Are CLO Collateral and Tranche Ratings Disconnected?*

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Abstract

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1. Introduction

COVID-19 has imposed significant financial stress across a wide-swath of companies with market forecasts calling for bankruptcy levels likely to exceed that of 2009.[1] This type of economic shock provides a window to examine credit rating agency responsiveness and processes in two large, inter-connected credit rating markets that differ in their structures. Rating agencies took downgrading actions against a large share of the corporate debt market from March through May. This debt, typically B-rated corporate loans, commonly backs the claims issued by a CLO. As a result, approximately one-fourth of the market capitalization of CLO collateral was downgraded by Moody's or S&P from March through August 2020. Yet, over this same period only two percent of tranches by par-value were downgraded and approximately five and one-half percent placed on credit watch. This paper examines six possible explanations for the attenuated relationship between asset and tranche downgrading behavior.

Credit rating agencies, like other organizations, often face conflicting forces of reputation and financial incentives. Rating agencies wish to build reputation through timely and unbiased credit ratings, but they also compete for business from underwriters who commonly make larger profits with higher credit ratings.[2] One aspect of credit ratings that received considerable attention in the last financial crisis is that structured finance ratings are often shrouded with complexity and opacity [Skreta and Veldkamp (2009) and Sangiorgi and Spatt (2017a)] which potentially allows for more rating inflation and catering. The competing forces could vary substantially within the organization based on market segment. In more transparent markets, reputational concerns are more apparent, but in sectors where the rating process is more opaque, financial incentives may increase in relative importance. For a corporation experiencing large negative financial shocks, it might be readily apparent to

[1] A report by Fitch indicates that: " At the current rate, the annual volume of corporate defaults could exceed the record set during the global financial crisis in 2009."

[2] Mathis et al. (2009) model how rating agencies may build and burn their reputation and Bolton et al. (2012) model how rating inflation is more likely to occur during booms.

market participants that credit risk has drastically increased; rating agencies will appear inept if they do not act quickly to downgrade. Direct market discipline may be less effective if rating accuracy is shrouded from market participants by a financial product's complexity. We examine rating agency activity in two markets that generate cash flows from a common set of underlying assets but with vastly different levels of rating opacity.

A tenant of rating agency methodologies is that credit risk of the underlying collateral pool determines the overall credit risk of a CLO's tranches. If assets in a CLO pool suddenly experience an increase in credit risk, this will decrease the value of the underlying assets and thus the value of tranches built upon these assets. Structured products are typically rated "at-the-edge," meaning that they are structured to maximize the permissible size of the higher-rated tranches while still retaining a given rating. Hence, CLOs have little cushion when structured. Given this institutional feature, one might expect that rating-implied deterioration of CLO collateral quality should map to a deterioration in tranche quality and ratings.

We examine the recent rating activity of $591B of CLO debt issued between 2014 and 2019 from a set of 1185 CLOs backed by approximately 337k pieces of collateral. Beginning in March and accelerating in April, both S&P and Moody's began downgrading large amounts of collateral. Collateral downgrades stabilized by mid-June, with S&P downgrades standing at 30% of the par-weighted CLO assets while Moody's downgraded 26% of their rated collateral at the end of August. In contrast, the par-weighted percent of tranches downgraded is 2% for S&P and 1.75% for Moody's. When considering tranches placed on negative credit watch these magnitudes increase slightly to approximately 3.5% and 5.5%, respectively.

We examine six potential explanations for this discrepancy in rating actions taken across the two markets. First, CLO collateral deterioration may have heterogeneous effects across tranches. If the change in model-implied risk is concentrated in the equity and subordinate tranches this could explain the small percentage of collateral downgrades. Second, perhaps rating agency models do call for more widespread downgrades, but rating agencies are placing weight on non-model considerations in determining ratings. Third, rating agencies could be delaying tranche downgrades because they were too aggressive in their collateral downgrades. Fourth, it is possible that CLOs accumulated a protective cushion through collateral out-performance between issuance and the start of the COVID-crisis. If this is the case, recent collateral deterioration may simply cut into the cushion, while tranches will experience little downgrading. Fifth, active CLO management may generate profits from distressed purchases.[3] Sixth, rating agency methodologies may be ill-suited to evaluate tranche risk. This might entail either strategic trading by managers to reduce model-implied collateral risk. This paper examines the empirical validity of each explanation for the disconnect between CLO collateral and tranche ratings.

We find evidence consistent with two main explanations. First, rating agencies appear to be taking into account non-model considerations in their rating actions. We find that the actions taken by Moody's against CLO tranches does not correspond to previous rating agency announcements, particularly for more senior tranches. For example, conditional on a 15% increase in collateral credit risk, Moody's announcements indicate that 29.2% of Aaa tranches are expected to experience a one notch downgrade, while no AAA tranche experiencing this level of collateral deterioration has been downgraded. We find similar patterns for tranches rated Aa1 down to A3. Based on Moody's disclosures and observed collateral deterioration, we estimate that 9.2% of Aaa rated tranches would be downgraded by August 2020. For S&P, 8% of AAA tranches do not meet S&P's primary modeling criteria according to trustee reports. S&P has not downgraded nor placed any AAA tranches on credit watch.

Second, managerial trading behavior reduces model-implied credit risk. This comes in two forms. First, managers sell lower-rated collateral and purchase safer collateral. The result is

[3] "This will be an opportunity for CLO managers to differentiate themselves, through credit selection, trading decisions and portfolio management" [Haunss (2020)].

a decrease in rating-implied collateral risk relative to static pools formed in January 2020.[4] Second, managers actively tilt collateral pools towards shorter-maturing collateral over the March through August 2020 period, with stronger effects among CLOs that experienced a greater deterioration of collateral quality. Both Moody's and S&P's rating methodologies consider collateral maturity when evaluating credit risk, with shorter maturing loans being assigned a lower default probability. While it is unclear from an economic standpoint why sequentially purchasing two three-year loans is safer than a six-year loan with the same credit rating, managers are actively trading into shorter credits and reducing their model-implied credit risk.

Ultimately, we do not find evidence consistent with four potential explanations. First, the model-implied effects of collateral deterioration fall relatively evenly across tranches rather than being heterogeneous in their effects. This result comes from both rating agency disclosures and simulations based on S&P's credit risk model. Second, initial collateral downgrades do not appear to be an overreaction; Collateral pricing data generally lines up with collateral rating actions. Third, an examination of overcollateralization ratios does not indicate any increase in collateral cushions prior to the COVID-19 crisis. Instead, we find that underlying pools generally increased in risk between issuance and January 2020. Fourth, we do not find consistent evidence of trading out-performance by collateral managers when comparing future returns of collateral purchases relative to sales.

Overall, we find evidence consistent with delayed rating agency action and strategic managerial trading, potentially in response to rating agency methodological choices. To gauge the relative magnitude of these effects, we model collateral risk under a set of counterfactual scenarios in which we shut down each active management channel. While 8% of AAA tranches have a reported SDR that exceeds its BDR in August 2020, we find that this share increases to 12.5% when removing the modeling effects of shortening a collateral pool's ma-

[4]Note, it is unclear if this action decreases CLO risk, as managers trading out of riskier assets and into safer collateral is typically associated with a reduction to either par amounts or the pool's weighted-average coupon.

turity. We find larger effects associated with managers trading out of risky collateral, as the share of CLOs with an SDR exceeding its BDR increases to 17.25% under a counterfactual where managers do not actively trade out of risky collateral. Overall, this suggests that model-implied collateral risk would be considerably greater, had managers not positioned their portfolios to at least appear safer to rating agency criteria. Interestingly, we also find that 2019 changes by S&P to their criteria have increased model leniency such that 13.4% of deals (instead of 8%) would be failing in August 2020 under the former approach.

Ultimately, we are not able to provide an explanation for the consideration of non-model criteria by rating agencies or the potential delay of downgrade actions. A large literature finds rating inflation [Ashcraft et al. (2010) and Griffin and Tang (2012)] and conflicts of interest [He et al. (2012), Griffin et al. (2013), and Efing and Hau (2015)] in RMBS and CDO ratings in the 2000 to 2007 period. These activities are linked to the problems of catering for higher ratings as summarized by Sangiorgi and Spatt (2017b) and modeled as a 'race-to-the-bottom' (Golan et al. (2015)) to compete for favorable ratings. Cornaggia et al. (2017) demonstrate that ratings are considerably less accurate in the asset classes with more complexity. As part of S&P's settlement with the DOJ from the financial crisis, a statement of facts states that S&P "company executives complained that the company declined to downgrade under-performing assets because it was worried that doing so would hurt the company's business." Substantial scrutiny and effort was spent on credit rating agency reforms as part of the 2010 Dodd-Frank Act. Nevertheless, Flynn and Ghent (2018) find catering with higher ratings among new entrants in the CMBS market from 2009 to 2014 and Baghai and Becker (2018) find that S&P issued higher ratings to regain market share on fusion CMBS ratings in 2012.[5] Overall, our work contributes to this literature by suggesting that rating agencies' standards may differ across asset classes even when dealing with similar underlying assets. These findings may have important implications for other areas of structured finance that also exhibit opacity in credit ratings. While market reforms

[5]Loumioti and Vasvari (2019) find evidence of CLO managers engaged in strategic trading to pass overcollateralization tests.

like Dodd-Frank sought to decrease reliance on credit ratings, current Fed actions segment debt markets (including CLOs) by credit ratings. These issues are important to policy makers and investors as inaccurate credit ratings have the potential to harm investors, mis-allocate capital, and create systemic risk.

2 Data and Summary Statistics

This section describes our data, sample selection procedure, and reports summary statistics for the final sample.

2.1 Data and Sample Selection

Our data are from Bloomberg and collected from trustee reports. Information on collateral pool holdings and trades, deal and tranche characteristics, some performance metrics (e.g., WARF), are obtained from monthly trustee reports. From Bloomberg, we gather information on tranche rating actions, collateral pricing information, and supplementary information regarding collateral pool holdings.

To construct a recent sample of CLOs, we begin by collecting the collateral holdings data for all CLOs with closing dates from 2014 through 2019. After identifying all deals closing on or after 2014, we collect all holdings reports (typically reported at the monthly level) from January 2020 to August 2020. This data typically includes information such as security and issuer names, loan quantities, reported ratings from Moody's, S&P, and Fitch. As our interest is on the relation between collateral and tranche performance, we restrict the sample to holding snapshots in which one of Moody's or S&P rates at least 85% of the par value of collateral. For these CLOs, we collect all trades from January to August 2020.

Next, we collect holdings data on collateral pools from Bloomberg, which provides additional fields not present in our primary holdings data. Specifically, Bloomberg collateral data typically includes reported Moody's and S&P industries as disclosed in the trustee reports and unique identifiers (i.e., FIGIs). We construct a matching algorithm based on commonality in holdings, quantities, maturity dates, and to some extent security names to establish a link between the two datasets, with a final par-weighted matching rate of 97.7%. Details of the procure can be found in the appendix. Note, while the ability to link the two holdings data is not necessary for all tests, it does lend itself to analysis that incorporates S&P's rating methodology or Bloomberg's valuation model of the underlying collateral values. For one test, we also collect data from 986 Moody's rating announcements obtained from Factiva.

2.2 Summary Statistics

With our sample in hand, we begin by briefly characterizing the structure of a CLO and the trading behavior of collateral managers. Table 1 reports summary statistics at the deal, holding snapshot, and trade level. Our sample consists of 1,185 CLOs representing 8,763 tranches. The average deal in our sample has a total tranche par of slightly less than \$500M, yielding an aggregate sample par size of \$591B. The average deal in our sample has 7.4 tranches, with a AAA tranche size of 60.6% and an equity slice of 10.3%. Backing these tranches is a collateral pool with an aggregate par of \$483M, made up of 285 loans from 255 obligors. The collateral is relatively diverse in its industry origins, with an inverse HHI of 22.9 (based on S&P's industry classifications). Finally, after mapping ratings to numerical values, we see that Moody's evaluation of the collateral is slightly more favorable than S&P, with average ordinal ratings of 14.43 for Moody's and 14.73 for S&P.[6] Finally, we see that the average collateral manager is quite active in trading, as 429k trades equates to approximately 47 trades per deal-month. These trades average \$514k in size, for loans that yield 6.8% and have a remaining maturity of 5.20 years.

We continue by graphically depicting the composition of ratings for collateral and tranches of a typical CLO. footnoteNote, here we restrict the sample to CLOs for which we have full coverage for tranche ratings. This results in a slightly smaller sample. Figure 1 shows the

[6]For reference, B+ and B map to ordinal values of 14 and 15).

average collateral composition on the left and average tranche structure on the right. S&P ratings are in blue, Moody's orange, and Fitch pink. Panel A shows that the vast majority of capital has ratings by both S&P and Moody's or all three major rating agencies. The tranche side shows that the majority of par is rated AAA, most frequently carrying a dual rating. Moody's has more market share in the AAA classes followed by Fitch and then S&P. Most tranches AA and below carry single ratings, typically from Moody's or S&P. Finally, CLO issuance in our sample generally increased from 2014 to 2018, before decreasing in 2019.

Panel B shows that the structure of collateral ratings has not experienced large changes over the period, with the majority of collateral holding a B rating. In contrast AAA tranche sizes have steadily increased from 2014 to 2017. This has largely been at the expense of more subordinate tranches. This could suggest that CLO modeling has become lenient over time; while interesting for context, our analysis is focused on the rating agency activity in 2020.

2.3 Market Conditions

COVID-induced stress on the economy brought with it a wave of firm bankruptcies and a non-trivial fraction of credit rating downgrades among corporate debt. To this end, we now examine the impact on the loans underlying CLOs. In evaluating the potential deterioration, we consider both the timing and magnitude of rating-implied changes in collateral risk.

Figure 2 begins by examining the relative change in implied risk by initial collateral rating. Specifically, we first map the credit rating of each underlying loan to the 10-year asset default rate for the corresponding rating agency, scaled by 10,000. Using rating agency terminology this corresponds to the 'rating factor' used by Moody's, from which a collateral pool's WARF (weighted-average rating factor) is derived. We then partition collateral based on credit ratings at the start of 2020 and re-compute the rating factor for each initial rating group through time, weighted by total par held across CLOs in the sample as reported in January 2020. Panel A reports the time-series evolution of WARF by initial rating, scaled by the initial value. The panel shows that S&P rated collateral began to deteriorate in early

March through early April, with a more gradual deterioration in May which extends to the start of July. By June, WARF has increased between 10% and 20% across rating classes, with the largest relative decline among BB-rated loans.

Moody's also started to downgrade collateral (e.g., relative increase in WARF) in early March, although the overall deterioration in collateral quality is not initially as severe. Instead, B- and BB-rated loans continue to experience downgrades in July and August. Importantly, this analysis is weighted by the par of CLO holdings across our full sample. Moreover, it does not reflect changes to the composition of collateral pools as managers execute trades. As such, the relative difference in rating downgrades is not necessarily indicative of expected rating agency actions taken on CLO tranches. In Internet Figure IA.1, we compare the rating agency actions for all pieces of collateral that had the same rating in January and find that while S&P is generally more aggressive in their downgrading, this is not always the case.

Panel B of Figure 2 further decomposes the change in collateral ratings. The panel reports the distribution of rating changes from January to August across initial rating classes. S&P's rating actions are quite widespread across rating categories with most of the categories experiencing between 20 and 35% downgrades, with actions taken on a larger share of collateral with an initial CCC rating. Moody's rating actions demonstrate a similar pattern.

3 Do Collateral and Tranche Ratings Lineup?

The general trends depicted in Figure 2 suggest that a large portion of the collateral underlying CLOs as of January 2020 deteriorated during the COVID crisis. However, it is difficult to gauge how broadly a given collateral pool was impacted by rating downgrades from the previous figure, which does not incorporate the relative par value held across rating categories.

To this end, Figure 3 illustrates the share of collateral experiencing a downgrade through time. More precisely, similar to the previous figure we collect the January holdings for each

CLO and report the (par-weighted) percent of this collateral that has been downgraded relative to its January 2020 credit rating.[7] When aggregating collateral up to the deal level, we see that S&P began downgrading collateral in substantial amounts in mid-March and accelerated their downgrading activity in April. By the first of May 2020, S&P downgraded 28.3% of the par-weighted CLO assets that it rated. While Moody's took action at a slower pace, by the beginning of July Moody's downgraded 25.2% of rated CLO assets. Neither agency's rating actions appear to significantly reverse course, with the share of downgraded collateral staying relatively constant in July and August. Against this broad downgrading activity of loans, we contrast the rating actions taken on CLO tranches. Interestingly, neither rating agency began to downgrade tranches in a meaningful way until the start of June. Each rating agency downgraded approximately 1% of tranches by the beginning of August, with S&P and Moody's issuing downgrades on 2% and 1.75%, respectively, by the end of August. In contrast, rating agencies were quicker to issue negative credit watches. By mid-June, Moody's issued a downgrade or negative watch on 8% of tranches while S&P took action on 2.7% of tranche par. However, these shares began to converge across the two rating agencies by the end of August at 3.5% (S&P) and 5.5% (Moody's). This presents a puzzle as to the relative imbalance in collateral and tranche downgrades.

To further understand this connection, we form bins by the percent of CLO collateral downgraded and examine tranche downgrade and negative watch activity (reported separately). Panel A of Figure 4 examines this cross-sectional relationship, indicating a positive relationship between credit downgrades of collateral pools and tranches for S&P. Yet, while correlated, the magnitude of rating actions continues to differ across the two groups. CLO collateral pools experiencing 35% downgrades have corresponding tranche downgrades of approximately 3%, with an additional 3% being put on watch. Moody's shows only a marginally stronger relation, where pools with between 35% and 40% collateral downgrades are associated with tranche downgrades between 5 and 10%. Moody's credit watch actions are slightly

[7]Note, we consider dynamic holdings due to active trading in other tests below.

more aligned with collateral downgrades. In Internet Figure IA.2, we repeat this exercise when considering rating actions as of June, approximately the height of negative watch actions. We find a similar relation with respect to credit watches, but virtually no relation to downgrades. Overall, the first panel in Figure 4 demonstrates a modest relationship between collateral deterioration and tranche rating activity.

We now turn to regressions to both better gauge the variation in tranche downgrades explained by collateral performance, as well as quantify the importance of other factors plausibly related to tranche credit risk. Table 2 reports the results of OLS regressions where the dependent variable is the par percent of rated tranches either downgraded or put on negative credit watch as of the start of August 2020, with standard errors clustered by issuance quarter. Our key variable of interest is the relative change in the pool's par-weighted rating factor (WARF) from January to August. Thus, in contrast to the previous figure, this variable considers the change in collateral pool risk due to trading. This test relies on Bloomberg tranche ratings, resulting in a slightly smaller sample relative to that reported in Table 1.

In Panel A of Table 2 we consider Moody's rating actions, where the outcome and variable of interest are in percentage points. When only considering controls for deal size and potential complexity (proxied by number of tranches), we see a one percentage point increase in the default probability of the collateral pool is associated with a 0.239 (t-stat=2.97) percentage point increase in the share of tranches downgraded or put on negative watch. This pattern continues to hold when controlling for issuance year in the second column. If CLOs are able to build up a cushion over time, this would predict out-performance of older vintages. Interestingly, we do not see an obvious pattern with respect to vintage year. Collateral performance continues to be a key driver in tranche rating actions when including two potential measures of deal aggressiveness (Column 3), as well as the recent prominence of a CLO's collateral manager and underwriter (Column 4). Panel B of Table 2 repeats the previous analysis when examining S&P's rating actions. The results generally mirror those of Panel A with a few minor exceptions. In particular, consistent with Figure 4, we generally see a larger effect of collateral deterioration on the share of tranches downgrades/watchlisted when considering S&P's actions.

The previous results are silent regarding the extent to which rating agency actions either exhibit heterogeneity across tranche classes (e.g., senior vs. junior/subordinate tranches) or instead uniformly impact the liability structure of CLOs. Panel B of Figure 4 shows the actions by S&P and Moody's for CLO tranches conditional on initial rating. Interestingly, most of the downgrade actions have occurred among more subordinate tranches. Between 25% and 45% of tranches rated BB or B have been moved to credit watch, while between 10% and 20% have been downgraded, with more aggressive actions for CCC-rated tranches. In contrast, tranches initially rated at or above A have experienced almost no rating change, with very few watch list actions. In fact, no AAA tranches have been placed on credit watch or downgraded, while 0.4% of AA-rated par has been placed on negative watch by Moody's. The panel also shows that lower tranches which have experienced the bulk of the downgrades/credit watches represent less than ten percent of the CLO capital. Taken together, these patterns explain why the rating actions illustrated in Panel B translate into the relatively economically small effect on overall tranche performance in Panel A.

These patterns are confirmed in Panel C (Moody's) and Panel D (S&P) of Table 2, in which we re-estimate the final specification in Panel A on individual CLO tranches when conditioning on January 2020 ratings. In line with the figure, the coefficient estimates are consistent with an increased sensitivity of initially lower rated tranches to collateral quality deterioration. In particular, we see the strongest effect of collateral deteriorations on tranches with an initial credit rating of BBB and BB. Note, we must omit tranches initially rated AA or greater from the analysis, as no remaining tranches in the sample experience a rating downgrade or credit watch when conditioning on information used in the regression.

