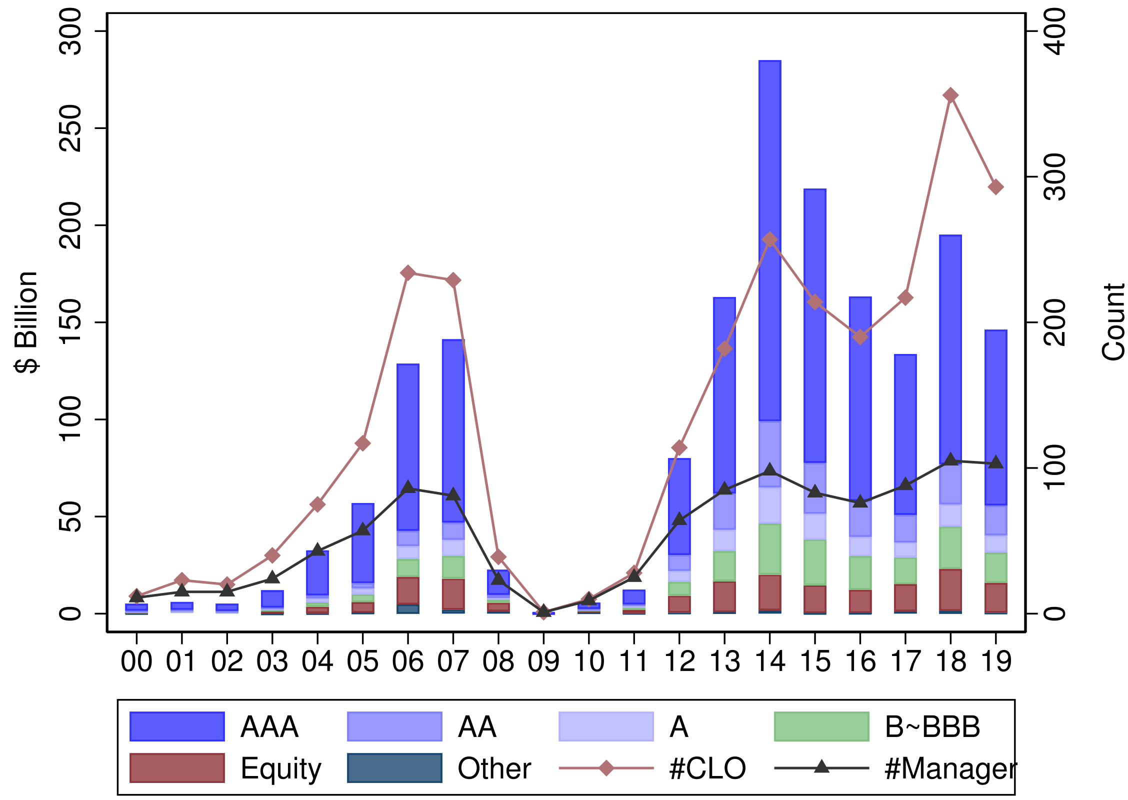
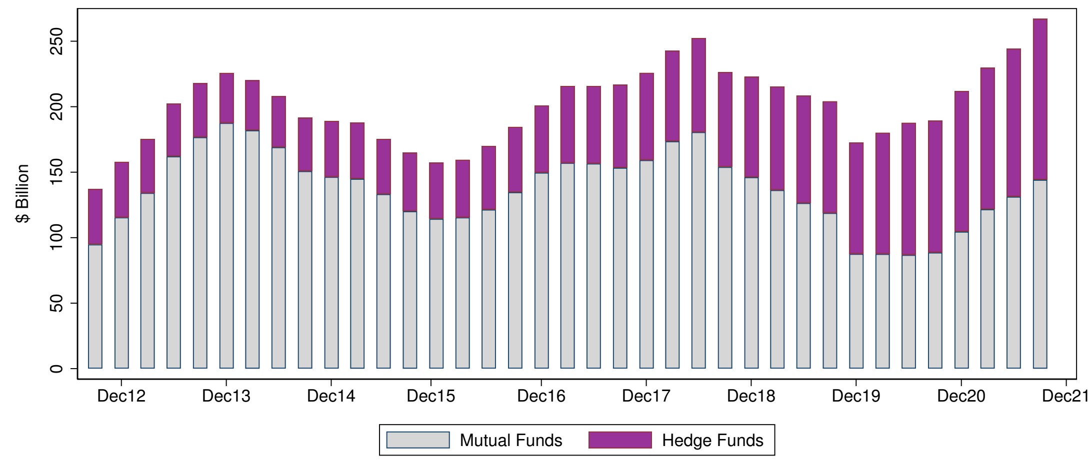
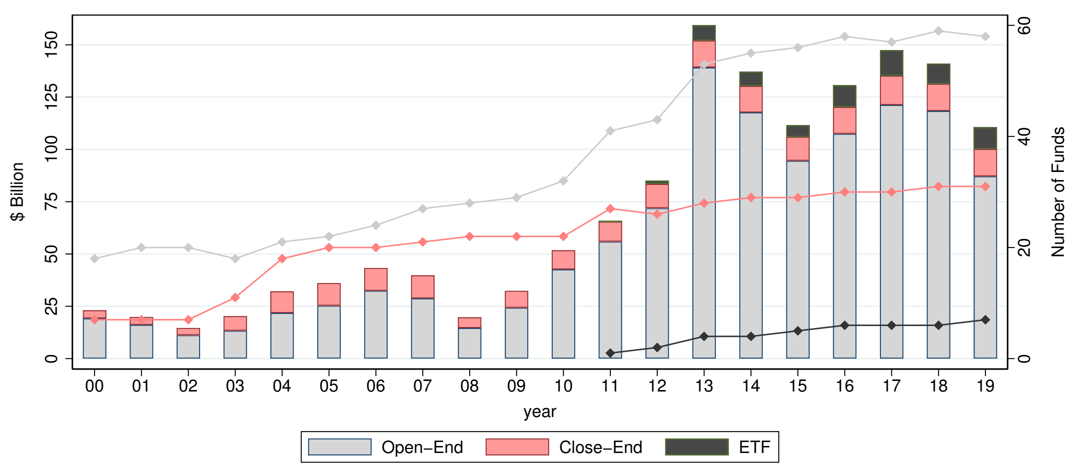


