CLOs' trading of brown loans when climate change draws attention

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Abstract

Collateralized Loan Obligations (CLOs) are non-bank entities securitizing high-yield loans and trading these on secondary markets. They are decisive for the functioning of the leveraged loan market and therefore refinancing opportunities of firms. We assess how CLOs change their trading behavior when public attention to climate change rises. We find that CLOs increase exposure to high emission loans at lower prices. CLOs with experience in trading brown loans and younger CLOs with a stable liability structure drive the effects. We conclude that CLOs take on the role of arbitrageurs when public attention to climate change is pronounced.

Keywords: climate change · sustainable investing · Paris Agreement · private markets · leveraged loans · institutional investors · shadow banks · non-banks · CLOs

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1 Introduction

Collateralized Loan Obligations (CLOs) are special purpose vehicles (SPVs), which securitize corporate loans and subsequently trade these on secondary markets. They are important non-bank entities to enable high yield market segments to exist and to reduce funding costs of borrowers. Meanwhile, awareness of climate change alters the playing field on financial markets. Retail investors demand sustainable financial products, and large asset managers form alliances to curb climate change.[1] In this paper, we address the question how public attention to climate change affects divestment in the non-bank or shadow banking sector. Do CLOs divest loans from high emitters as public attention to climate change rises?

The process of securitization of corporate loans can increase efficiency in firm lending. Banks can sell (parts of) their loans and move these off-balance sheet to non-bank entities, also called "originate-to-distribute". Thereby, banks share risk with investors, which reduces costs for borrowers (Nadauld and Weisbach, 2012). Moreover, if borrowers are under stress, lenders with access to securitization are enabled to continue their support (Gallo and Park, 2022).[2] The secondary market for corporate loans, in particular, for leveraged loans, has experienced strong growth since the global financial crisis. From 2010 to 2020, the number of transactions has increased tenfold according to CLO-i market data.[3] CLOs dominate the market in trading leveraged loans. According to Kundu (2022a) in 2021, CLOs purchased 75% of all new leveraged loans, followed by mutual funds and other market participants. The trading behavior of CLOs is therefore decisive for the functioning of the secondary market of corporate loans.

Studying CLOs' trading behavior is an ideal laboratory to investigate how shadow banking

[1] E.g. asset managers such as Vanguard, BlackRock, State Street among others, have formed alliances to restrain climate change. Founded in December 2020, the Net Zero Asset Managers Initiative (NZAM) brings together large asset managers to strengthen common action against climate change. In 2021, they merged with the umbrella climate finance organization Glasgow Financial Alliance for Net Zero (GFANZ). These alliances, however, are not uncontroversial - in December 2022, Vanguard exited the alliance due to political pressure (see Financial Times, Dec 7. 2022).

[2] Meanwhile, there is mixed evidence on whether corporate loans that are securitized are more risky than loans not securitized (Bord and Santos, 2015), or not (Benmelech et al., 2012).

[3] See Figure 1.

entities react when climate change is drawing attention. In contrast to traditional banks, CLOs are only lightly regulated and investors are institutional rather than retail, therefore CLOs stand less in the public. Plus, in contrast to mutual funds and hedge funds, their liability structure is stable especially in the early phase of existence and liabilities become redeemable, at a later stage in their life cycle (see for example Irani et al., 2020). This allows us to study trading behavior dependent on investors' ability to redeem investments. From the institutional features of CLOs, we are expecting that they can follow profit opportunities rather than public preferences.

To assess trading behavior of CLOs when public attention to climate change rises, we proceed in two steps. First, we measure public awareness of climate change with the news attention scores by Bybee et al. (2020) over the time period 2010-2017 and report associations with CLO trading behavior. We use transaction data on CLO trading by Creditflux' CLO-i dataset that uses CLO trustee reports to infer leveraged loan trading activity of CLOs. We find that when attention to climate change increases, CLOs increase the number of purchases of brown loans significantly, and raise volumes of brown loans purchased. Meanwhile, we can see that CLOs purchase brown loans at lower prices. However, from these estimations, we can only draw conclusions on associations between public awareness and CLO trading, but we cannot decide on causal relationships. The reason is that we might face omitted variable bias (OVB).[4] Also, we need to study a setting in which we can control for brown loan supply from the primary lending market.[5]

Second, in order to infer a causal relationship between public attention and CLO trading behavior, we estimate a difference-in-differences regression model, using the Paris Agreement (PA) as an unexpected event that caused a raise in public awareness for climate change. Other

[4]For instance, when governments decide regulatory measures to curb climate change, this might rise awareness to climate change while at the same time changes the trading environment.