4 Why are CLO tranches not Experiencing more Downgrades?

We now turn to investigating previously discussed explanations for the relatively infrequent rate of tranche downgrades, and why rating actions fall squarely on tranches lower in the seniority structure. To summarize, the six explanations we consider are: a) model-implied heterogeneous effects of collateral downgrades across tranches, b) weight being placed on non-model considerations, c) overly aggressive downgrading of underlying assets, d) accumulation of a protective cushion built up from prior excess performance, e) active management creating value during the COIVD-crisis, and f) strategic trading by CLO managers to avoid downgrades.

4.1 Model-Implied Heterogeneous Effects or Non-Model Considerations?

This section examines two potential explanations related to rating agency modeling. The first is that the change in model-implied risk due to collateral deterioration is heterogeneous across tranches. If model-implied risk is concentrated in equity and subordinate tranches this could explain the small percentage of tranche downgrades. The second possibility is that rating agency models do imply broadly-hitting downgrades, but rating agencies are incorporating non-model considerations in ratings.

4.1.1 Moody's Modeling

In most circumstances, examining potential model-implied heterogeneity would be a tall order, requiring either access to the true model or an ability to replicate it. Fortunately, for a large portion of rated CLOs Moody's issues a statement that gives guidance on expected credit rating implications associated with collateral deterioration scenarios (usually an increase in WARF of 15% or 30%).[8]

[8]For example, the May 22, 2018 press release for ALM VI, LTD states: "This sensitivity analysis includes increased default probability relative to the base case. Below is a summary of the impact of an increase in default probability (expressed in terms of WARF level) on the Refinancing Notes (shown in terms of the number of notch difference versus the current model output, whereby a negative difference corresponds to

Figure 5 graphically summarizes the expected effect of collateral deterioration across tranche seniority levels for a hand-collected sample of 986 CLO announcements released by Moody's. The figure reports the expected rating notch change following a 15% increase in WARF, partitioned by the initial credit ratings. We scale each hollow blue bubble such that its area represents the share of tranches expected to be downgraded by N notches, such that the shares sum to one for each initial credit rating. Interestingly, following a 15% increase in WARF, the majority of tranches with initial ratings of Aa1 down to Baa3 should experience a one or two notch downgrade according to Moody's guidance. Aaa tranches should experience a one notch downgrade in 29.2% of the cases. Panel A of Figure IA.3 repeats the previous analysis for a 30% increase in the WARF and finds that with the exception of B-rated tranches the most severe downgrades should be borne out by collateral initially rated between Aa1 and A3. Overall, it appears that Moody's modeling projects that expected actions should be broad-based across most tranches and not solely centered on junior tranches, inconsistent with the first explanation.

Figure 5 also reports Moody's rating actions (green solid dots) for CLOs in which the underlying collateral has experienced more than a 15% increase in WARF (260 CLOs) as of August. The figure illustrates the stark contrast between initial guidance provided by Moody's and future rating actions. Moody's has placed tranches on credit watch, but predominantly among subordinate CLO claims initially rated Baa1 or worse. To provide economic content, given the WARF increases observed in the data, Moody's guidance would predict downgrades for 9.2% of Aaa-rated tranches.[9] Likewise, Panel A of Figure IA.3 superimposes actions for the 2 CLOs experiencing more than a 30% increase in WARF and finds an even larger mismatch between expected and actual actions. Because it is possible

higher expected losses), assuming that all other factors are held equal."

[9]There are a total of 1084 Aaa tranches with Moody's ratings and observed WARF data. Of the 1084 tranches, 324 tranches faced between a 15% and 30% increase in WARF and 4 tranches faced more than a 30% increase. Based on Moody's reports, the expected downgrade rate due to a 15% WARF increase is 29.9% while the share increases to 81.3% when WARF increases by 30%. If Moody's anticipated actions were applied relative to the observed WARF increases then approximately 9.2% of Moody's deals would have experienced a downgrade action (324 * 29.9% + 4 * 81.3%) / 1084 = 9.2%.)

that the sample of deals with a corresponding announcement is not representative of our sample, in Panel B of Figure IA.3 we restrict the sample to deals for which we are able to link rating histories to guidance reports and who experience WARF increases of over 15%; we find similar results to Figure 5. Overall, the guidance issued by Moody's is not consistent with the observed pattern of downgrades among only the lowest tranches. Instead, the contrast between Moody's guidance and actions taken to date is consistent with the second explanation of non-model considerations.

4.1.2 S&P's Modeling

While Moody's provides tranche-specific guidance regarding collateral deterioration, this does not necessarily imply that the prescribed effects are similar under S&P's modeling framework. To better understand potential asymmetries between the two agencies, we now turn to S&P's modeling of collateral risk. S&P represents the riskiness of a collateral pool with a value referred to as a Scenario Default Rate (SDR), which is equivalent to the value-at-risk of the collateral pool's default distribution. This collateral risk metric is then compared to a tranche's Break-even Default Rate (BDR), which represents the share of the collateral pool that must default before the tranche holder is unlikely to be made whole. Simply put, a rating is typically earned when the expected default rate in an extreme circumstance (SDR) is less than what the tranche can withstand (BDR).[10] Importantly, for a given collateral pool, S&P's approach yields a *set* of rating-contingent SDR values (e.g., AAA, AA, etc.).[11] Thus, for a tranche to merit a AA credit rating, for example, the BDR of the tranche should be greater than the AA-rating SDR. Since S&P's SDR methodology is well outlined, we are able to replicate the full set of SDRs [as outlined by Nickerson and Griffin (2017)], needed to evaluate potential heterogeneous effects across tranches.

[10]The required credit support necessary to obtain a AAA rating is linearly increasing in the SDR when the timing of defaults and cash-flow diversions (e.g., O/C tests) for a deal is ignored.

[11]The only modification necessary to generate each rating-specific SDR is to change the threshold (area under the curve) used to determine the Value-at-Risk. A safer credit rating corresponds to smaller threshold, and thus a larger SDR value.

We begin by undertaking an exercise which bears many similarities to the approach taken by Moody's above, but instead uses our replication of S&P's methodology. Intuitively, the exercise is designed to measure the effect of collateral deterioration on each rating-specific SDR. To do this, we begin with the sample of S&P-rated deal-month observations for which we have all the necessary collateral information needed to generate the pool's default distribution, and thus a set of SDRs. For each deal-month observation, we then simulate one draw of hypothetical downgrades in collateral and re-estimate each SDR. We repeat this process 50 times, yielding 50 unique realizations of rating downgrades and 50 sets of AAA SDRs, AA SDRs, etc.[12] With these simulated outcomes, we are able to easily measure the sensitivity of a rating-specific (e.g., AAA) SDR to a change in collateral quality. This entails regressing the resulting SDRs on the relative change in the collateral pool's default probability (due to our simulated downgrades).

Table 3 presents the resulting point estimate from OLS regressions, one for each rating category. The only other covariate included beyond the relative change in collateral default probability is a deal-month fixed effect. This ensures that we are measuring changes in SDR due to our simulated collateral deterioration, and not cross-sectional differences attributed to another characteristic of the collateral pool (e.g., number of loans). The first column demonstrates the extremely strong effect that a deteriorating collateral pool has on the AAA SDR. The coefficient of 0.295 indicates that a 10% increase in the default probability of a CLO's underlying collateral would result in a 2.95 percentage point increase in the AAA SDR (0.10 x 0.295 = .0295). We provide economic context for this effect below. Recall, our goal is to examine potential model-implied heterogeneity across initial tranche ratings. To this end, we repeat the previous specification in the remaining columns when replacing the dependent variable with the other SDRs (e.g., AA SDR, etc.). Two observations emerge. First, while the point estimates indicate an increased sensitivity of non-AAA SDRs

[12] We calibrate the downgrade probabilities so that the relative change in a pool's weighted average default probability is between 2% and 12%. While this range is arbitrarily chosen, our primary goal is to generate sufficient variation in downgrades needed to estimate the relation with SDRs. Extremely tight standard errors confirm this is the case. Details of this process are described in much more detail in the appendix.

to collateral deterioration, the differences are relatively small in an economic sense. The most sensitive rating class (BBB) is only 10% more sensitive than the AAA SDR. Second, sensitivity is not monotonic, with the B-rated SDR exhibiting the second lowest coefficient. In this way, our estimates offer similar implications to Moody's guidance as summarized in Figure 5 above, which also exhibit a "humped" shape in the expected effect across tranches. Thus, it is difficult to reconcile the rating downgrades issued by S&P, which are concentrated among the most junior tranches with differential model-implied sensitivities across tranches.

While the previous approach offers a controlled environment, it does so at a potential cost. Namely, the key source of variation is generated by simulating downgrades, but these simulations may not fully capture the dynamics of rating downgrades realized in the midst of the COVID-crisis. Moreover, the composition of collateral pools may have shifted in response to downgrades, somehow offsetting some of the increase in AAA SDRs.

To better understand potential variation in SDR changes across tranches, we turn to the change in actual credit quality of CLO collateral portfolios in 2020. More precisely, using the same sample of deal-month holdings used in Table 3 above, we compute the full set of rating-contingent SDRs. Panel A of Figure 6 shows the change in the SDR across each rating class through time. For ease of interpretation, we report the difference in SDRs between each deal-month and the deal as of January. SDR changes are centered around zero for all tranches in February but begin to creep upward in March. By April, the average SDR exhibits an increase of nearly two percentage points, with SDRs again increasing slightly in May before stabilizing in June. While SDRs in July (and to a lesser extent August) decrease relative to their previous month values, SDRs continue to be more than one percentage point greater than January values on average, with larger increases among some CLOs. Importantly, there appears to be little difference in the average increase of SDRs across seniority levels. In fact, SDRs for B-rated tranches exhibit slightly smaller increases throughout the sample period. This pattern is confirmed when examining deals that experienced above-average increases in collateral risk (e.g., 90th percentiles). Thus, like Moody's methodology, neither simulations nor estimates using changes to actual collateral pools offer any evidence consistent with a heterogeneous effect across subordination levels able to explain downgrades predominantly among lower tranches.

One limitation of the previous analysis is that it ignores potential changes in deal characteristics that impact a tranche's BDR. Recall, that the condition typically necessary for a tranche to be awarded a given credit rating is that the tranche's BDR is greater than the rating-specific SDR. However, unlike the methodology used to generate the SDR, S&P does not publish sufficient details to replicate the cash flow modeling needed to compute a tranche's BDR. Fortunately, for a subset of S&P-rated deals the monthly trustee reports disclose both the SDR and BDR for AAA tranches. For this set of deals, we gauge the economic magnitude of a change in SDR due to collateral deterioration by benchmarking it against typical BDR−SDR cushions. Moreover, the reported BDR values allow us to examine the possibility that cash flow protections of tranches changed at the onset of the COVID-crisis, potentially offsetting the effects of collateral downgrades.

Panel B of Figure 6 contrasts the difference between SDR and BDR (SDR−BDR) in February, June, and August 2020, reporting the kernel density as solid red, blue, and green lines, respectively.[13] In February, 2.05% of deals have a reported SDR that exceeds the BDR. By June of 2020, this share increases substantially to 12.50% of deals. Put differently, in June the AAA tranche in one-eighth of the reporting CLOs would not be able to withstand the level of collateral pool defaults that S&P's methodology estimates could occur in a scenario which S&P states that a AAA rated tranche should be able to survive. A non-trivial 8% of CLOs continue to have an SDR that exceeds the corresponding BDR declines in August, approximately five months after the start of the COVID-19 crisis. Somewhat paradoxically, S&P has not placed any AAA tranches on credit watch, an action for which we do not have a definitive explanation. While it is possible that S&P is currently evaluating senior tranches

[13]Throughout our analysis, we generally focus on changes as of June and August. While August corresponds to the last month in our sample, June is also of particular interest as it represents a point at which ratings agencies had approximately three months to consider rating actions (and did so for some junior tranches).

using an alternative methodology, we have been unable to find an announcement to this effect. Alternatively, S&P may be delaying action on these CLOs consistent with the second explanation put forth in this section. Note that (unlike the values in Panel A) the values in Panel B are taken directly from trustee reports, and thus do not rely on our replication of S&P's model.

4.2 Are Original Collateral Downgrades an Overreaction?

Credit rating agencies rapidly downgraded collateral in March and April of 2020 but took minimal actions on tranches. This contrast is interesting given the value that rating agencies place on the stability of their ratings (Moody's (2006)). One potential explanation for this divergence in actions is that credit rating agencies are taking signals from the market that their collateral downgrades were too severe. Stated differently, it is possible that following the actions taken against collateral, market conditions began to stabilize in April before rating agencies had an ability to evaluate the effect of these actions on CLO tranches. However, this explanation is somewhat dissatisfying from the standpoint of credit rating consistency across asset classes [Cornaggia et al. (2017)], especially when considering both Moody's and S&P's methodologies determine collateral default probabilities directly from loan credit ratings. Moreover, this explanation suggests that collateral rating downgrades enacted should be reconsidered. However, Panel A of Figure 2 indicates that rating agencies continued to downgrade collateral in May and into mid-June, inconsistent with an initial over-reaction regarding collateral quality.

Nevertheless, in the event that rating agencies are taking a signal from the market regarding the creditworthiness of collateral, it likely comes in the form of market prices. Although CLO tranches are illiquid, the loans backing CLOs trade more frequently producing reasonably active prices. This increased trading activity has facilitated the development of pricing algorithms by financial data providers (and in particular by Bloomberg). Using Bloomberg's valuation algorithm (BVAL), we now examine the evolution of collateral prices through the

COVID-crisis to asses if market prices align closely to a collateral over-reaction explanation.[14]

Panel A of Figure 7 reports the distribution of the value-weighted price of CLO collateral pools through the crisis.[15] The average price of CLO loans started around \$97.50 before experiencing a precipitous drop in March, settling near \$83. Following this decline, average prices recovered to slightly more than \$90 by the beginning of July. Interestingly, asset values increased only slightly over the two-month period from July through the end of August. Ultimately, after approximately six months the average price of a CLO's collateral pool still stands roughly \$5 lower than its pre-COVID value. This lack of a rebound in market prices is consistent with the deterioration in collateral quality reflected in rating downgrades rather than an over-reaction with respect to collateral ratings.

While the previous panel shows a deterioration in collateral prices, it is difficult to assess the impact of this change on tranche risk. We now present a simple measure, motivated by the idea of an overcollateralization (OC) ratio, to provide some economic content to the decrease in collateral prices. In essence, the OC ratio of a tranche (or more generally a CLO class) represents the par value of a collateral pool relative to the liability of the tranche and all tranches more senior. For example, if a CLO has collateral with a par value of \$150 million, a \$100 million AAA tranche, and a \$20 million AA tranche, then the AAA OC ratio will be 1.5 while that of the AA tranche is 1.25 (150/(100+20)). Intuitively, a larger OC ratio indicates a greater collateral cushion against unforeseen shocks. We adapt this idea in two ways. First, we consider the aggregate market value of the collateral pool rather than the par value. Second, when the value of a given tranche and all more senior tranches exceeds the aggregate collateral value, we instead consider the ratio of the tranche's value to the aggregate collateral value in excess of all tranches more senior, as these tranches would be paid off first. The result is a ratio we refer to as the Tranche Liability Coverage Ratio.

[14]Unfortunately, we do not have traded prices or BVAL valuations for CLO tranches.

[15]Specifically, for each CLO we compute the par-weighted average price at a weekly interval using the holdings information from the monthly trustee report immediately preceding each weekly interval. We account for changes in the aggregate par value of a collateral pool by multiplying each value by the ratio of current-period aggregate par divided by the corresponding value in January 2020.

Panel B of Figure 7 contrasts the distribution of tranche liability coverage ratios in June and August against February ratios. The first thing to note is that tranche liability coverages declined considerably by June 2020. To provide economic content, a ratio less than one indicates that if the CLO pool were to be liquated at current market prices, and tranches paid off by seniority using the resulting proceeds, the owner of the tranche in question would not be made whole. Note, as long as pools are not forced to liquidate, a tranche with a ratio below one can still have considerable value as it can continue to collect interest and principle payments in the future. With this in mind, liability coverage ratios experienced considerable declines between February and June among BB-rated tranches, as well as those more junior. Moreover, while some AA, A, and BBB tranches would be impaired if faced with liquidation under June prices, all AAA tranches would be made whole. In contrast, liability coverage ratios have increased slightly as of August 2020. At the same time, these ratios suggest that little cushion remains for the senior tranches of some CLOs, exposing tranche holders to risk if loan default rates increase and values decline in the immediate future. Overall, the response of CLO asset prices appears to generally be consistent with the large number of collateral downgrades issued since March while CLO tranches appear riskier than in February 2020.

4.3 Did CLOs Accumulate a Protective Buffer prior to February 2020?

The previous results are consistent with both rating agency and market perceptions of a degradation in asset pools during the COIVD-crisis, which did not carry through to ratings of senior tranches. One possible explanation for this disconnect is that current deals have accumulated a cushion since issuance, either in the form of growing collateral pools which bolster overcollateralization rates or pre-crisis increases in the credit quality of collateral pools. If true, this would suggest that pre-COVID ratings were overly conservative and were only brought back in line during the crisis.

We examine this explanation in two ways. As described by Coval et al. (2009b), CLOs are typically rated "at-the-edge," meaning that they are structured to maximize the permissible tranche size while still retaining a given rating, leading to little cushion when structured. Thus, any cushion is likely to have accumulated since issuance. We begin by examining the change in credit risk of collateral pools. Panel A of Figure 8 reports the change in WARF since issuance for yearly vintages of CLOs from the start of 2018 to present. The positive values as of January 2018 indicate that the average collateral in older vintages has increased in risk since issuance. Moreover, between July 2018 and January 2020 the average credit risk for each yearly vintage has trended upward. Thus, the March and April downgrades only served to increase the WARF of collateral pools that had already experienced an increase in risk since issuance. Panel B illustrates the distribution of the change in WARF since issuance. While most earlier vintage CLOs experienced some increase in WARF between issuance and January 2020, it is dwarfed by the increase in April 2020. As of August 2020, the collateral pools of almost no CLOs are safer than they were at issuance.

The active management component of CLOs offers a second avenue through which deals can accumulate a cushion, as managers sell collateral that has improved in quality to finance a larger share of collateral with risk characteristics in line with the collateral pool. The result of this process would be an increase in overcollateralization ratios over time. Panel A of Figure 8 examine this possibility, reporting the difference in OC ratios for different rating classes relative to the ratio at issuance. The panel indicates that the average OC ratio has remained relatively stable since issuance, with January 2020 overcollateralization ratios slightly lower than their levels at issuance. In fact, the only class with an average OC ratio that improved as of January 2020 relative to its issuance value belonged to B-rated tranches. Taken together, these results do not support the hypothesis that more senior tranches accumulated a protective cushion since issuance.

4.4 Is Active CLO Trading Profitable?

The results to this point highlight the stress placed on CLO tranches from deteriorating collateral pools. However, the delay in response may reflect rating agency expectations over the ability of collateral managers to take advantage of the volatile climate to purchase assets at undervalued prices to bolster the collateral pool going forward.[16] We now consider this interesting feature of CLOs.

As the potential for collateral managers adding value arises through trading, we begin by first documenting trends in broad trading behavior around the COVID-crisis. Panel A of Table 4 presents the results of OLS regressions where the dependent variable is either the number of trades or log quantity, measured at the CLO-day level. The variables of interest are a set of indicators corresponding to each trading month from February to August (with January 2020 serving as the base case). In the first specification, which only includes, as additional controls, day-of-week fixed effects, daily trades appear to increase in February and March (relative to January) before beginning to decrease in April. By May, trade activity is statistically indistinguishable from January levels, while July trading activity is statistically less than that in January. When including deal fixed effects in the second specification, trading rates in May through August become statistically less than their January counterparts. However, the previous pattern changes substantially when considering how traded par volume evolves. While trading volume increases in February, trading volume in each month from March onwards is significantly less than January levels. In particular, when including deal fixed effects in the final specification, trading volume exhibits roughly a 45% drop in May, July, and August. Smaller, but still statistically significant, declines are present in April and June. Panel B of Table 4 extends the previous analysis to consider possible heterogeneity in trading activity, where the key variable of interest is the month-over-month

[16] "This will be an opportunity for CLO managers to differentiate themselves" (New York Times, https://nyti.ms/3i8PCmm). Note, it is unclear why the formal incorporation of this channel in a rating agency methodology would not simply be reflected ex-ante in ratings at issuance, rather than a departure from stated methodology ex-post.

percent change in the WARF of a collateral pool. Interestingly, we find some evidence that deals experiencing a greater deterioration in collateral quality (increase in WARF) reduce their trading activity more than their better performing counterparts. Thus, if managers of distressed deals are creating value through active trading, it is being achieved with less trading volume.