Figure IA.1: **CLO Issuance.**
This figure plots annual issuance of open-market CLOs in the US and Europe between 2000–2019. The issuance amount is by CLO tranche, identified based on initial credit ratings. Tranche size denominated in Euros are converted to USD using the exchange rate at issuance date. 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.

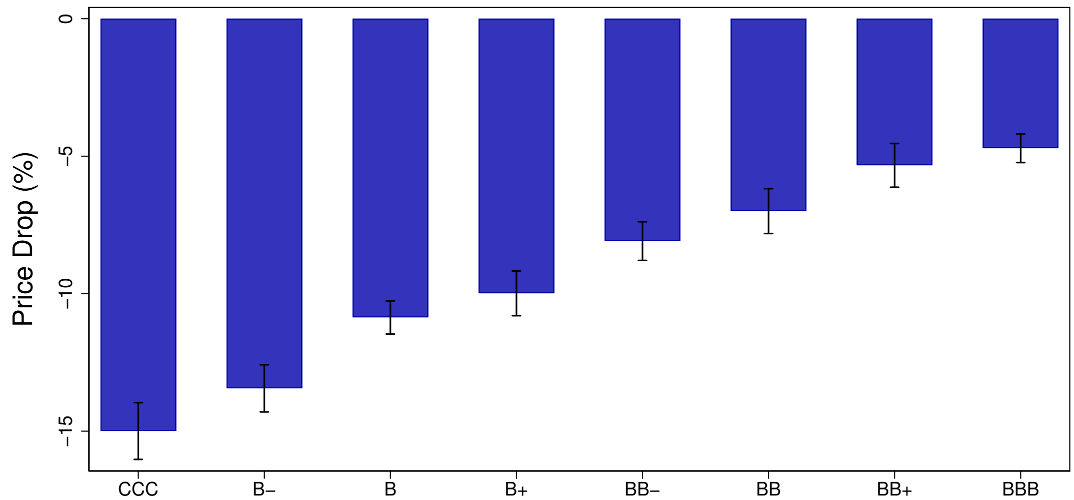


(a) Leveraged Loans Held by Mutual Funds and Hedge Funds

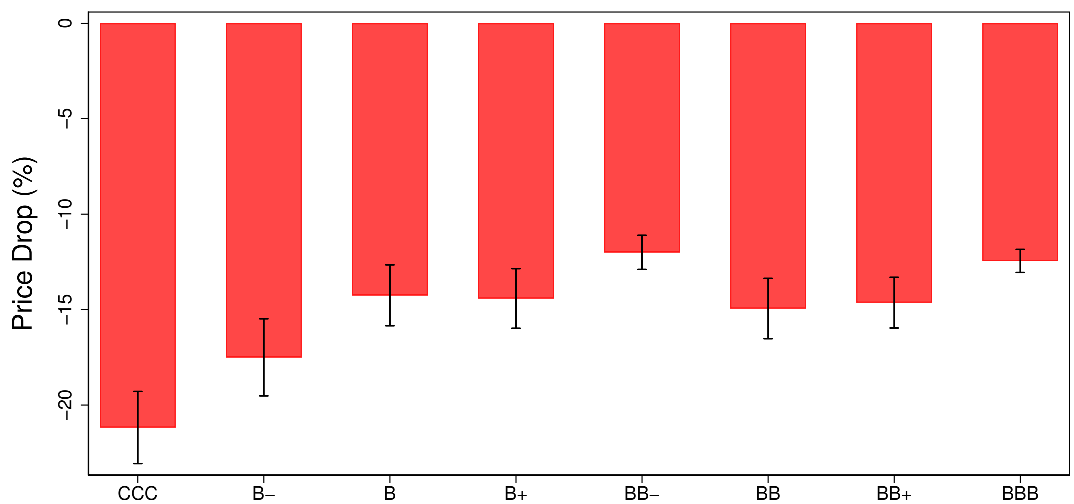


(b) Composition of Public Loan Funds

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.

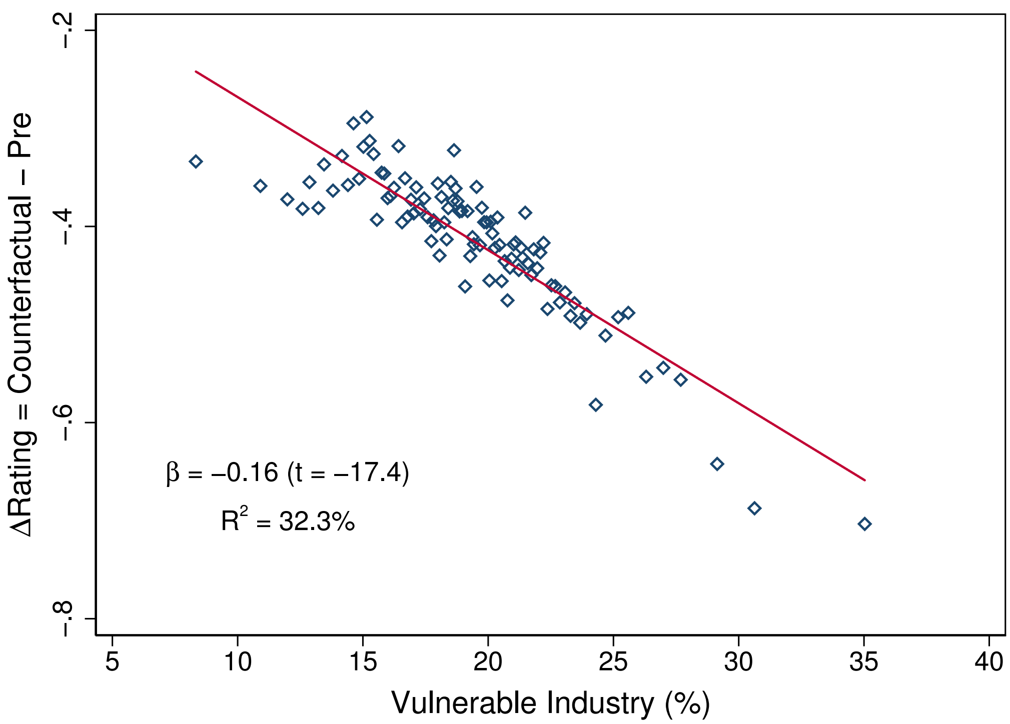
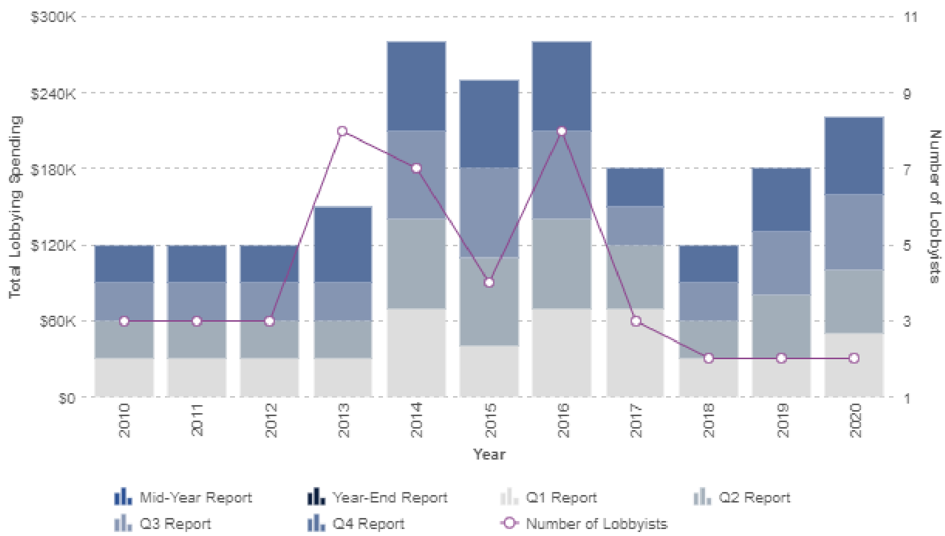
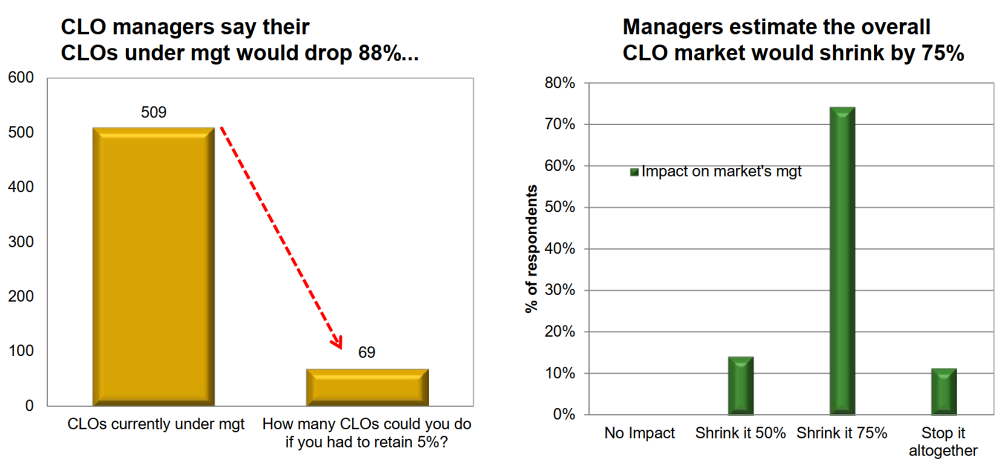