[5]It is unclear how supply of brown loans from the primary market changes during times of high attention: There is evidence that banks issue fewer loans to high emission firms when committing to carbon neutrality (e.g. Kacperczyk and Peydro, 2021), whereas for example Mueller and Sfrappini (2021) find increases of lending by U.S. banks to high emitters. Meanwhile, Müller et al. (2022) show that the probability for banks to securitize loans rises with firms' transition risks.

researchers have used the PA as an exogenous shock to public awareness on climate change before (see for example Degryse et al. (2023); Delis et al. (2019); Ehlers et al. (2021); Mueller and Sfrappini (2021); Reghezza et al. (2021)). We compare CLOs' trading of high emission loans over time windows of 20, 25 and 30 days before and after the PA. We find that CLOs purchase larger face amounts of high emission loans, while benefiting from lower prices reflecting results from the first part of the paper. In terms of economic magnitudes, we find that face amounts of high emission loans increases on average by around $491,000 in comparison to other loans, while CLOs pay 40 basis points less.

CLOs, which are more experienced in trading high emission loans, are driving the effect. Similar to Peristiani and Santos (2019), who demonstrate the relevance of information for CLO trading, we show that experts are able to detect profit opportunities from low price high emission loans. Also, we can show that CLOs purchase larger loans that are rated B2 or better, hence decide for the high emission loans with lower risk profiles. This finding complements results from Giannetti and Meisenzahl (2022), who show that CLOs must sell loans that are facing downgrading risk. Moreover, we provide evidence that younger CLOs drive increases in volumes of high emission loans traded. After the closing date, CLOs enter a reinvestment period which lasts around four years. The first two years of which is the so-called "non-call phase", where equity investors into CLOs cannot call on their investments. CLOs are shielded from calls and hence can divert more strongly from investor preferences. Afterwards, a CLO enters the "call-phase", and investors can redeem their capital.[6] Our results show that CLOs that are with a high probability in the non-call phase, increase the face amount of brown loans. That is, CLOs benefit from the stable liability structure when exploiting profit opportunities.

Finally and importantly, we provide several robustness checks for our analyses. We can show in placebo tests that in the following years over the same time periods, we do not observe changes in trading behavior or pricing of brown loans. Moreover, we demonstrate that the results hold varying controls, level of clustering and fixed effects (as in Fabozzi et al., 2021), as well as

[6]In addition, CLOs do not have to mark-to-market their assets, and hence are less prone to runs in contrast to mutual funds, for example.

when we log-linearize the dependent variable face amount. In addition, we look descriptively at mutual funds, the other large investors on the leverage loan market. In line with our hypothesis, we find that the weights of monthly brown loan holdings indeed decline after the PA suggesting the divestment of brown loans contrary to CLOs.

This research contributes to the fast-growing literature on climate finance (see Bolton et al. (2021) and Giglio et al. (2021) for an overview). To date, the majority of literature is concerned with how climate change risks affect equity markets. Research finds that shocks in climate change exposure correlate negatively with firm valuations (Sautner (2021)). Furthermore, investors demand compensation for exposure to carbon emission risk by demanding higher returns from firms with higher carbon emissions (Bolton and Kacperczyk (2020); Bolton and Kacperczyk (2022); Görgen et al. (2020)). For fixed income, Huynh and Xia show on the corporate bond market that news and environmental disasters affect prices (Huynh and Xia (2021); Huynh and Xia (2022)). From the best of our knowledge, we are the first to study implications from climate change on secondary leveraged loan markets.