To evaluate the potential for value creation through active trading, we contrast the future returns of purchased collateral relative to collateral sold. More precisely, for each piece of collateral we construct a set of daily prices based on reported transaction price from all CLOs in our sample. For any day t with no trades, we linearly interpolate a price using the pair of observed trade dates that bracket date t. From these prices, we then compute 15-day and 30-day returns from the trade date. Finally, although we keep the unit of observation at the trade level to allow for more granular controls, we weight each trade by its par divided by the aggregate par for all trades in that direction (buy vs. sell) for the CLO-month. Thus, point estimates can be interpreted as a value-weighted portfolio return for all trades transacted in a given month.

Panel A of Table 5 reports the results of OLS regressions testing for differential 15-day returns between loans purchased versus those sold, with point estimates broken out by trading month. While the inclusion of trade-month fixed effects subsumes the holding period returns for the base case (sold collateral), the interaction of trade-month indicators with an indicator for a purchase transaction estimates the difference in returns for purchases relative to sells. An interesting pattern appears in the first specification, which controls for average profitability of a CLO's purchases and sells with a deal fixed effect. Prior to March, 15-day returns of purchased collateral outperform those of collateral sold. However, this pattern subsequently reverses with an underperformance of purchased collateral in April through June, and statistically indistinguishable differences in July and August. This pattern continues to hold when including deal-month fixed effects in the second specification. One potential reason for this change in performance is the constraint faced by managers, inducing the purchase of safer collateral in the crisis (something we explicitly examine below). We consider this possibility by including granular rating (e.g., AA+ vs AA) fixed effects interacted with trade-month to control for the average return of all collateral of a given rating in a given trading month. We see a general decrease in the magnitude of coefficients when including controls based on S&P ratings in the third specification. Moreover, while managers continue to underperform in April, 15-day returns of purchased versus sold loans are statistically indistinguishable from each other in later months. This pattern continues in the final specification, which instead incorporates controls based on Moody's credit ratings. Panel B of Table 5 presents largely consistent findings when considering 30-day returns.[17] Taken together, these results are not consistent with the idea that collateral managers are able to create value through active trading in the midst of the COIVD-crisis, forestalling rating actions against tranches.

4.5 Is Active Trading Making CLOs Appear Safer?

The final class of explanations that we consider relate to both manager trading and the models employed by credit rating agencies. Managers may trade in a way to improve their risk metrics. This could be due to selling loans with high credit risk, or strategically trading loans which are favored by rating agency models. Managers could also make portfolios appear safer by exploiting stale ratings or trading in a manner to prioritize senior tranches. We examine these four related possibilities.

4.5.1 Do Current Risk Metrics Reflect Trading into Safety?

As collateral pools experience strain from a wave of downgrades, the incorporation of restrictive covenants written on collateral quality likely induce managers to trade into safer assets. However, while this feature mitigates credit risk, if the sale of risky collateral to finance the purchase of safer assets reduces to aggregate par value of the pool, this reduction in overcollateralization will undermine the cash flow protection of the deal. Thus, while

[17] Note, one set of coefficients flip sign when considering 30-day returns, with collateral purchased in July outperforming that of sold loans.

these actions reduce a deal's collateral risk profile (e.g., SDR), they do so at the expense of another modeled aspect (e.g., BDR). This, in effect, locks in losses from credit deterioration, which will not be reflected in current metrics of a collateral pool's credit risk.

Nevertheless, we now consider the extent to which managers reduce model-implied credit risk through the replacement of lower-rated collateral with higher rated loans. Panel A of Figure 9 examines this possibility, contrasting the par-share of collateral purchases with sells across rating categories. Prior to March, there appears to be little difference between buying and selling propensities for a given credit rating, as denoted by the solid circles. This relation appears to change in post-February trading activity, with a greater share of loan purchases with a B credit rating or better, and conversely, a smaller share of purchases for lower-rated categories.

This suggests that managers are actively reducing credit risk through their trading activity. To provide more economic content, we now contrast the realized change in collateral pool credit risk to that of a counterfactual where pools are not actively managed. Panel B of Figure 9 presents the resulting distributions across reporting months. More precisely, the left half of each violin plot reports the difference in WARF for a collateral pool relative to its January 2020 value, had the pool been frozen in January and stayed static thereafter. We contrast this with the distribution of realized WARF differences, which reflect active trading, denoted by the right half of each violin plot. Two patterns emerge from this panel. First, consistent with Panel A, the actively traded pools experience a smaller increase in WARF relative to their static counterparts. Second, the difference in increased credit risk between active and static pools does not appear to be particularly large in a relative sense, when contrasted with the overall change in credit risk. For example, while the average WARF of a static pool in May is 51 points greater than that of true (actively managed) pools, this only represents a 20.4% increase relative to the deterioration that the actively managed collateral pools experienced.

4.5.2 Are Manager's Strategically Trading into Model-Preferred Loans?

A potential risk arises when those being evaluated (collateral managers) are made aware of the precise means by which they are evaluated (CRA models). While rating agency disclosures are important from a transparency perspective [Griffin et al. (2013)], they also introduce the concern of managers "gaming the system," exploiting potential weaknesses in CRA models. Loumioti and Vasvari (2019) find evidence of managers' strategic trading and inflating loan fair values to avoid CLO overcollateralization test violations, resulting in worse future performance. This concern is akin to the recent literature studying so called "adversarial" attacks on DNN machine learning classifiers (Moosavi-Dezfooli et al. (2016), Szegedy et al. (2013)).

One way in which trading behavior may respond to CRA modeling choices stems from the distinction between a CLO's expected life span and that of the loans which make up the collateral pool. Actively managed CLOs are typically structured with two distinct segments, a reinvestment period and an amortization period. During the reinvestment period, which lasts an average of 5.15 years in our sample, collateral managers are free to reinvest the proceeds from maturing assets and pursue other discretionary trades. Only in the amortization period is the collateral pool frozen, with the proceeds from maturing assets used to pay down tranche principle. The result of this two-phase structure is a CLO whose underlying collateral pool exhibits a shorter weighted average life than that of its tranches (which reflect expected reinvestment). However, while managers are exposed to credit risk from both existing collateral and future collateral purchased during the re-investment period, both Moody's and S&P incorporate the maturity (WAL) of the *current* collateral pool when determining the pool's default probability.[18] While it is unclear from an economic standpoint why pur-

[18]In many circumstances, Moody's adds one year to the current WAL of the collateral pool (Moody's (2019)) when determining the pool's expected default rate. In contrast, S&P switched from using the covenanted CLO maturity to the weighted-average maturity (WAM) of the collateral pool in a recent 2019 methodological update (Standard and Poor's (2020)). However, an examination of trustee reports is consistent with the use of the pool WAM prior to the methodology change, an action for which we do not have an explanation but might be of interest for future academic work.

chasing a four-year loan of a given credit rating is riskier than sequentially purchasing 2 two-year loans with the same credit rating, this modeling choice provides a potential lever available to collateral managers to reduce the model-implied risk of a collateral pool.

Panel A of Table 6 reports the results of OLS regressions examining this possibility, contrasting the remaining years to maturity of loans purchased against those sold through time. The key variables of interest are a set of trading month dummy variables interacted with an indicator for the transaction being a purchase. The inclusion of trade-month fixed effects subsumes the average remaining maturity of loans sold in each trading month. In the first column, the coefficient on 1(Purchased) indicates that loans purchased are, on average, 0.899 years longer-lived than those sold in the base case month of January. This is to be expected, as many purchases are made with the proceeds of maturing loans or loans nearing maturity as capital is rolled over during the reinvestment period. Interestingly, the remaining point estimates indicate that the difference in the lifespan of purchased versus sold loans narrows in March, and continues through the end of the sample in August. From an economic standpoint, the difference is quite large, with point estimates ranging from a 0.325 year decrease (March) to a 0.72 year decrease (July). These inferences remain relatively unchanged when including deal-month fixed effects in the second column. To ensure our results are not being driven by the substitution of higher-rated collateral documented in Figure 9 above, we include rating-month fixed effects in the final two specifications, with results unchanged.

If managers are tilting collateral pools towards shorter-lived assets, it is plausible that this action would be exacerbated in deals experiencing a greater deterioration of collateral. Panel B of Table 6 explores potential heterogeneity in the previous result. To focus on the cross-section of the effect, all specifications include the interaction of trade direction (purchase vs. sell) and trade-month, thus subsuming the time-series relation documented in Panel A of Table 6. The variable of interest in the first four columns is the interaction of 1(Purchase) with a measure of recent collateral performance, *Change WARF*, which equals the month-over-month percentage change in the WARF of a collateral pool. Here, a negative coefficient implies that CLOs experiencing a bigger decline in collateral quality (increase in WARF) as of their most recent trustee report tilt their purchases more towards short lived collateral. When measuring WARF using Moody's ratings, we see a negative and statistically significant coefficient on the interaction term. In the second specification, which accounts for potential heterogeneity in manager propensity to buy longer vs. shorter lived assets with a deal-by-trade direction (purchase vs. sell) fixed effect, the point estimate of -1.163 indicates that deals experiencing a 10% relative increase in WARF reduce the average life of loans purchased by 1.4 months (-1.163 x .10 x 12 months). We find similar, if not somewhat stronger, effects when measuring collateral deterioration using S&P's credit ratings. In the fourth specification, the point estimate of -1.491 indicates that a 10% increase in collateral risk is associated with a 1.78 month decrease in the relative years to maturity of purchased loans compared to sold loans. Note, the previous specifications focus on deteriorating collateral, which may not capture the overall change in CLO tranche risk (e.g., if cash flow protections are also changing). Fortunately, for a subset of S&P-rated CLOs we are able to observe both components, SDR and BDR. In the final two columns, we shift focus to the difference between AAA SDR and BDR (measured in percentage points). Here, an increase in the difference corresponds to an increase in the AAA tranche risk. In the final specification, the coefficient of -0.018 (t-stat=-1.90) on the interaction term indicates that a 1% decrease in the AAA cushion (a 1% increase in SDR $-$ BDR) is associated with a 0.22 month relative decrease in the life of purchased collateral (-0.018 x 12). Taken together, the results presented in Table 6 indicate that managers tilted collateral portfolios toward shorter-lived assets during the COVID-crisis, with stronger effects among CLOs that experienced a greater deterioration of collateral quality. Through the lens of rating agency methodologies, this action reduced the model-implied default probability of the underlying collateral. While we cannot rule out other possible reasons for a change in managerial behavior, this result is consistent with a change in collateral manager actions to exploit particular features of CRA models.

4.5.3 Are Manager's Exploiting Stale Ratings?

An additional means by which managers may take strategic actions in response to rating agency methodologies also relates to the assignment of asset default probabilities. Specifically, both S&P and Moody's rely on loan credit ratings when determining default risk, mapping ratings into default probabilities. However, Löffler (2005) and Hand et al. (1992)), among others, documents the potentially stale nature of credit ratings. Moreover, by their nature credit ratings are a coarse measure of credit risk, yielding variation in risk within a given rating. Both of these rating characteristics lend themselves to potential exploitation, whereby managers seek out loans with the highest credit risk, and thus greatest expected returns, within a rating category. This would predict that managers "reach for yield" in a similar manner to the findings of Becker and Ivashina (2015), as a way to boost cash flows available to tranche and equity holders.

Table 7 explores this possibility, contrasting the yield-to-maturity of loans purchased to those sold. Here the dependent variable is YTM for each transaction, which we compute using the transaction price, maturity date, and coupon yield (assuming coupons are paid on a quarterly basis). We exclude all trades with an estimated yield less than 0% or greater than 50%, which likely reflect data errors. All regressions include a credit rating by trade-month fixed effect for both Moody's and S&P, thus allowing us to compare within-rating variation in yields. Here, our key variable of interest is the interaction of 1(Purchase) with a trade-month indicator, as the base case captures the yield of loans sold. Interestingly, in the first column we find consistently negative coefficients prior to June. This indicates that managers are purchasing (rating-adjusted) lower yielding loans in the earlier part of the sample. This pattern appears to be accentuated at the onset of the COVID-crisis, with an estimated yield on March and April purchases that is between 1.41% and 1.28% less than that of loans sold. However, we see this pattern reverse in June, at which point purchased loans begin to exhibit greater rating-adjusted yields than their sold counterparts. This pattern holds when including a deal-month fixed effect in the second column. In the final specification we include a deal fixed effect interacted with trade direction (buy vs. sell) to account for the average difference in yields across all trades for a given deal. Doing so subsumes the January trade month interaction, which becomes the base case. We continue to see a decrease in rating-adjusted yields of purchases relative to sells in March and April of 2020. Panel B finds similar results when computing yields using weekly valuations from Bloomberg's BVAL model. In sum, these results are not consistent with managers reaching for yield and exploiting within-rating bucket variation in collateral risk in the midst of the COVID-19 crisis. Instead, this result is consistent with Elkamhi and Nozawa (2020), which examines the potential consequences of fire-sales when CLOs holding similar collateral are forced to sell in response to a correlated tightening of covenant restrictions. However, the results do suggest an increase in managerial appetite for risk-adjusted yields in the recent months of our sample.

4.5.4 Are Manager's Prioritizing the Credit-Worthiness of Senior Tranches?

One potential way to reconcile downgrades concentrated among more junior tranches with a lack of model-implied heterogeneity across seniority levels is if managers are able to selectively trade in a way that reduces the risk that senior tranche holders face from *future* collateral deterioration. However unlikely, given their inability to tilt credit risk of realized downgrades towards junior tranches, we now briefly consider this alternative.[19] To do so, we repeat the exercise performed in Table 3, in which we evaluate the effect of simulated collateral downgrades on the AAA SDR (default risk) of a collateral pool. However, here our focus is on any time-series variation in sensitivity. If managers are able to selectively trade to better protect senior tranches going forward, we would expect to see a decrease in AAA SDR sensitivity during the COVID-crisis. Table 8 reports the results of OLS regressions which test this hypothesis, breaking out the collateral deterioration sensitivity by holding period month. As a whole, the specifications do not present results consistent with a decreased sensitivity

[19]Note, Figure 6 illustrates the impact of realized downgrades across tranche ratings, depicting relatively uniform increases in credit risk across differing levels of seniority.

in the midst of the crisis. Thus, it does not appear that managers are strategically trading to differentially protect senior tranches from future downgrade risk.

5 Discussion of Relative Economic Magnitudes

5.1 Economic Assessment of Manager Trading Activities

In sum, we find partial support for two theories seeking to reconcile the disconnect between underlying collateral downgrades and the lack of tranche downgrades. First, we find evidence consistent with weight being placed on non-model considerations. Second, our findings are consistent with two forms of strategic trading by managers in response to rating agency methodological choices, manifesting as both a flight to safety and trading into shorter-maturing loans. However, the previous results are silent regarding the economic magnitude of these explanations.

We briefly benchmark the relative importance of these three findings under a common framework. Intuitively, we contrast the observed outcome (which reflects all three channels) with one in which we shut down the managerial action channels, one at a time. Given its flexibility and relative transparency, we do so by adapting S&P's Monte Carlo-based approach to accommodate our set of counterfactual scenarios. Specifically, to gauge the impact of managers trading into safer assets, we re-estimate the SDR for each deal-month when freezing the collateral pool as of January 2020. In contrast, to measure the effect of managers tilting asset portfolios towards shorter-maturing debt, we re-compute each SDR when fixing the weighted-average life of collateral at its January 2020 value.[20]

Panel A of Figure 10 illustrates the distribution of AAA SDRs under each counterfactual through time. For each series, the figure depicts the monthly kernel density of the difference in SDR under the counterfactual (e.g., static January 2020 collateral pool) and the SDR using the true collateral portfolio values. While each distribution exhibits some cross-sectional

[20] Here, we allow the pool to change composition, but add a constant to each loan's remaining years to maturity such that the WAL equals its January 2020 value.

variation, as of March we see little average difference in the true SDR and that of either counterfactual. This may be a partial artifact of the March distribution including CLOs reporting at any point in March (as opposed to end-of-month values). SDR differences under both counterfactuals begin to turn positive in April. By June, both managerial actions have an economically meaningful impact on reducing a collateral pool's SDR, with a median increase of 1% had pool composition been frozen in January and a 0.7% increase had pool maturity not decreased. By August, each effect exhibits a slight increase in economic magnitude, with approximately a 1% greater SDR when fixing the CLO's WAL and a 1.5% increase had pools been fixed at their January composition. For reference, the average AAA cushion (BDR − SDR) in August is 5.12%. Thus, the effect of decreasing collateral maturities for the median deal is equivalent to 19.5% of August cushions.

Panel B of Figure 10 illustrates this point in a slightly different manner, reporting the kernel density of SDR − BDR differences under each counterfactual. Specifically, we take the true SDR − BDR difference disclosed in trustee reports and add the difference in SDRs reported in Panel A. Note, here we consider the individual effects of each counterfactual, not their combined effect. Following this change, we see a considerable increase in the number of CLOs that would have an SDR greater than the share of defaults a AAA tranche is able to withstand before suffering losses. While 12.5% of tranches have a reported SDR that exceeds its BDR in June, this share increases to 15.5% when removing the modeling effects associated with the shortening of a collateral pool's maturity. In contrast, had managers not actively traded out of riskier collateral, the share of CLOs exceeding their break-even rate would increase to 20.2%. Interestingly, while the share of CLOs with an SDR exceeding the corresponding BDR decreases to 8% as of August, this decrease is greater than that under either counterfactual. For instance, when ignoring the effects of shortening loan maturities, approximately 12.5% of CLOs exceed their thresholds as of August. This suggests that both actions undertaken by collateral managers help contribute to reducing model-implied collateral pool risk.

5.2 Economic Assessment of Recent Modeling Changes

Before concluding, we make note of two additional features of S&P's modeling approach which have implications for the evaluation of collateral risk. First, in 2019 S&P updated its rating methodology regarding the evaluation of collateral pool risk. When evaluating the expected impact on SDRs, S&P states that SDRs are likely to decrease by between 3% and 5% (Standard and Poor's (2020)). Importantly, it appears the updated approach was not applied retroactively to CLOs issued prior to the methodological change (approximately May 2019). Yet, if a portion of CLOs currently outstanding are using a methodology S&P acknowledges is less stringent, this raises the question what share of deals would currently have a AAA SDR that exceeds the share of defaults the tranche is expected to withstand had the old standards continued to be used? To evaluate this effect, we apply the old methodology to deals currently being evaluated under the new regime. The resulting SDR following this change is reported in Panel C of Figure 10 as the blue line. Had S&P continued to evaluate collateral pools under the old regime, the percent of CLOs with a AAA SDR exceeding its BDR would have increased to 19.35% (from 12.5%) in June and increased to 13.4% (from 8%) in August 2020.

The second institutional detail we take note of is that in 2016 S&P introduced a 'non-model version' of its SDR calculation. In essence, using a set of test pools S&P fit a linear model of six collateral pool summary characteristics (e.g., average default probability, industry diversification, etc.) to the set of SDRs generated by its Monte Carlo approach.[21] Doing so allowed collateral managers and trustees to report a non-model SDR using coefficients from the fitted OLS model rather than re-compute the Monte Carlo simulations. To evaluate the effect of a change to this non-model version, for each deal we estimate the SDR using S&P's original Monte Carlo simulations and when using the non-model approach. Taking a difference between the two values yields the deal-specific expected change in SDR under the original simulation approach. We add this differential to the reported gap between

[21] The fitted values were updated in 2019 along with the new methodology.

non-model SDR and BDR as an approximation of a counterfactual where the non-model approach was not introduced. The resulting difference is reported in Panel C of Figure 10 as the orange line. Had S&P continued to evaluate collateral pools under the old regime, the percent of CLOs with a AAA SDR exceeding its BDR would have increased to 14.9% (from 12.5%) in June and increased to 9.6% (from 8%) in August, indicating a larger fraction of CLOs would have an SDR that exceeded their BDR had S&P not introduced the non-model approach.

5.3 Economic Assessment of Distance to Impairment

As a final step, we undertake an exercise to provide some economic content regarding the sensitivity of rating agency models. Specifically, we start with the Monte Carlo approach used by S&P and then invert the model to determine how much further existing collateral must degrade in quality before the AAA SDR exceeds the corresponding BDR. The result of this exercise is a stress factor for each deal-month, representing the scalar which when applied to the default probability of the collateral pool equates the SDR with the BDR. Figure 11 reports the distribution of this stress factor by trustee reporting month. From February to June the amount of additional default rate increase that the median CLO can withstand has fallen by more than half. The median (75th percentile) collateral pool as of June is able to withstand an 11% (19%) increase in default risk before broaching the BDR threshold. In contrast, the break-even rate only increases moderately in July and August. Interestingly, even after the wide-spread downgrades witnessed in March and April, many CLOs still sit relatively far from their break-even point. This result is perhaps not completely surprising, as the tail risk measured by a pool's SDR is largely a function of the perceived diversification of the pool, captured through modeled default correlation. Nickerson and Griffin (2017) show that while these correlation assumptions increase post-financial crisis, they fall well-below estimates that incorporate model frailty. Our analysis here takes CRA modeling assumptions as given and assesses the impact of collateral deterioration on tranche downgrades within this framework. If defaults cluster, these protections may be not be sufficient and future work could additionally examine other important modeling choices beyond the previously discussed loosening of SDR criteria by S&P in 2019.