Figure IA.4: **Exposure to Vulnerable Industries and Counterfactual Quality Deterioration.**
This figure is a scatter plot that groups CLOs into 100 bins by portfolio weight in industries vulnerable to the COVID-19 pandemic before February 15, 2020 and depict the average counterfactual portfolio value-weighted average credit rating change between February 15 and June 30, 2020 within each bin.



(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.

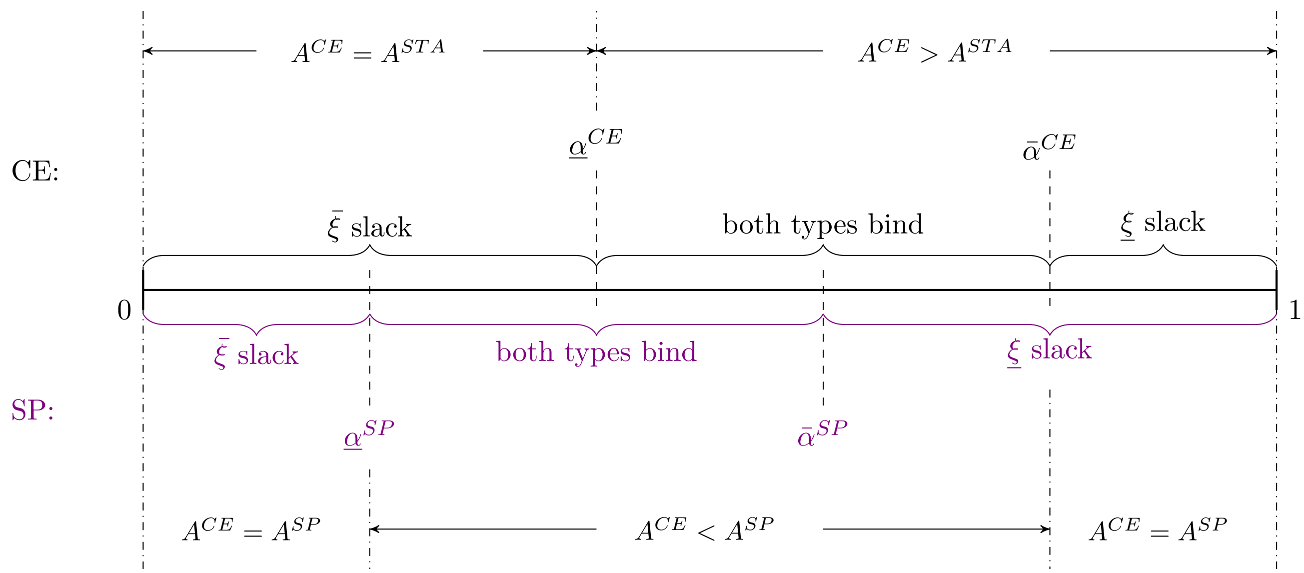


Figure IA.6: **Two-Type Case: Competitive and Planner's Allocations.**
This figure illustrates how the competitive and planned allocations in the two-type case depend on $\alpha \in (0, 1)$, the fraction of low-cost type institutions.

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