6. Conclusion

This paper examines the health of the CLO market by comparing recent downgrading activity of CLO collateral to tranches. Although both rating agencies have taken considerable downgrading actions on CLO loans, few tranches have been downgraded. It is difficult to reconcile the current lack of tranche rating actions with either rating agency's methodology, based on prior disclosures or current model outputs. We are not able to explain the potential reliance on non-model considerations by rating agencies. Additionally, roughly twice as many CLO tranches would be considered failing by S&P standards had managers not engaged in trading that made the portfolios appear to be safer.

While our research explores the implications of the relation between collateral and tranche ratings, there are other important issues to consider in accurate CLO ratings that we have not explored. This includes dimensions such as collateral rating quality, CLO correlations [Nickerson and Griffin (2017)], parameter uncertainty [Coval et al. (2009a)], recovery rate assumptions [Dubitsky (2020)], and other modeling choices. These may have further consequences for current CLO rating performance. Our results have substantial potential implications for current market conditions and regulators. First, a large emphasis of Dodd-Frank and other policies was to reduce reliance on credit ratings, but recent Fed policy operationalizes the purchasing of assets according to credit ratings, including static CLO tranches rated AAA. We are unaware of any process the Fed undertakes to verify rating accuracy. Second, banks, insurance companies, and mutual funds which hold such assets could contribute to systemic risk if assets are downgraded or experience correlated losses, as often happens with structured products during distress states. Third, favorable credit ratings can not only harm less sophisticated investors but also lead to mispricing of risk and mis-allocations of capital.

Future research could examine the relationship between ratings and record COVID debt issuances, robust volume in CLO issuances, and profits to rating agencies.

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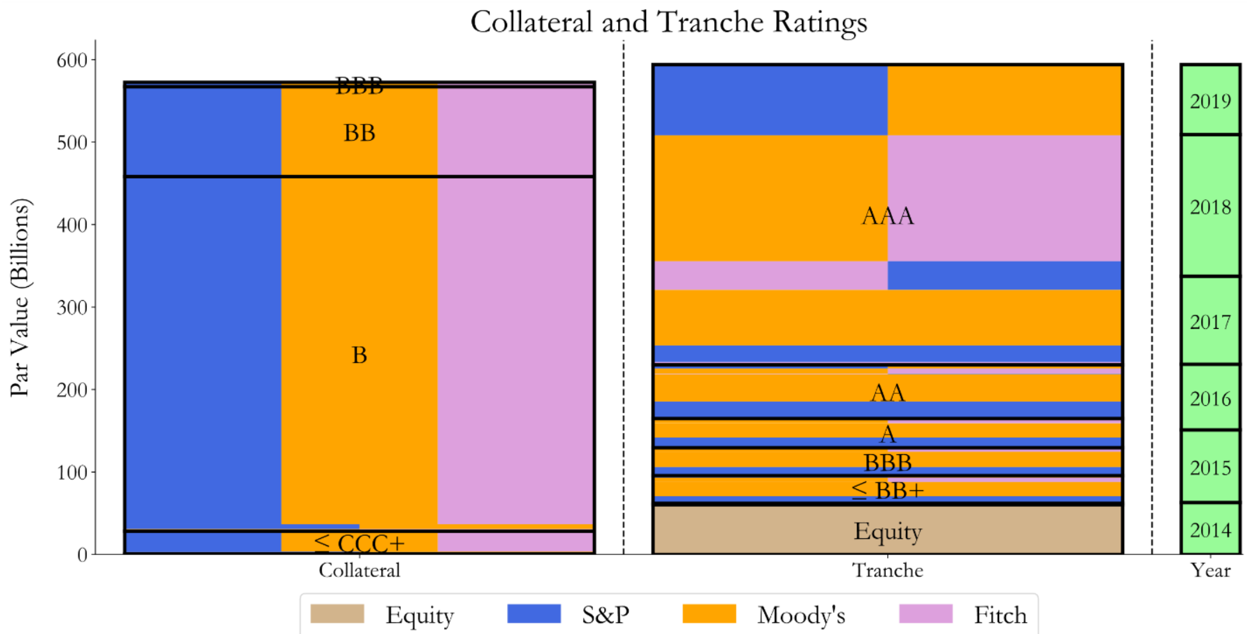
Figure 1. CLO Market

This figure shows the total amount of CLO issuance between 2014-2019 (Panel A) and by issuance year (Panel B). For Panel A, the collateral and tranche bars is divided vertically into sections based on average rating (sections with black borders) and then each rating section is further divided proportionally based of the collateral/tranches rated by each agency or set of agencies. The light green bar on the right of Panel A shows a breakdown of CLO issuance by year. For sections representing collateral/tranches rated by multiple agencies, the section is evenly split horizontally and colored to represent each agency. Vertical sections that are at least partly blue represent collateral/tranches rated by S&P, orange by Moody's, pink by Fitch, and grey by none of S&P, Moody's, and Fitch. For Panel B, each bar is normalized by total par value of CLOs issued in the given year and then divided based on the proportion of the collateral/tranches with a given rating. This figure is based on collateral/tranche par value and ratings as of January 2020.

Panel A.



Panel B.

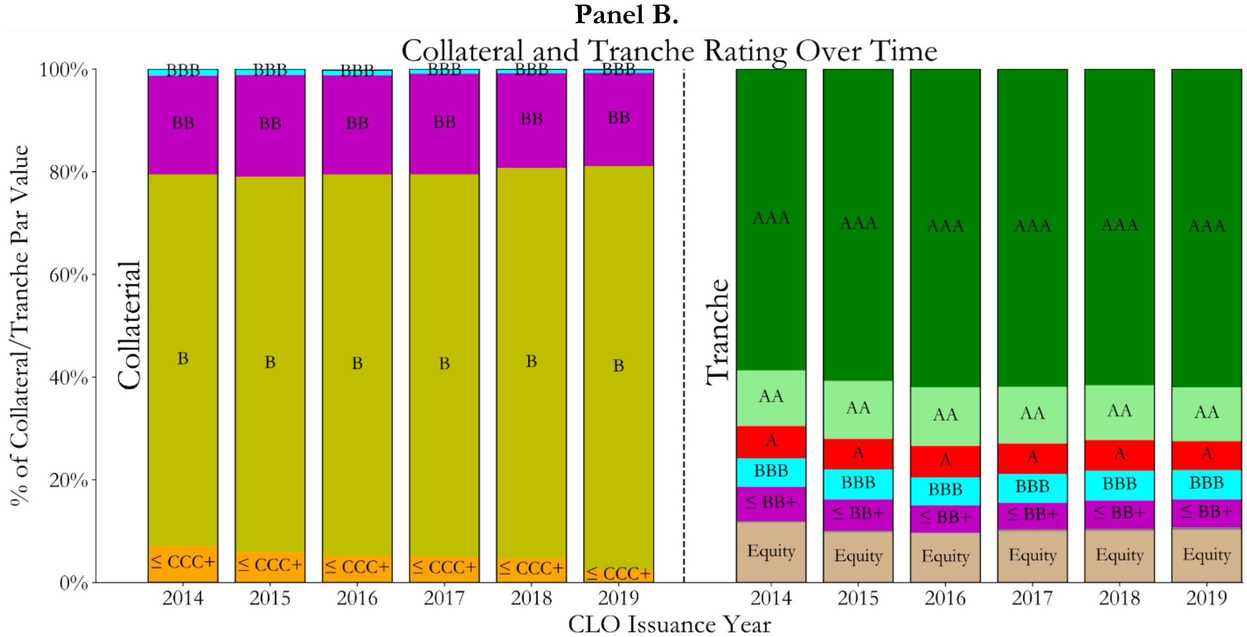
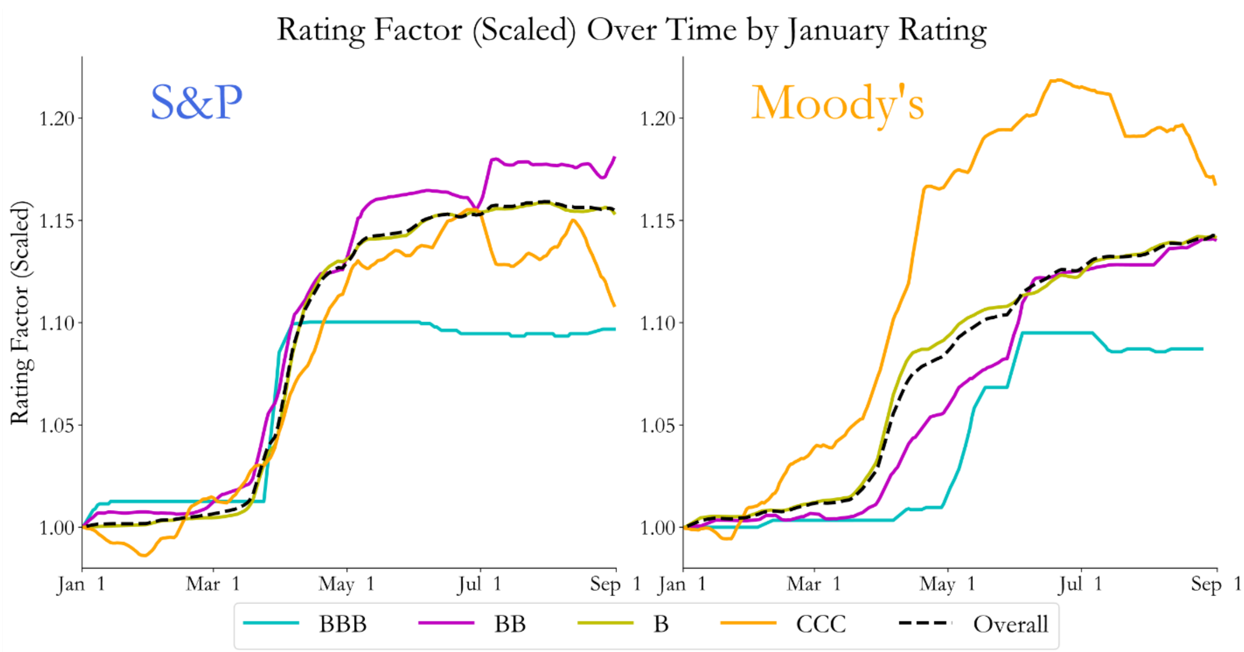


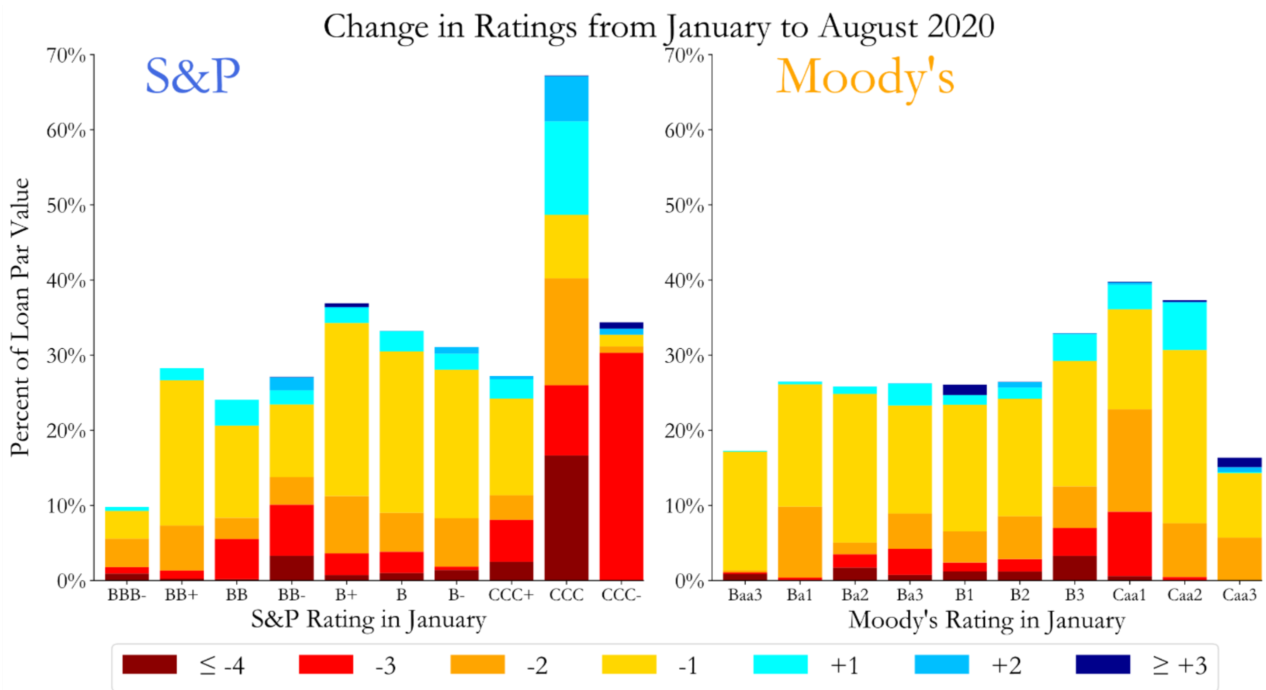
Figure 2. Collateral Ratings Factors by S&P and Moody's Over Time

Panel A displays the change in the collateral rating factors by S&P and Moody's from January 2020 to August 2020. The data is split based on the loan's rating by S&P/Moody's in January. Note that each rating class includes the corresponding plus/minus rating (e.g. BBB includes BBB+, BBB, BBB- for S&P and Baa1, Baa2, Baa3 for Moody's). The rating factor is updated daily based on rating updates across all CLO holdings and is weighted based on total par value held by CLOs as of January. A rolling seven-day average is taken to smooth the curves. The blue line represents BBB rated loans, purple line BB rated loans, yellow line B rated loans, orange line CCC rated loans, and the dashed black line represents all loans. Loans with ratings of AAA, AA, A, CC, C, D are not shown as separate series since they represent a small part of the CLO holdings. Panel B displays the number of notches that S&P and Moody's changed their ratings on the collateral underlying the CLOs by between January and August 2020. The data is split based on the collateral's rating in January and the bar for each initial rating is proportionally colored based on the percent of loans, with the given initial rating, that faced differing degrees of notch changes. The color for each degree of notch change is shown the legends below Panel B.

Panel A.



Panel B.



Change in Ratings from January to August 2020
S&P
Moody's
Percent of Loan Par Value
70%
60%
50%
40%
30%
20%
10%
0%
BBB-
BB+
BB
BB-
B+
B
B-
CCC+
CCC
CCC-
S&P Rating in January
Baa3
Ba1
Ba2
Ba3
B1
B2
B3
Caa1
Caa2
Caa3
Moody's Rating in January
≤ -4
-3
-2
-1
+1
+2
≥ +3

Figure 3. Ratings Actions on Collateral and Tranches by S&P and Moody's Over Time

This figure displays the rating actions taken by S&P and Moody's on the collateral underlying the CLOs and the CLO tranches over time. Rating downgrades are based on changes from the loan/tranche's January 2020 rating and weighted based on par value of CLO holdings in January 2020. The orange lines represent actions by Moody's and the blue lines by S&P. The solid lines represent the percent of the loan par value that is downgraded by Moody's/S&P. The dashed lines represent the tranche par value that was downgraded or put on credit watch by Moody's/S&P. The dotted lines represent the tranche par value that was downgraded by Moody's/S&P.

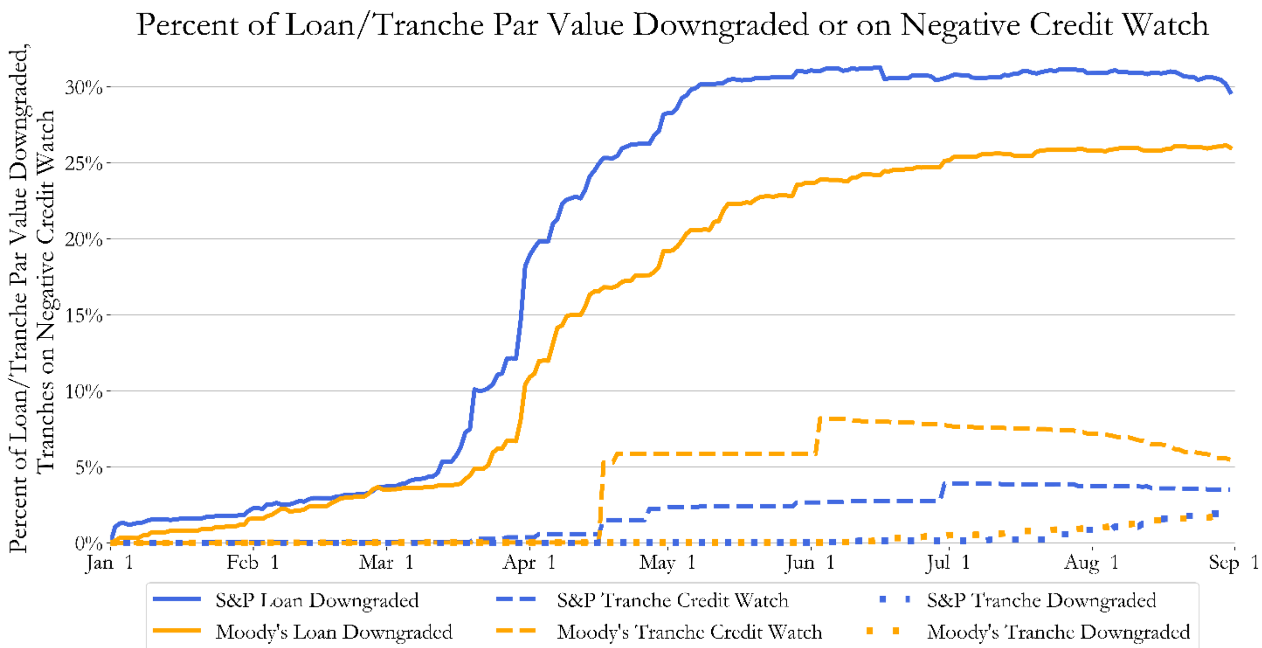
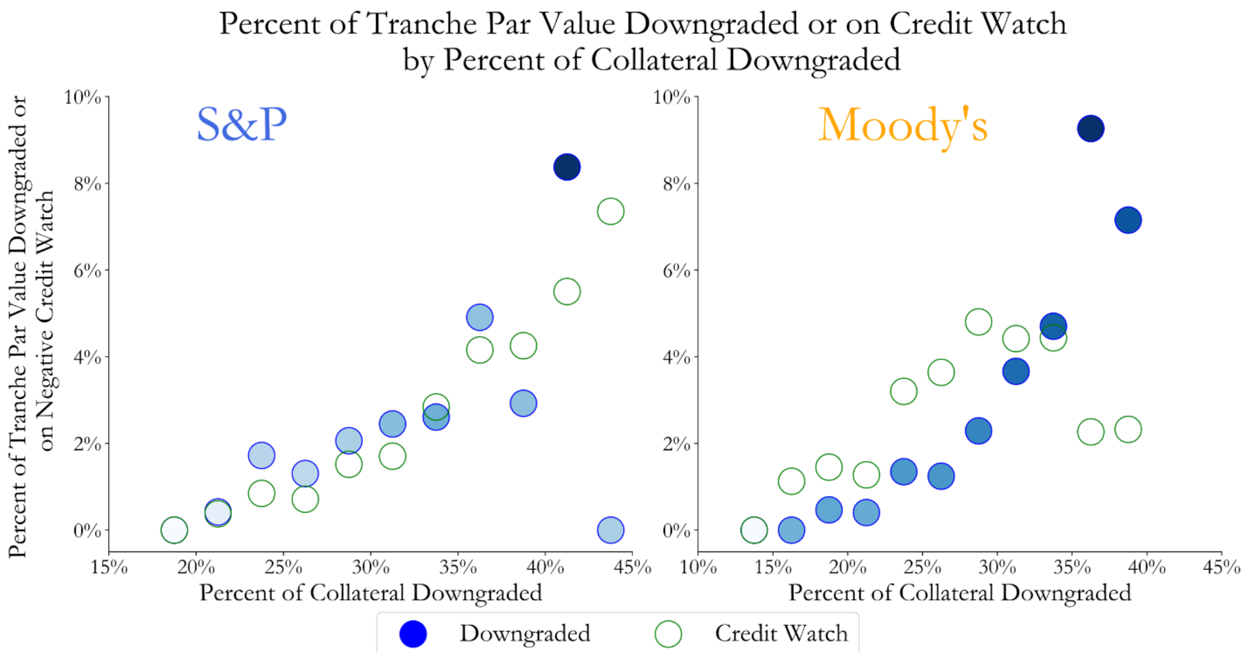


Figure 4. Ratings Actions on Collateral and Tranches by S&P and Moody's

This figure displays the rating actions S&P and Moody's took on CLO tranches. Panel A shows tranche actions based on their rating actions on the collateral underlying the CLO and Panel B compares the actions of Moody's and S&P on tranches. For Panel A, the percent of total tranche par value in the bin that was downgraded is denoted by blue filled circles, while credit watch is denoted by green hollow circles. The shade of blue fill is based on the weighted average notch changes of collateral (darker shading means higher notch change) that was downgraded as of August 2020 (compared to its rating in January 2020). Bins with only one CLOs are excluded. For Panel B, the data is split based on the tranche's rating in January 2020 and the circles are sized based on the percent of tranche par value that received a given action by S&P (blue circles) or Moody's (orange circles). The bars represent the percent of tranche par value with a given rating by the credit rating agency.

Panel A.



Panel B.

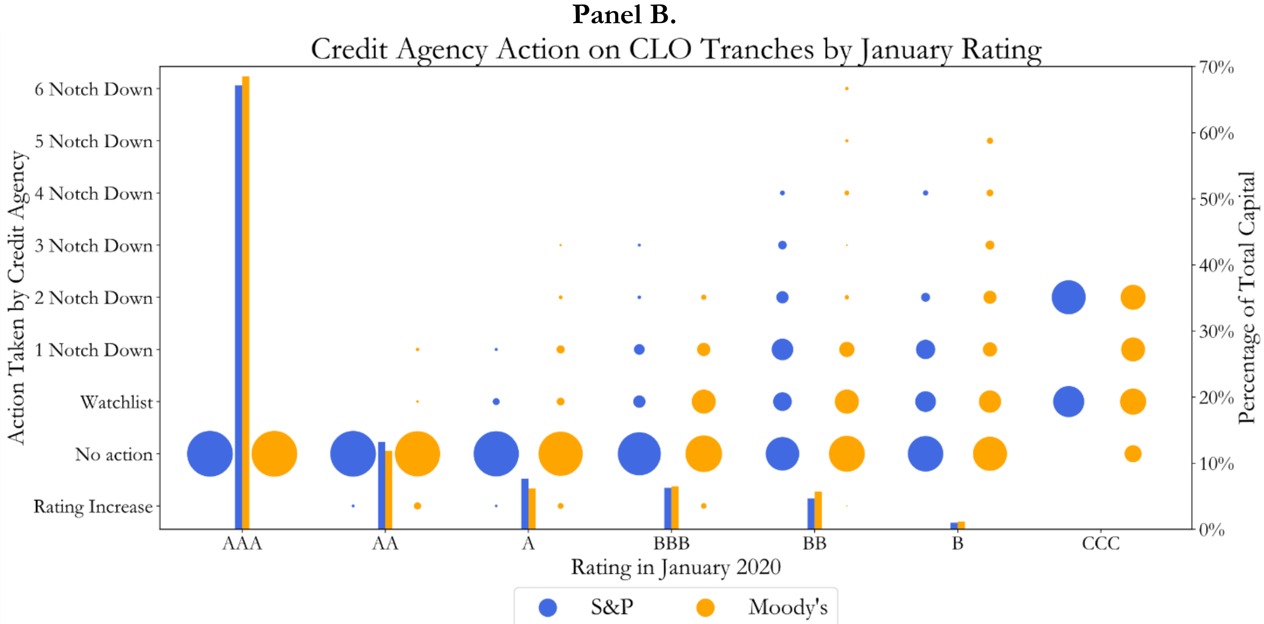


Figure 5. Moody's Expected and Actual Rating Actions for CLO Tranches

This figure displays the expected rating actions forecasted by Moody's if the pool's WARF increased by 30% (Panel A) or 15% (Panel B) as well as the actual rating actions that Moody's took when CLO pools faced increases in WARF of at least of these magnitudes. The data is split based on the initial rating of the tranche. The blue hollow circles represent Moody's projections reported in its press releases, and the green solid circles represent the actions Moody's actually took based on tranche and loan level data. Each circle's area is proportional to the percent of tranches with a given initial rating that were expected to receive or actually received a particular action. For the actual actions, the initial rating is as of January 2020 and the increase in WARF is based on WARF reported in trustee reports in January 2020 versus August 2020. Data from investor press releases regarding 986 Moody's rated CLOs is used to construct the expected rating actions and data from 260 deals that faced a WARF increase of at least 15% is used to construct the actual actions.

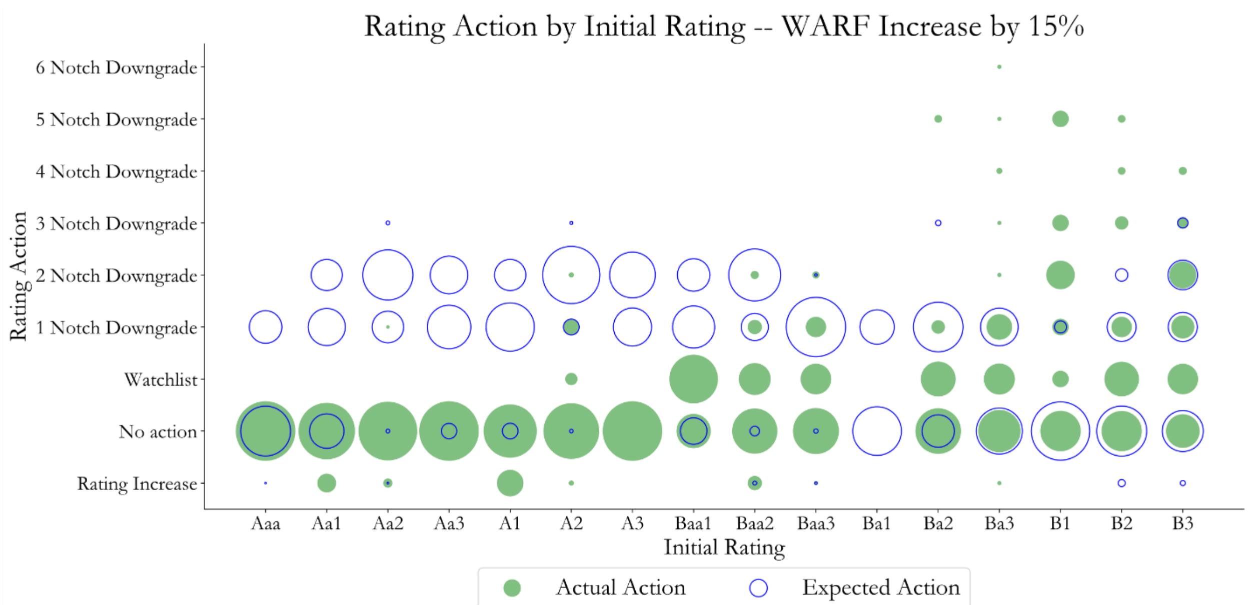
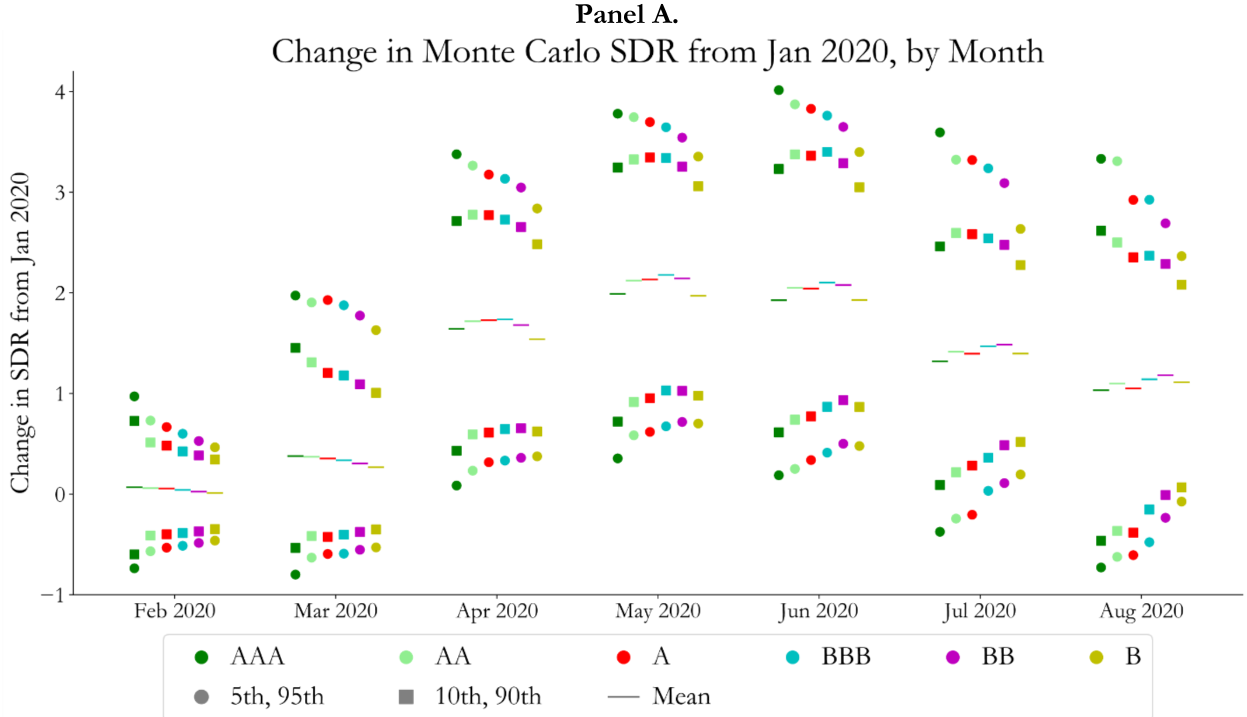


Figure 6. Change in SDR During 2020

This figure reports the change in S&P's collateral risk metric, SDR, over time. In Panel A, we estimate the SDR for each rating class using Monte Carlo simulations based on S&P's methodology. Reported is the distribution of the change in SDR for each CLO-class relative to its corresponding value in January 2020. Panel B reports the distribution of the difference in SDR and BDR, as reported in trustee reports. This panel reports the distribution as of February, June, and August 2020. Numerical labels denote the share of CLOs with an SDR that exceeds its BDR.

Panel A.



Panel B.

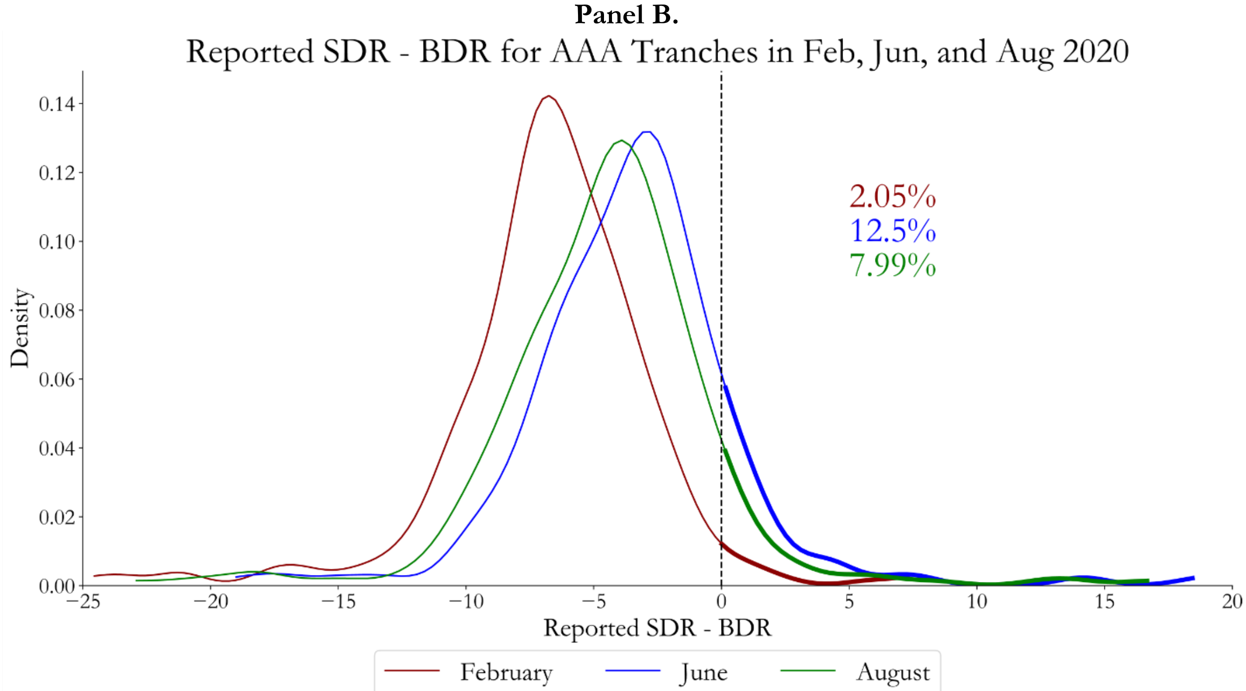
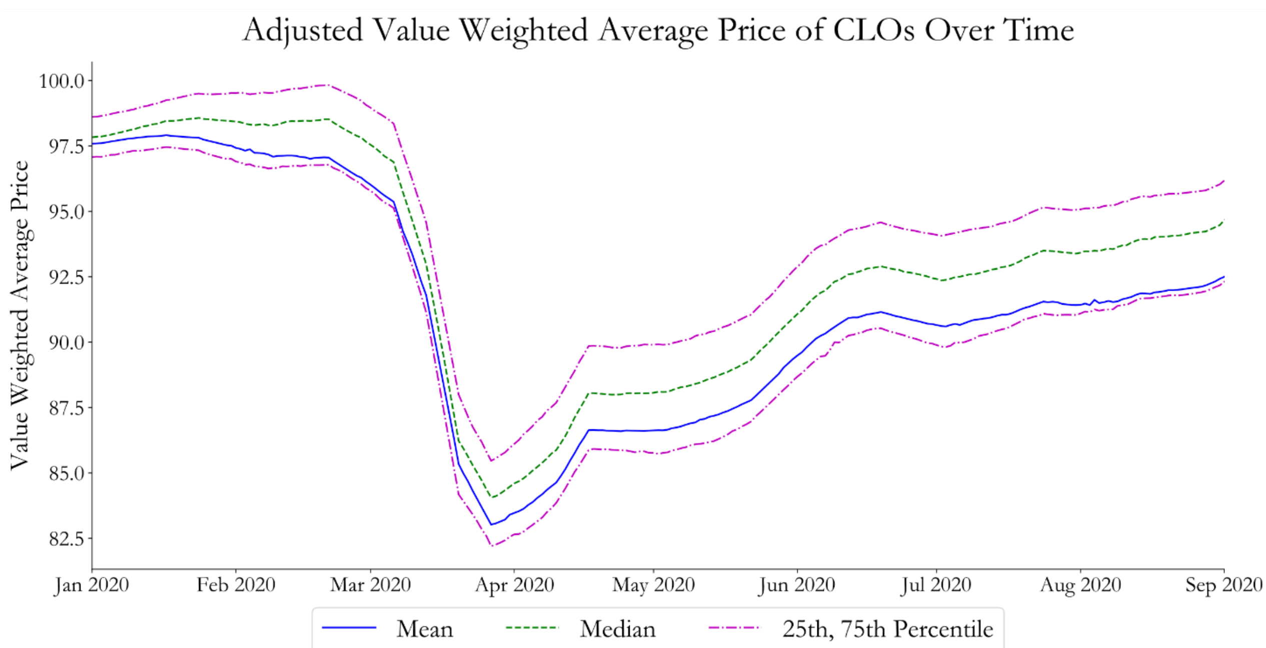


Figure 7. Collateral Prices and Tranche Liability Coverage During Crisis

This table reports the collateral pool value over time, based on Bloomberg's BVAL valuation model. Panel A reports the par-weighted valuation price, deflated by the change in aggregate collateral par from January to the current holding period. Panel B reports the distribution of the 'liability coverage ratio.' The measure is defined for a given tranche (e.g. BBB+ rated) as the estimated market value of the collateral pool in excess of all tranches more senior (e.g., A- and above) divided by the par value of the tranche. All negative values are reset to zero. The panel reports the distribution of ratios across rating classes for February, June, and August 2020.

Panel A.



Panel B.

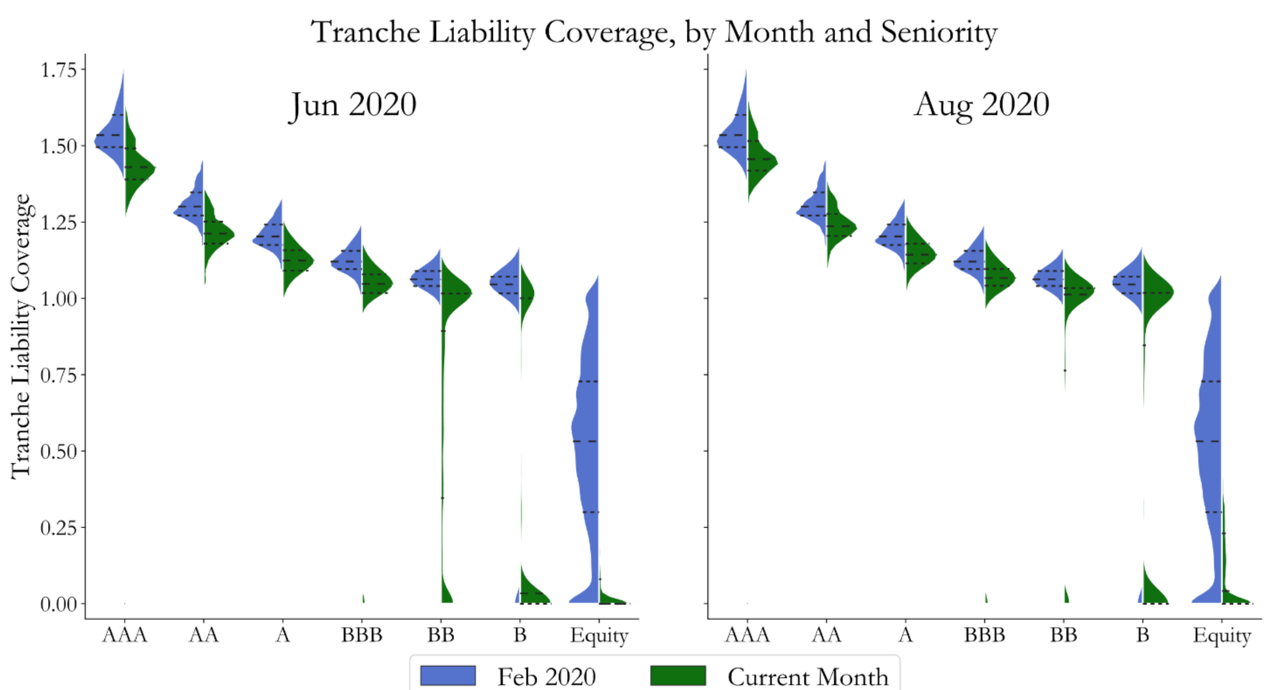
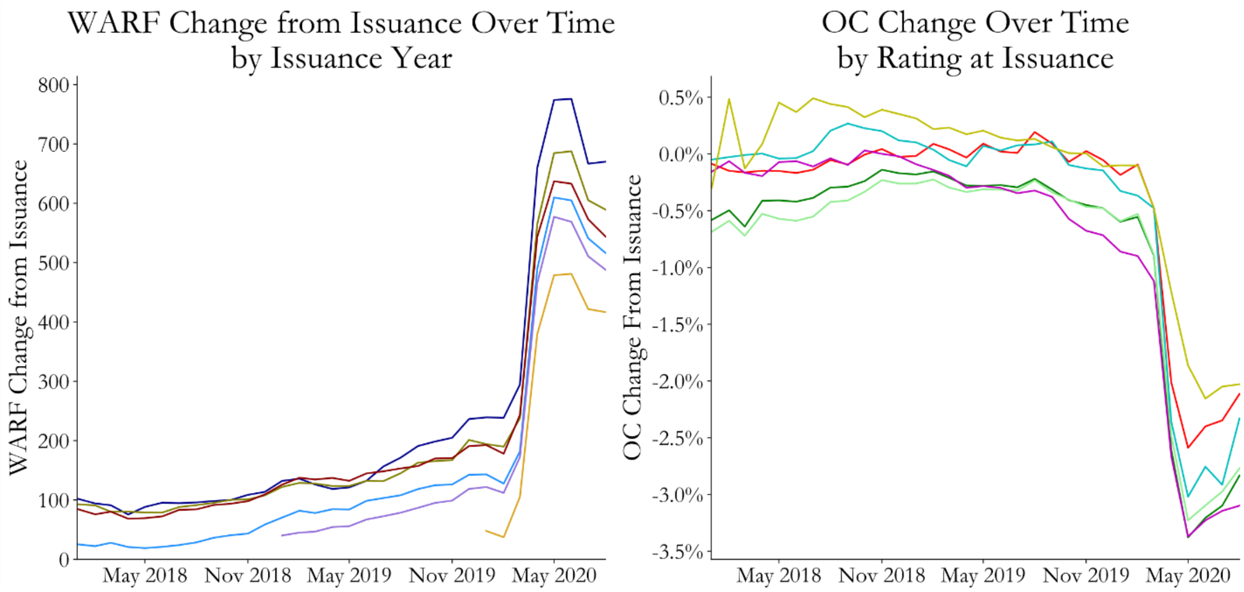


Figure 8. WARF and OC Before and During the COVID-19 Crisis

This figure displays the change in WARF and OC before and during the COVID-19 crisis. For both panels, the data on WARF is divided by the CLOs' issuance year and the data on OC is divided the CLOs' rating at issuance. Panel A shows the change in WARF from the value at issuance over time. Panel B shows the change in WARF and OC, relative to the CLO's WARF and OC at issuance, in January to August 2020 using violin plots for each month by vintage.

Panel A.



Panel B.

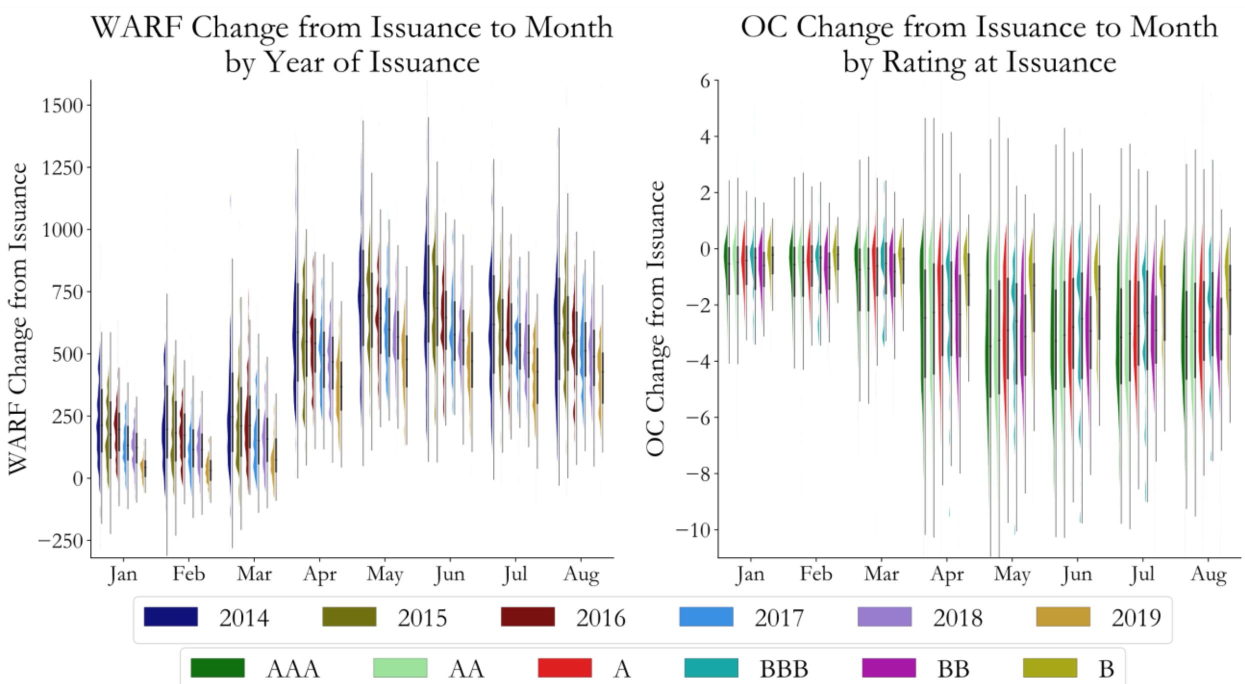
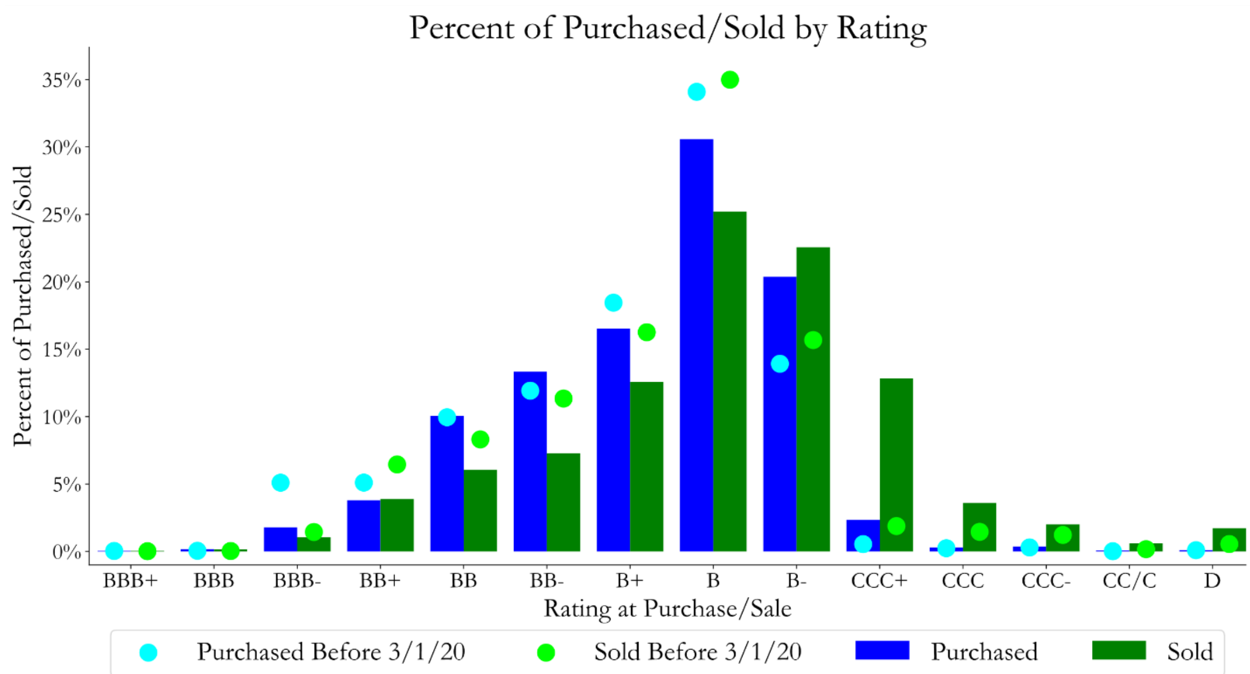


Figure 9. Ratings of Loans Purchased and Sold During COVID-19 Crisis

This figure displays the rating distribution of the loans being sold and purchased (Panel A) by CLOs during the COVID-19 crisis and a comparison of overall collateral risk for active versus static portfolios (Panel B). Rating from S&P were used for this figure. For Panel A, blue bars represent purchases and green bars represent sales. For Panel B, WARF represents the par-weighted 5-year default probability implied by Moody's ratings. The static portfolio corresponds to collateral pool as of January 2020.

Panel A.



Panel B.

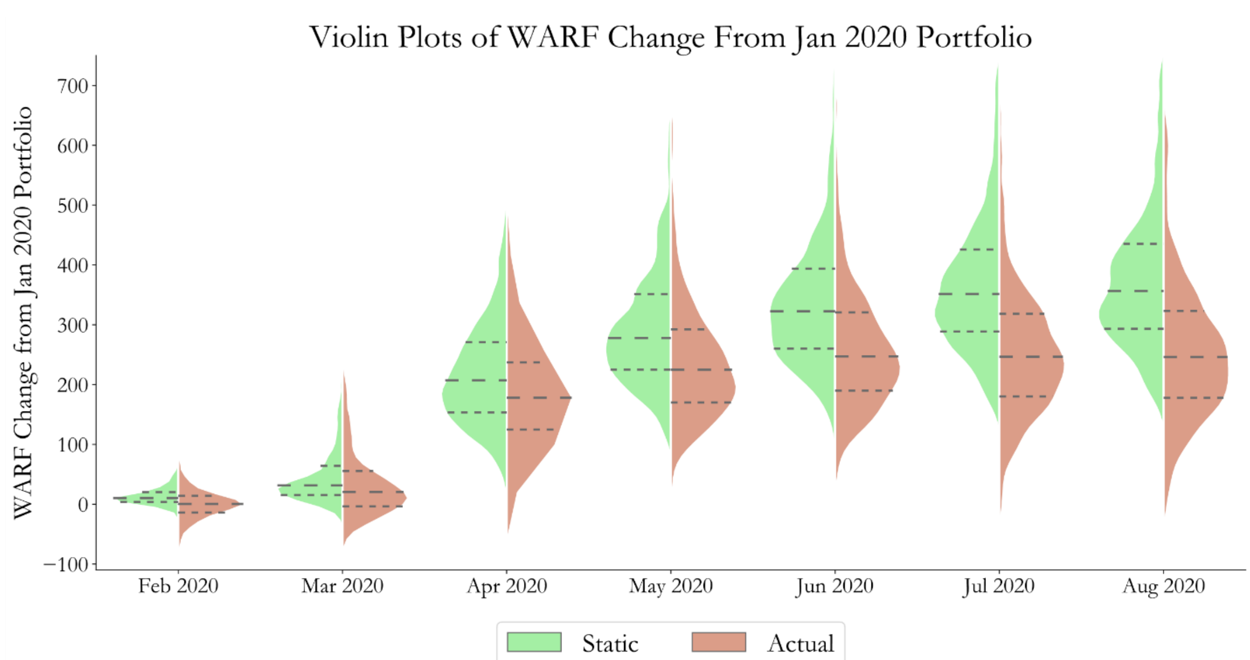
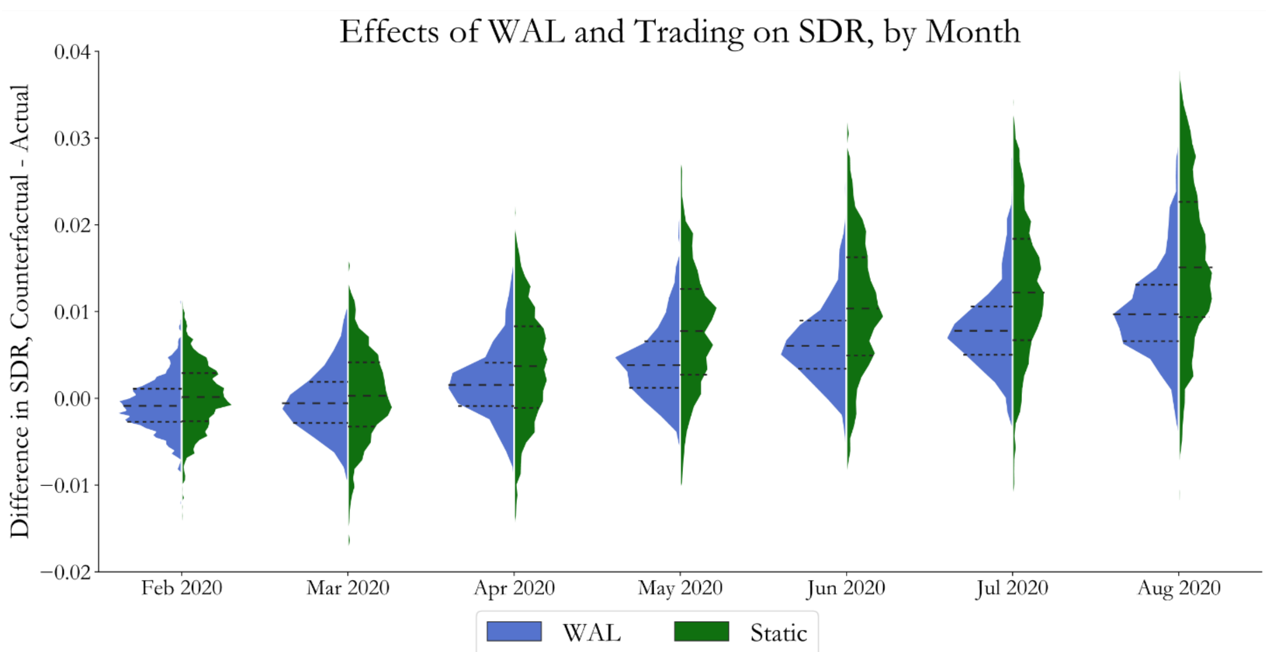


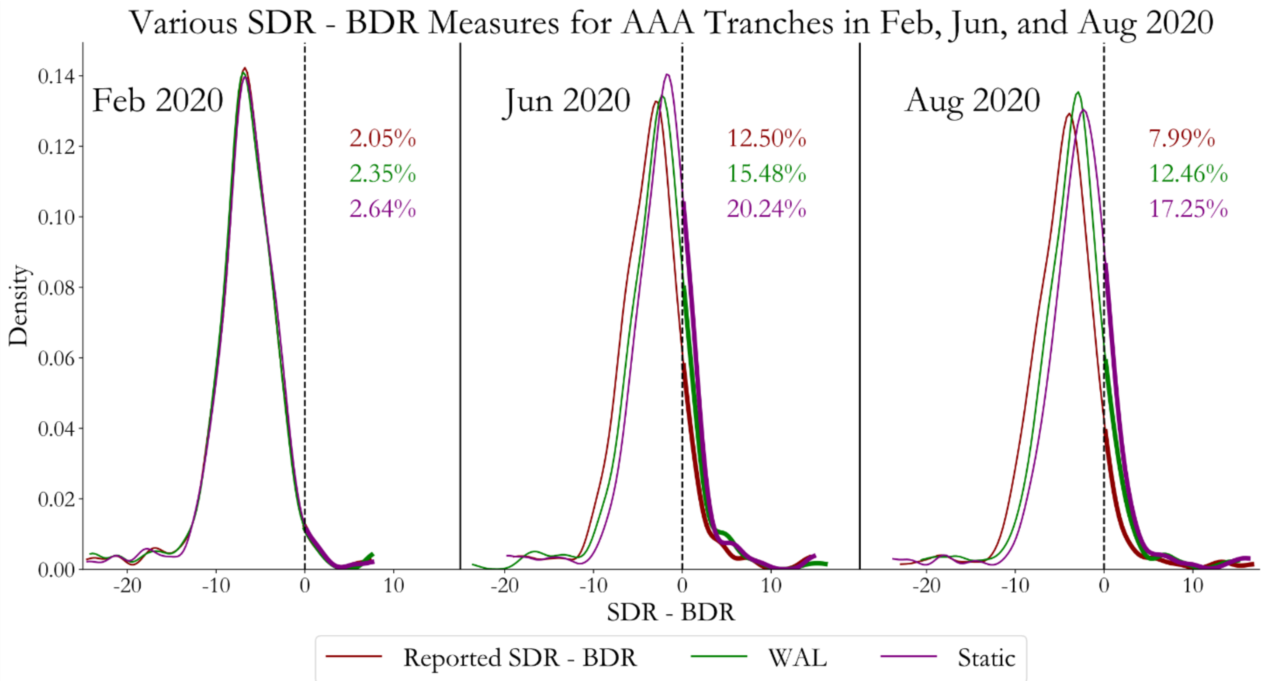
Figure 10. Effects of Active Management Modeling Changes on Model-Implied Risk

This figure illustrates the effects of two counterfactual scenarios related to active management on the overall risk of a collateral pool, as represented by the Scenario Default Rate (SDR). In the 'WAL' scenario, we compute the weighted-average life of collateral for a CLO as of January 2020. For each future holding snapshot, we then add a scalar to the remaining life of all collateral such that the weighted-average life of the collateral pool equals its corresponding January value, at which point we re-compute the SDR. In the 'Static' scenario, we freeze the collateral pool's composition as of January 2020. In Panel A, we report the distribution of the difference in SDR under each counterfactual relative to the SDR value using the true collateral pool. In Panel B, we begin with the sample of CLO-months for which we have a reported SDR and BDR from trustee reports (as used in Panel B of Figure 6). To each reported SDR – BDR difference, we add the difference in SDR associated with each counterfactual scenario performed in Panel A. Panel C performs a similar exercise when considering the effects of the 2019 change in S&P's methodology ('Prev. Non-Model'), and of using Monte Carlo simulations to estimate SDRs rather than fitted values from an OLS regression ('Monte Carlo'). In each scenario we compute the difference in SDR under the counterfactual relative to the actual method (which uses fitted values, with recent vintage deals falling under a new regime), which we add to the reported difference in SDR – BDR.

Panel A.



Panel B.



Panel C.

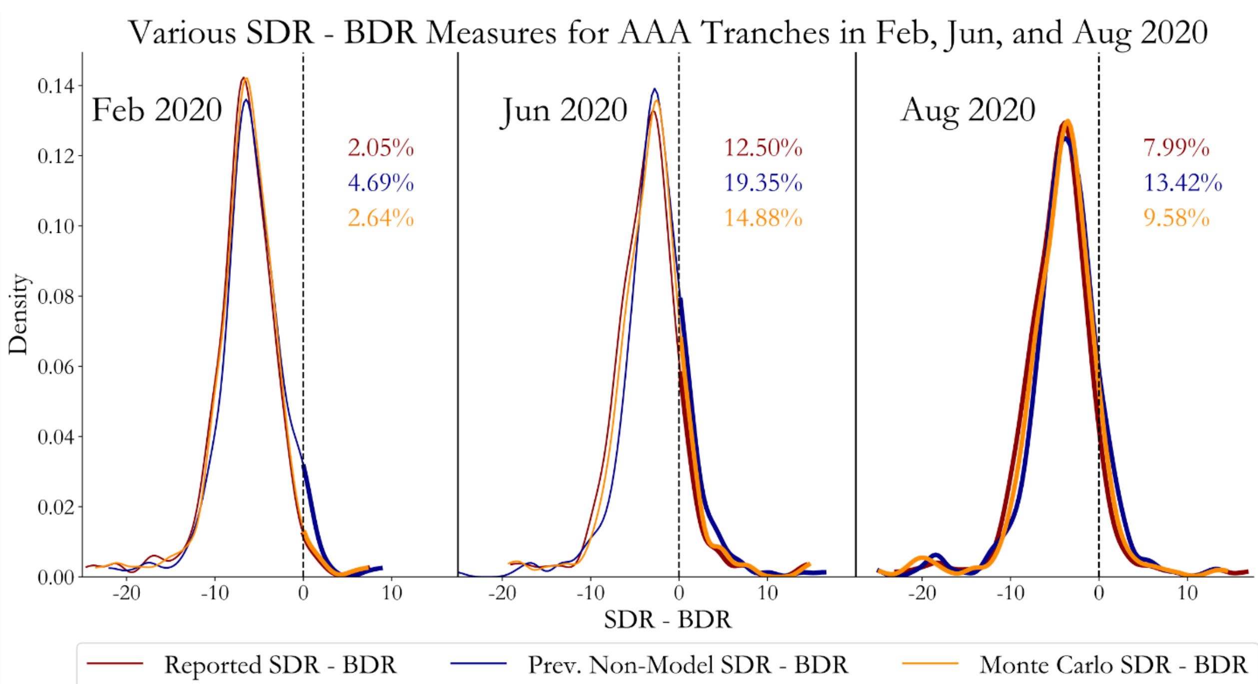


Figure 11. Portfolio Stress Before Break-Even

This figure displays the distribution of stress a collateral pool can withstand before the Scenario Default Rate (SDR) exceeds the Break-Even Default Rate (BDR). For each CLO-month holdings, we begin by computing the asset default probability for each piece of collateral using actual ratings and maturities. We then solve for the scaler factor, which when multiplied by each default probability, results in an SDR equal to the CLO-month's BDR. Reported is the kernel density by month, with a box-plot on the right edge.

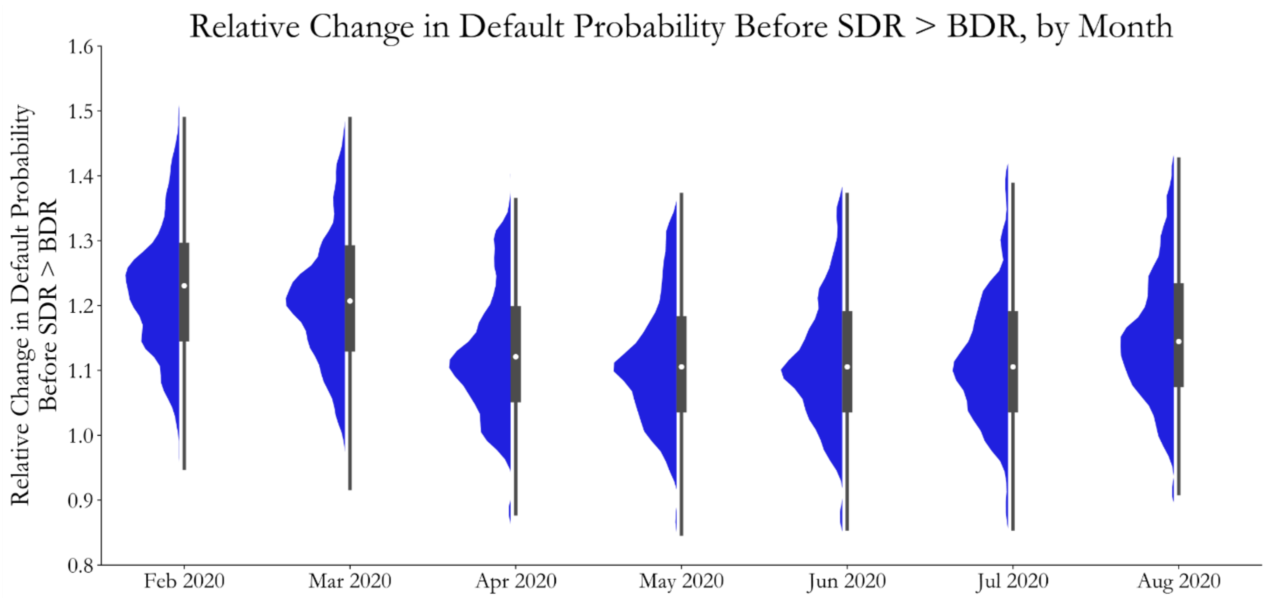


Table 1
Summary Statistics

This table reports summary statistics for our final sample. Reported are deal-level characteristics measured in January 2020 (*Deals*), holding-month snapshots gathered from trustee reports spanning January to August 2020 (*Holding Snapshots*), and individual collateral transactions from January to August 2020 (*Trades*).

	Mean	Std. Dev.	p25	p75
Deals (N = 1,185)				
Tranche Par ($M)	499.1	140.8	408.7	553.2
% AAA	0.606	0.0604	0.597	0.636
% Equity	0.103	0.0434	0.0894	0.104
# Tranches	7.395	1.319	6	8
Holding Snapshots (N = 9,193)				
Pool Par ($M)	483.2	143.8	398.3	536.5
Moody's Rating	14.43	0.379	14.18	14.59
S&P Rating	14.73	0.317	14.53	14.87
# Loans	285.2	108.7	203	344
# Obligors	255.5	97.51	177	309
Industry Inv. HHI	22.90	5.031	20.00	25.42
Trades (N = 429,039)				
Quantity ($k)	514.0	672.8	125	600
Price	93.59	8.450	91	99.50
Yield-to-Mat.	6.780	4.224	4.544	7.554
Remain Mat. (Yrs)	5.198	1.495	4.233	6.370

Table 2
Collateral Performance and Tranche Rating Actions

This table reports the results of OLS regressions. In Panels A and B the dependent variable is the percent of rated tranches downgraded or put on credit watch, and observations are at the deal level. In Panels C and D the dependent variable is an indicator taking on a value of one if a tranche is downgraded or put on credit watch (scaled by 100), and observations are at the tranche-level. All tranche ratings are measured as of August 1st, 2020. In Panels A and C, the dependent variable and collateral pool rating factors are determined by Moody's ratings, while Panels B and D use S&P ratings. *Change Pool WARF* is the percent change in the weighted-average rating factor of a collateral pool from January to August 2020. *Deal Size* is the aggregate par value of all tranches in a CLO, while *# Tranches* is the total number of tranches. *Vintage* denotes the closing year for the CLO. *Deal % AAA Tranche* is the par percent comprised of AAA-rated tranches, with a similar construction for *Deal % Equtiy Tranche*. *Underwriter Activity* is set equal to the total par value of tranches issued by an underwriter in 2018 and 2019, with $1 added to the sum. *Coll. Man. Activity* is constructed in a similar fashion by collateral manager. *t*-statistics (in parentheses) are heteroscedasticity-robust and clustered at the issue-quarter level. ***p <0.01, **p <0.05, *p <0.1.

Panel A: Pct. Rated Tranches Downgrades/Watchlist (Moody's)				
	(1)	(2)	(3)	(4)
Change Pool WARF (%)	0.239***	0.163*	0.183**	0.182**
	(2.97)	(2.05)	(2.10)	(2.09)
ln(Deal Size)	1.628	0.713	0.438	0.397
	(1.32)	(0.59)	(0.34)	(0.31)
ln(# Tranches)	6.410***	6.633***	5.406**	5.418**
	(3.24)	(3.56)	(2.55)	(2.57)
1(2016 Vintage)		-3.102**	-3.328***	-3.330***
		(-2.78)	(-3.01)	(-3.00)
1(2017 Vintage)		-1.720	-1.849	-1.849
		(-1.33)	(-1.43)	(-1.44)
1(2018 Vintage)		-2.829**	-2.923**	-2.923**
		(-2.41)	(-2.46)	(-2.43)
1(2019 Vintage)		-6.215***	-6.106***	-6.130***
		(-3.96)	(-3.81)	(-3.78)
Deal % AAA Tranche			-0.003	-0.002
			(-0.03)	(-0.02)
Deal % Equity Tranche			-0.195***	-0.197***
			(-2.92)	(-2.90)
ln(Underwriter Activity)				-0.093
				(-0.28)
ln(Coll. Man. Activity)				0.097
				(0.32)
Observations	819	819	819	819
R^2	0.037	0.082	0.093	0.093

Panel B: Pct. Rated Tranches Downgrades/Watchlist (S&P)

	(1)	(2)	(3)	(4)
Change Pool WARF (%)	0.336***	0.303***	0.289***	0.290***
	(6.03)	(6.53)	(6.41)	(6.46)
ln(Deal Size)	-2.676*	-1.849	-1.169	-0.490
	(-1.96)	(-1.35)	(-0.97)	(-0.40)
ln(# Tranches)	-2.107	-1.659	-2.418	-2.047
	(-1.40)	(-1.05)	(-1.46)	(-1.20)
1(2016 Vintage)		-2.732***	-2.545***	-2.270**
		(-3.08)	(-2.89)	(-2.39)
1(2017 Vintage)		-3.701***	-3.491***	-3.382***
		(-3.35)	(-3.10)	(-2.96)
1(2018 Vintage)		-4.547***	-4.315***	-4.180***
		(-5.92)	(-5.58)	(-5.08)
1(2019 Vintage)		-5.589***	-5.175***	-5.089***
		(-6.91)	(-6.23)	(-5.77)
Deal % AAA Tranche			-0.096**	-0.103**
			(-2.24)	(-2.23)
Deal % Equity Tranche			-0.136***	-0.134***
			(-4.50)	(-4.49)
ln(Underwriter Activity)				-0.635
				(-1.41)
ln(Coll. Man. Activity)				-0.352
				(-1.67)
Observations	417	417	417	417
R^2	0.133	0.287	0.302	0.314

Panel C: Tranche Downgrade/Watchlist Actions, scaled by 100 (Moody's)

	(1)	(2)	(3)	(4)
Class:	A	BBB	BB	B
Change Pool WARF (%)	0.982***	1.121***	1.208**	0.876
	(3.16)	(3.15)	(2.36)	(1.08)
Observations	635	590	590	225
R^2	0.025	0.181	0.169	0.240

Panel D: Tranche Downgrade/Watchlist Actions, scaled by 100 (S&P)

	(1)	(2)	(3)	(4)
Class:	A	BBB	BB	B
Change Pool WARF (%)	0.667**	1.652***	1.539***	0.678
	(2.07)	(4.01)	(3.04)	(1.06)
Observations	322	307	300	101
R^2	0.102	0.118	0.194	0.421

Table 3
SDR Sensitivity to Rating Downgrades across Rating Classes

This table reports the results of OLS regressions. The dependent variable is the SDR corresponding to a given rating class (noted in the column header), computed from Monte-Carlo simulations as described in Section 4. *Change Coll. Def. Prob.* is the percent change in the collateral pool's weighted-average default probability induced by simulated rating downgrades. For each collateral pool (observed at the CLO-month) level, we simulate 50 draws of rating downgrades. *Deal-Month FE* denotes a fixed effect for each CLO-month holding snapshot. *t*-statistics (in parentheses) are heteroscedasticity-robust and clustered at the CLO deal level. ***p <0.01, **p <0.05, *p <0.1.

	(1)	(2)	(3)	(4)	(5)	(6)
Class:	AAA	AA	A	BBB	BB	B
Change Coll. Def. Prob.	0.295***	0.315***	0.323***	0.324***	0.317***	0.303***
	(992.54)	(823.46)	(688.51)	(591.37)	(489.61)	(413.34)
Deal-Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	378,050	378,050	378,050	378,050	378,050	378,050
R^2	0.999	0.999	0.999	0.999	0.999	0.999

Table 4
Collateral Manager Trading Activity

This table reports the results of OLS regressions. The dependent variable is either *# Trades / Day*, the number of trades per day or *Qty Traded*, natural log of collateral par traded per day (as noted in the column header). 1() denotes an indicator function, taking on a value of one for each trade month. In Panel B, *Change Pool WARF* is the month-over-month percent change in the weighted-average rating factor of a collateral pool as of the most recent holding period reported prior to a trade, as measured using either Moody's (M) or S&P (SP) ratings. *DoW* is an abbreviation for day-of-week. *t*-statistics (in parentheses) are heteroscedasticity-robust and clustered at the CLO deal level. ***p <0.01, **p <0.05, *p <0.1.

Panel A: Trading Activity across Time

Dep. Variable:	# Trades/Day		ln(Qty Traded)	
	(1)	(2)	(3)	(4)
1(February)	0.488***	0.475***	0.136***	0.112***
	(8.61)	(8.15)	(9.90)	(8.32)
1(March)	1.651***	1.388***	-0.084***	-0.122***
	(7.66)	(7.25)	(-4.38)	(-6.74)
1(April)	1.188***	0.812***	-0.222***	-0.250***
	(5.00)	(3.90)	(-10.85)	(-12.78)
1(May)	-0.178	-0.565***	-0.426***	-0.456***
	(-1.58)	(-5.09)	(-22.88)	(-25.30)
1(June)	-0.077	-0.371***	-0.158***	-0.192***
	(-1.04)	(-5.10)	(-9.26)	(-11.66)
1(July)	-0.420***	-0.869***	-0.446***	-0.497***
	(-4.31)	(-10.85)	(-22.14)	(-25.13)
1(August)	-0.201	-0.488***	-0.383***	-0.454***
	(-0.99)	(-3.26)	(-11.39)	(-14.92)
DoW FE	Yes	Yes	Yes	Yes
Deal FE		Yes		Yes
Observations	107,064	107,057	107,027	107,020
R^2	0.014	0.394	0.035	0.170

Panel B: Trading Activity across CLO Pool Performance
Dep. Variable: Ln(Qty Traded)

	(1)	(2)	(3)	(4)
Change Pool WARF (M)	-2.049***	-0.431		
	(-8.60)	(-1.59)		
Change Pool WARF (S&P)			-1.954***	-1.020***
			(-10.32)	(-4.57)
1(February)		0.110***		0.112***
		(8.09)		(8.04)
1(March)		-0.122***		-0.123***
		(-6.66)		(-6.54)
1(April)		-0.235***		-0.200***
		(-10.53)		(-8.48)
1(May)		-0.442***		-0.438***
		(-23.44)		(-22.27)
1(June)		-0.187***		-0.193***
		(-11.25)		(-11.39)
1(July)		-0.499***		-0.520***
		(-25.20)		(-25.46)
1(August)		-0.456***		-0.476***
		(-15.01)		(-15.14)
DoW FE	Yes	Yes	Yes	Yes
Deal FE	Yes	Yes	Yes	Yes
Observations	106,020	106,020	100,798	100,798
R^2	0.140	0.166	0.143	0.170

Table 5
Collateral Manager Trading Performance

This table reports the results of OLS regressions. The dependent variable is either the 15- or 30-day return on all trades made at the CLO-trade month level, value-weighed by their respective par. The unit of observation is at the CLO-trade month-direction (buy vs. sell) level. *1(Purchase)* takes a value of one for trades that are purchases. *Rating-Month FE* denotes an interaction of trade-month indicators and a vector of indicators for the ordinal ratings of either S&P (SP) or Moody's (M). All remaining variables are defined in Table 4. *t*-statistics (in parentheses) are heteroscedasticity-robust and clustered at the CLO deal level. ***p <0.01, **p <0.05, *p <0.1.

Panel A: Trading Performance, 15-day V.W. Return				
	(1)	(2)	(3)	(4)
1(Purchase) × 1(January)	0.005	0.000	0.003***	0.002***
	(1.64)	(0.53)	(8.62)	(4.65)
1(Purchase) × 1(February)	0.017***	0.011***	0.010***	0.010***
	(6.06)	(9.35)	(12.49)	(10.33)
1(Purchase) × 1(March)	-0.026**	-0.007**	-0.001	-0.004*
	(-2.16)	(-2.39)	(-0.60)	(-1.85)
1(Purchase) × 1(April)	-0.044***	-0.038***	-0.009***	-0.013***
	(-6.27)	(-6.88)	(-6.21)	(-7.38)
1(Purchase) × 1(May)	-0.018***	-0.020***	0.001	-0.009***
	(-4.84)	(-7.85)	(0.67)	(-5.44)
1(Purchase) × 1(June)	-0.018***	-0.021***	0.002	-0.001
	(-3.21)	(-3.99)	(1.42)	(-0.59)
1(Purchase) × 1(July)	-0.006	-0.009	-0.007	-0.010
	(-0.89)	(-1.43)	(-1.35)	(-1.46)
1(Purchase) × 1(August)	-0.002	-0.004***	-0.002	-0.000
	(-0.87)	(-3.17)	(-1.30)	(-0.36)
Month FE	Yes			
Deal FE	Yes			
Deal-Month FE		Yes	Yes	Yes
Rating-Month FE			S&P	M
Observations	419,291	418,916	398,146	414,323
R^2	0.127	0.231	0.268	0.414

Panel B: Trading Performance, 30-day V.W. Return

	(1)	(2)	(3)	(4)
1(Purchase) × 1(January)	-0.007***	-0.006***	0.002***	0.000
	(-3.64)	(-4.25)	(3.48)	(0.12)
1(Purchase) × 1(February)	0.013***	0.014***	0.009***	0.015***
	(3.58)	(5.86)	(6.89)	(9.32)
1(Purchase) × 1(March)	-0.001	-0.001	0.001	-0.004*
	(-0.31)	(-0.61)	(0.37)	(-1.67)
1(Purchase) × 1(April)	-0.060***	-0.052***	-0.016***	-0.021***
	(-10.24)	(-10.60)	(-8.18)	(-10.80)
1(Purchase) × 1(May)	-0.027***	-0.026***	-0.005***	-0.010***
	(-8.39)	(-8.35)	(-3.88)	(-5.44)
1(Purchase) × 1(June)	-0.029***	-0.027***	0.003**	-0.001
	(-4.60)	(-4.40)	(2.43)	(-0.36)
1(Purchase) × 1(July)	0.006	0.000	0.004***	0.004***
	(0.78)	(0.03)	(3.70)	(4.47)
Month FE	Yes			
Deal FE	Yes			
Deal-Month FE		Yes	Yes	Yes
Rating-Month FE			S&P	M
Observations	385,644	385,414	366,753	381,290
R^2	0.165	0.316	0.373	0.539

Table 6
Maturity of Collateral Trades

This table reports the results of OLS regressions. The dependent variable is remaining years until maturity for collateral trades, where unit of observation is at the trade level. *1(Purchase)* takes a value of one for trades that are purchases. In Panel B, *Change Pool WARF* is the month-over-month percent change in the weighted-average rating factor of a collateral pool as of the most recent holding period reported prior to a trade, as measured using either Moody's (M) or S&P (SP) ratings. *Rating-Month FE* denotes an interaction of trade-month indicators and a vector of indicators for the ordinal ratings of either S&P (SP) or Moody's (M). All remaining variables are defined in Table 5. *t*-statistics (in parentheses) are heteroscedasticity-robust and clustered at the CLO deal level. ***p <0.01, **p <0.05, *p <0.1.

Panel A: Remaining Maturity of Trades across Time

	(1)	(2)	(3)	(4)
1(Purchase)	0.899***	0.895***	0.795***	0.805***
	(35.84)	(34.07)	(34.05)	(34.24)
x 1(February)	-0.004	0.027	0.073***	0.075***
	(-0.13)	(0.95)	(2.79)	(2.92)
x 1(March)	-0.325***	-0.307***	-0.358***	-0.324***
	(-9.42)	(-8.31)	(-12.36)	(-10.75)
x 1(April)	-0.700***	-0.723***	-0.800***	-0.769***
	(-18.19)	(-19.18)	(-23.83)	(-22.52)
x 1(May)	-0.392***	-0.376***	-0.492***	-0.407***
	(-9.37)	(-9.17)	(-13.94)	(-10.79)
x 1(June)	-0.349***	-0.344***	-0.480***	-0.415***
	(-8.28)	(-7.86)	(-11.04)	(-9.62)
x 1(July)	-0.721***	-0.737***	-0.701***	-0.730***
	(-12.47)	(-12.11)	(-11.63)	(-13.28)
x 1(August)	-0.407***	-0.469***	-0.311***	-0.421***
	(-5.99)	(-6.35)	(-5.21)	(-6.55)
Month FE	Yes			
Deal FE	Yes			
Deal-Month FE		Yes	Yes	Yes
Rating-Month FE			S&P	M
Observations	460,452	460,194	433,610	452,990
R^2	0.121	0.161	0.247	0.232

Panel B: Remaining Maturity of Trades across CLO Pool Performance

	(1)	(2)	(3)	(4)	(5)	(6)
1(Purchase) x Change WARF (M)	-1.134**	-1.163***				
	(-2.47)	(-4.09)				
1(Purchase) x Change WARF (S&P)			-1.824***	-1.491***		
			(-6.33)	(-5.41)		
1(Purchase) x SDR-BDR Diff.					-0.023***	-0.018*
					(-3.53)	(-1.90)
Month-Direction FE	Yes	Yes	Yes	Yes	Yes	Yes
Deal-Direction FE		Yes		Yes		Yes
Deal-Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Rating-Month FE	M	M	S&P	S&P	S&P	S&P
Observations	451,172	451,156	431,254	431,229	132,146	132,231
R^2	0.233	0.249	0.247	0.262	0.196	0.186

Table 7
Collateral Trade Yields

This table reports the results of OLS regressions. The dependent variable is the yield-to-maturity for collateral trades, where unit of observation is at the trade level. Yields are computed using the current trade date, maturity date and coupon yield, assuming coupons are paid out quarterly. The price used in the YTM computation is either the listed trade price (Panel A), or Bloomberg's BVAL estimated price (Panel B). *1(Purchase)* takes a value of one for trades that are purchases. *Deal-Direction FE* denotes an interaction of a CLO fixed effect and an indicator variable for the direction of the trade (buy vs. sell). *Rating-Month FE* denotes an interaction of trade-month indicators and a vector of indicators for the ordinal ratings of either S&P (SP) or Moody's (M). All remaining variables are defined in Table 5. *t*-statistics (in parentheses) are heteroscedasticity-robust and clustered at the CLO deal level. ***p <0.01, **p <0.05, *p <0.1.

Panel A: Yield to Maturity (Traded Price)

	(1)	(2)	(3)
1(Purchase) × 1(January)	-0.663***	-0.643***	
	(-22.23)	(-20.98)	
1(Purchase) × 1(February)	-0.435***	-0.458***	0.116***
	(-14.24)	(-15.49)	(3.79)
1(Purchase) × 1(March)	-1.415***	-1.429***	-0.747***
	(-20.32)	(-24.13)	(-12.78)
1(Purchase) × 1(April)	-1.228***	-1.241***	-0.548***
	(-11.43)	(-11.34)	(-5.95)
1(Purchase) × 1(May)	-0.496***	-0.552***	0.048
	(-7.65)	(-9.06)	(0.81)
1(Purchase) × 1(June)	0.129***	0.068	0.707***
	(2.78)	(1.40)	(12.81)
1(Purchase) × 1(July)	0.322***	0.268***	0.980***
	(6.45)	(5.15)	(15.40)
1(Purchase) × 1(August)	0.157***	0.167***	0.811***
	(2.91)	(2.64)	(7.58)
Rating-Month FE	M, S&P	M, S&P	M, S&P
Deal-Month FE		Yes	Yes
Deal-Direction FE			Yes
Observations	424,639	424,396	424,389
R^2	0.476	0.533	0.545

Panel B: Yield to Maturity (Bloomberg Based)

	(1)	(2)	(3)
1(Purchase) × 1(January)	-0.340***	-0.341***	
	(-9.81)	(-9.67)	
1(Purchase) × 1(February)	-0.197***	-0.237***	0.019
	(-6.35)	(-8.27)	(0.50)
1(Purchase) × 1(March)	-1.061***	-1.099***	-0.751***
	(-20.26)	(-23.88)	(-13.16)
1(Purchase) × 1(April)	-0.926***	-0.908***	-0.542***
	(-8.56)	(-8.14)	(-5.70)
1(Purchase) × 1(May)	-0.422***	-0.482***	-0.203***
	(-5.92)	(-7.12)	(-3.20)
1(Purchase) × 1(June)	0.088	0.015	0.338***
	(1.53)	(0.25)	(5.51)
1(Purchase) × 1(July)	0.336***	0.289***	0.679***
	(7.00)	(5.50)	(9.90)
1(Purchase) × 1(August)	0.304***	0.338***	0.699***
	(5.28)	(5.26)	(6.90)
Rating-Month FE	M, S&P	M, S&P	M, S&P
Deal-Month FE		Yes	Yes
Deal-Direction FE			Yes
Observations	365,180	364,896	364,882
R^2	0.503	0.561	0.572

Table 8
AAA SDR Sensitivity to Rating Downgrades through Time

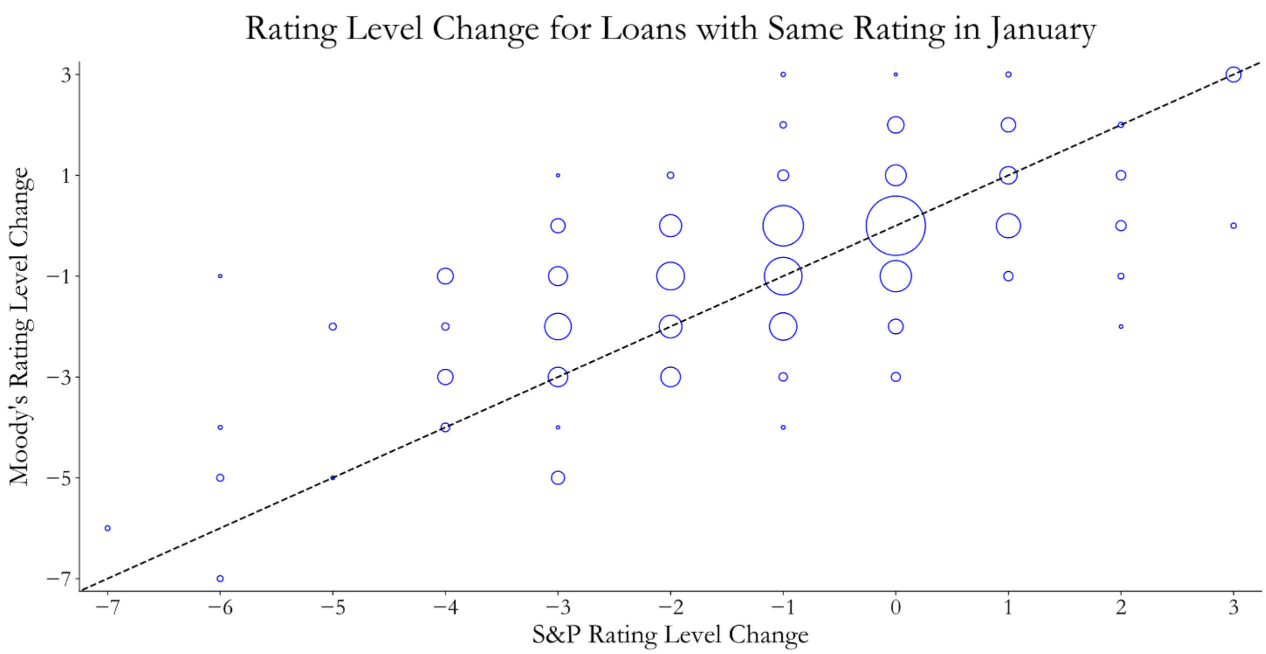
This table reports the results of OLS regressions. The dependent variable is the AAA SDR, computed from Monte-Carlo simulations as described in Section 4, when simulating rating downgrades. For each collateral pool (observed at the CLO-month) level, we simulate 50 draws of rating downgrades. *Change Coll. Def. Prob.* is the percent change in the collateral pool's weighted-average default probability induced by simulated rating downgrades. 'x 1()' denotes the interaction of *Change Coll. Def. Prob.* and an indicator for the month of the holding period. *Deal-Month FE* denotes a fixed effect for each CLO-month holding snapshot. *Deal Slope* denotes an interaction of *Change Coll. Def. Prob.* and indicators for each CLO deal. *t*-statistics (in parentheses) are heteroscedasticity-robust and clustered at the CLO deal level. ***p <0.01, **p <0.05, *p <0.1.

	(1)	(2)
Change Coll. Def. Prob.	0.294***	
	(836.86)	
x 1(February)	0.000	0.000
	(0.83)	(0.16)
x 1(March)	0.000	0.000
	(1.23)	(0.16)
x 1(April)	0.003***	0.002***
	(9.14)	(8.94)
x 1(May)	0.002***	0.002***
	(7.94)	(7.64)
x 1(June)	0.001***	0.001***
	(3.90)	(2.83)
x 1(July)	0.000	-0.000
	(1.06)	(-0.31)
x 1(August)	-0.001**	-0.001***
	(-2.27)	(-3.73)
Deal-Month FE	Yes	Yes
Deal Slope		Yes
Observations	464,800	464,800
R^2	0.999	0.999

Figure IA.1. Ratings Actions on Collateral by S&P and Moody's

This figure compares the rating actions taken (Panel A) and ratings given (Panel B) by S&P and Moody's on loans underlying the CLOs. For Panel A, only loans that had equivalent rates in January 2020 (e.g. Baa1 from Moody's and BBB+ from S&P) are considered and for Panel B, only loans with ratings from both S&P and Moody's in August 2020 are considered. For Panel A, the circles are sized based on the percent of loan par value that received a given action by S&P (x-axis) and by Moody's (y-axis) as of August 2020 and for Panel B, the circles are sized based on the percent of loan par value with given S&P (x-axis) and Moody's (y-axis) ratings. The dashed line in Panel A and B is the 45° line.

Panel A.



Panel B.

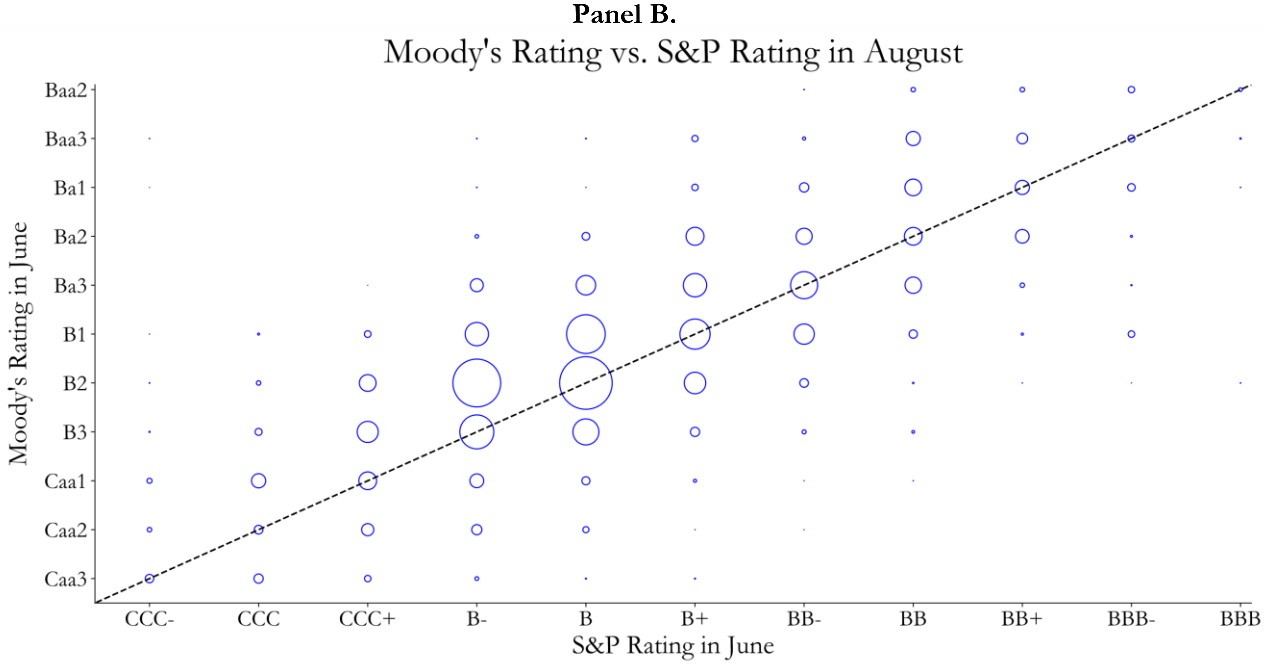
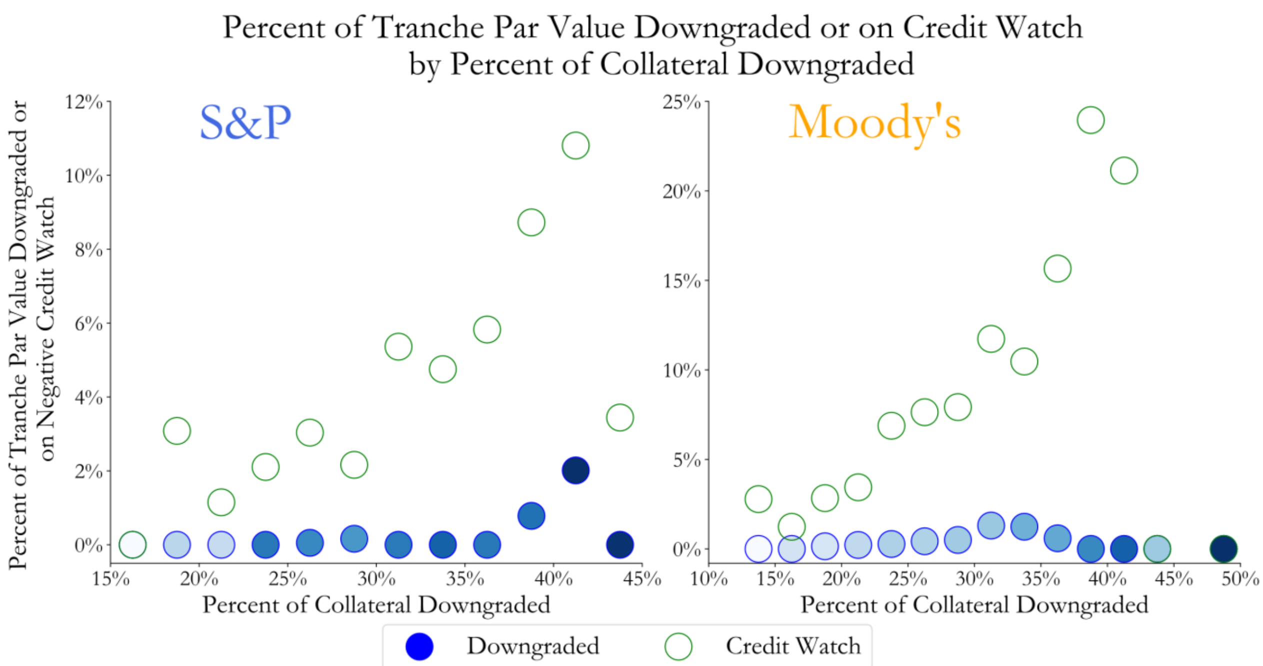


Figure IA.2. Ratings Actions on Collateral and Tranches by S&P and Moody's

This figure repeats the analysis in Figure 4, using rating actions as of June 2020. Panel A shows tranche actions based on their rating actions on the collateral underlying the CLO and Panel B compares the actions of Moody's and S&P on tranches. For Panel A, the percent of total tranche par value in the bin that was downgraded is denoted by blue filled circles, while credit watch is denoted by green hollow circles. For Panel B, the data is split based on the tranche's rating in January 2020 and the circles are sized based on the percent of tranche par value that received a given action by S&P (blue circles) or Moody's (orange circles). The bars represent the percent of tranche par value with a given rating by the credit rating agency.

Panel A.



Panel B.

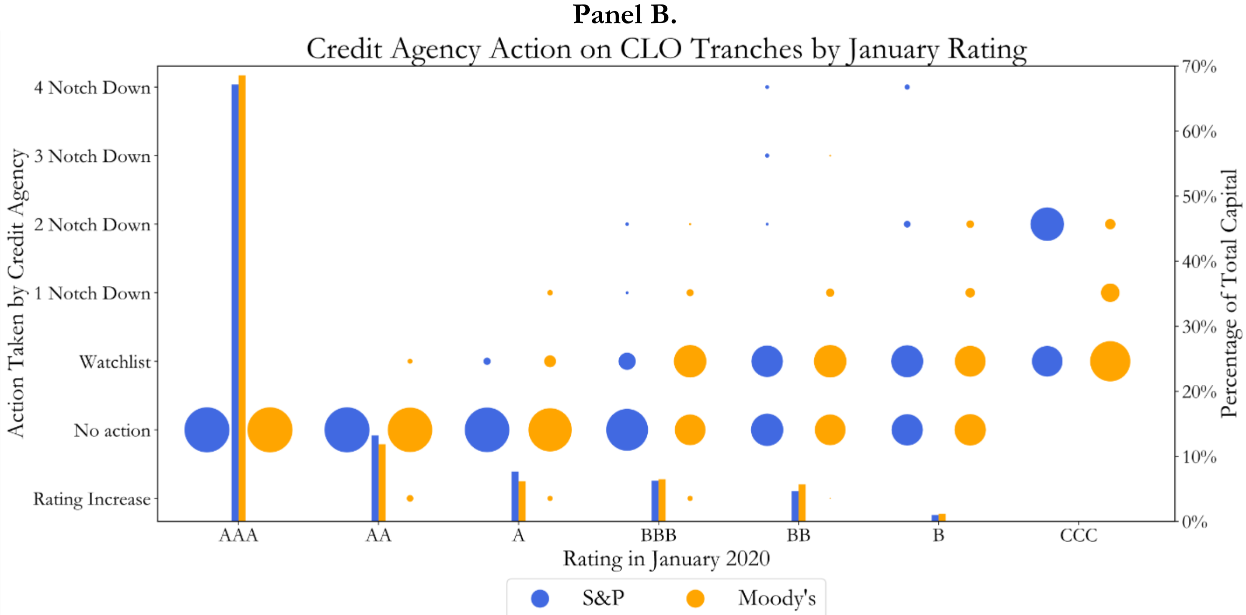
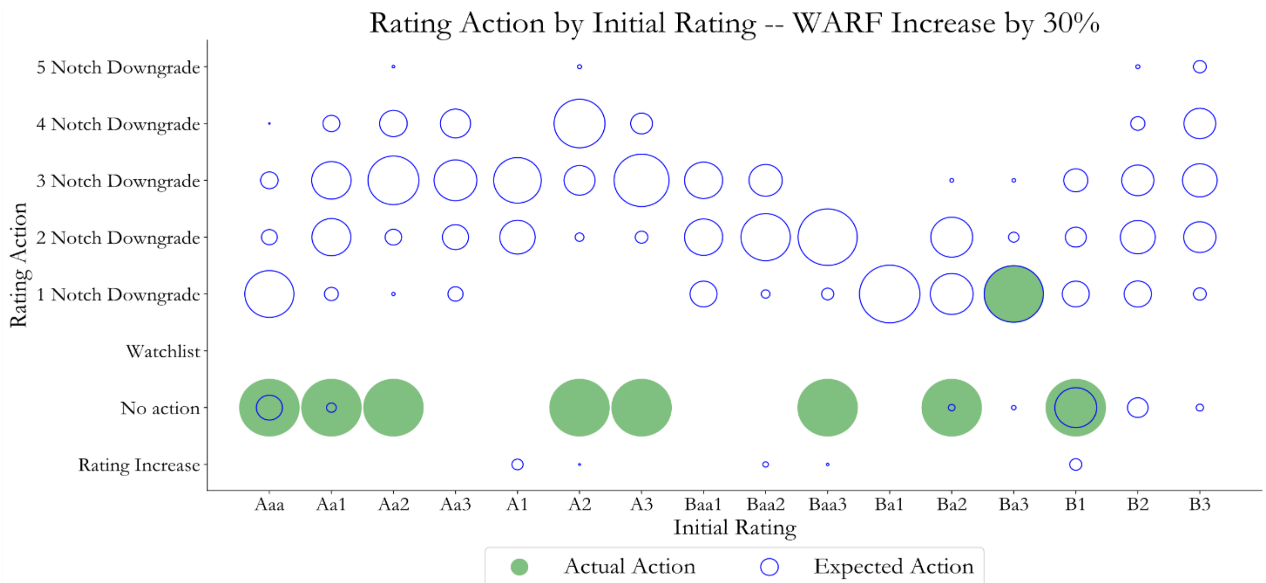


Figure IA.3. Moody's Expected and Actual Rating Actions for CLO Tranches in the Same Deals

This figure displays the expected rating actions forecasted by Moody's if the pool's WARF increased by 30% (Panel A) or 15% (Panel B) as well as the actual rating actions that Moody's took when CLO pools faced increases in WARF of at least of these magnitudes. The data is split based on the initial rating of the tranche. The blue hollow circles represent Moody's projections reported in its press releases, and the green solid circles represent the actions Moody's took based on tranche and loan level data. Each circle is sized by the percent of tranches with a given initial rating that were expected to receive or actually received a particular action. The increase in WARF is based on WARF reported in trustee reports in January versus August 2020. For Panel B, only deals faced at least a 15% increase in WARF and are present in both the investor press releases and in the tranche level data are included; this leaves us with a sample of 158 deals.

Panel A.



Panel B.

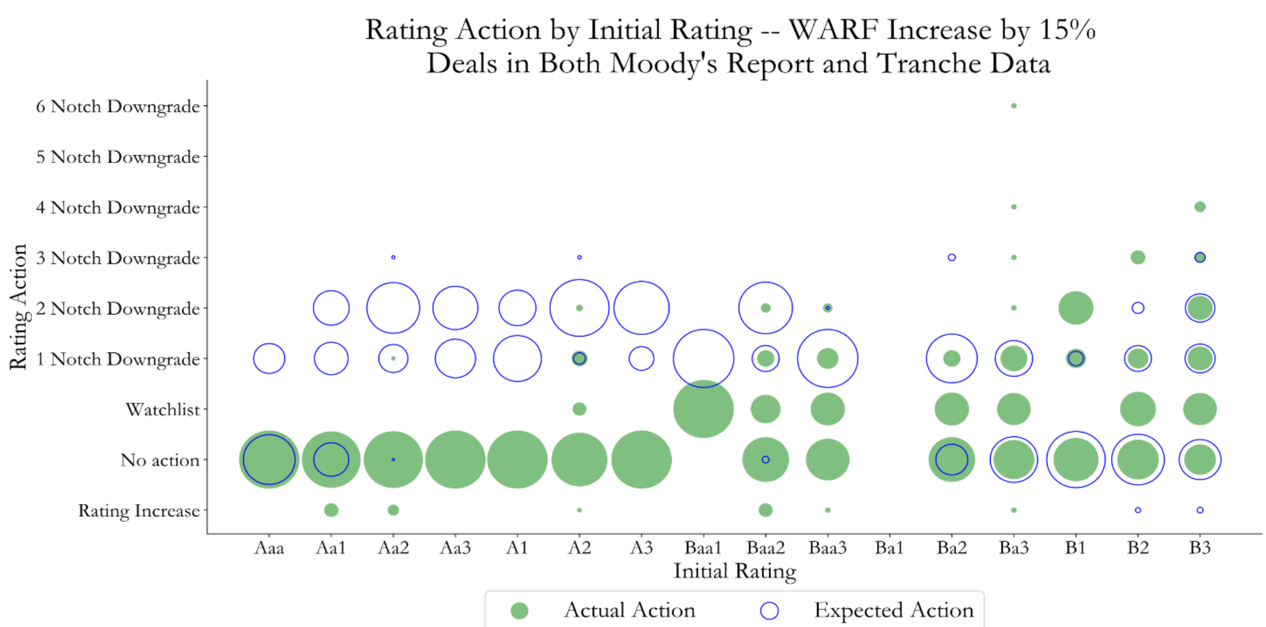
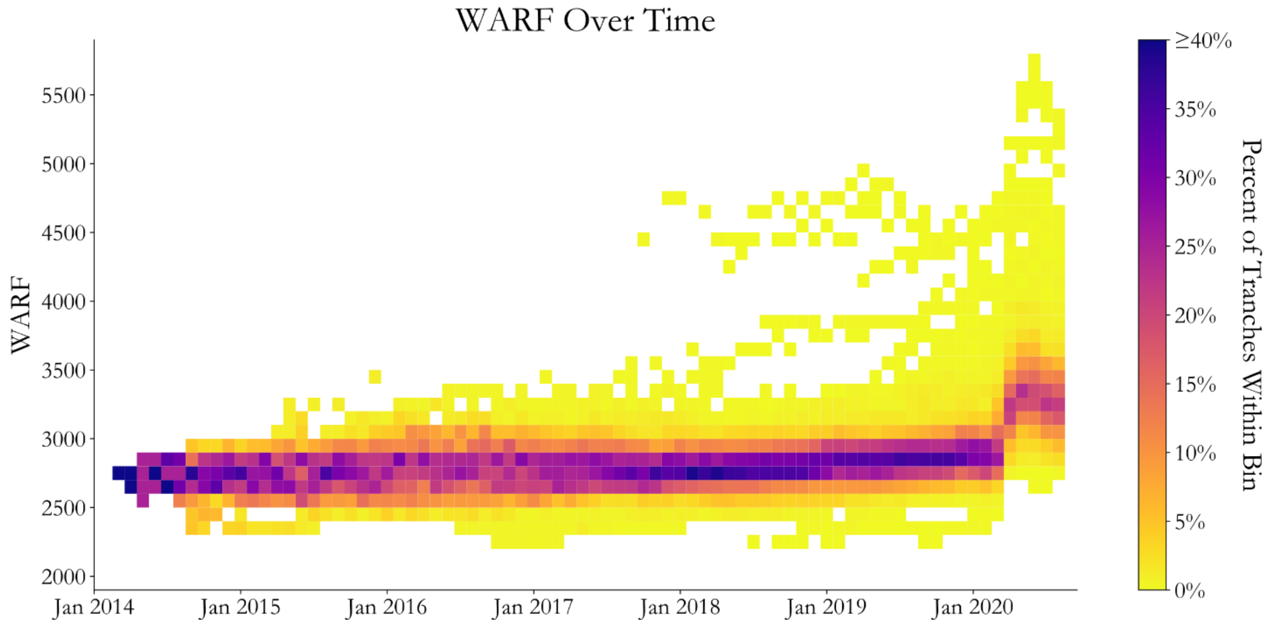


Figure IA.4. WARF Before and During the COVID-19 Crisis



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