Another research strand focuses on firms' financing abilities. Firms with higher exposure to climate risk face a reduction in leverage (Ginglinger and Moreau (2021); Nguyen and Phan (2020)). This is in line with research by Delis et al., who found that bank lending is affected by climate change risk (Delis et al. (2019)). Further, Kacperczyk and Peydro (2021) show that firm-level carbon emissions affect bank lending of syndicated loans. Brown (green) firms with higher (lower) emission levels, previously borrowing from banks, receive less (more) total bank credit making new commitments. Our paper contributes to the understanding of how attention to climate change affects refinancing conditions of firms by looking through the lens of trading in the secondary loan market.

As the most extensive commitment to reduce the emission of greenhouse gases, the PA from December 2015 marks a beacon for climate change activism. A large body of literature argues that the PA is a signpost and external shock to investors and banks, reconsidering climate risk premia on financial markets (Degryse et al. (2023); Delis et al. (2019); Ehlers et al. (2021);

Mueller and Sfrappini (2021); Reghezza et al. (2021)). For example, Ehlers et al. (2021) find a significant “carbon premium” in syndicated loans since the PA. This effect seems to be most prominent among European firms (Mueller and Sfrappini (2021); Reghezza et al. (2021)). We follow this literature and apply the PA as a shock on the leveraged loan market. Importantly, by exploiting the PA as an exogenous shock to public awareness, we can distinguish alterations in loan ratings from the public attitude on climate change, because ratings of brown firms in the U.S. do not decline with the Paris pledge (Carbone et al., 2021).

Previous studies show that institutional investors are concerned about climate change risk (Bolton and Kacperczyk (2020); Krueger et al. (2020)). We apply a similar setting on a private market and assess investors’ behavior when they trade over-the-counter (OTC). Further literature studies the effects of regulation such as carbon disclosure requirements (Jouvenot and Krueger (2019); Tomar (2022)). We show trading behavior of market participants that are subject to less regulation and disclosure policies.

Finally, researchers have studied trading behavior of CLOs. Kundu (2022a) provides a comprehensive analysis on the structure of CLOs. Peristiani and Santos (2019) assess the role of the CLO manager and find that CLOs linked to banks as managers benefit from information advantages on the loans traded. Kundu (2022b) and Elkamhi and Nozawa (2022) depict the risk of fire sales in CLO markets. Giannetti and Meisenzahl (2022) finds that CLOs quickly sell loans when loans are downgraded in contrast to mutual funds and hedge funds. Fabozzi et al. (2021) find that CLOs that trade loans more actively perform better. We contribute to this strand of literature by showing how CLOs change behavior in the context of climate change.

The structure of the paper is the following: In chapter 2, we give insights into the institutional background on leveraged loans and CLOs, explain the economic mechanism and develop hypotheses. In chapter 3, we present our data. In chapter 4 we show our empirical models, building up to chapter 5, in which we provide results. Robustness checks are shown in chapter 6 before we conclude in chapter 7.

2 Institutional background and economic mechanism

2.1 Institutional background

In July 2021, the size of the total US leveraged finance market has topped 3 T USD for the first time ever, emphasizing the tremendous size this field has gained. This paper focuses on leveraged loans, which next to high-yield bonds (1.5 T USD outstanding) is the largest segment in leveraged finance, with an outstanding volume of 1.4 T USD in mid-2022. CLOs are the most important institutional investors purchasing 75% of all new leveraged loans in 2021 (Kundu, 2022a).

The increasing primary market presence of institutional investors fostered the establishment of a secondary market. Trading activity by CLOs has inflated from less than 0.2 B USD to 398 B USD between 2005 and 2019, according to CLO-i data. That is an increase from to almost 30% of the current total outstanding par volume. We visualize the rise in number of trades of CLOs in Figure 1. CLOs hold the major share of leveraged loans with approximately 50-60%, followed by loan mutual funds and exchange-traded funds (ETFs) for which the market share oscillates around 15% (e.g. PartnersGroup (2019)). During the financial crisis in 2008, CLOs basically ceased trading, slowly picking up during 2010-2014, until it started growing strongly from 2015. Trading takes place over-the-counter (OTC), with most transactions concluded on an intermediated basis; i.e., trades pass through decentralized loan dealer desks, located at large investment banks acting as lead arrangers or transfer agents for a given facility. The market generally lacks pre- and post-trade transparency. Hence, any potential trader cannot observe all dealer quotes in a central location or on a computer screen. Instead, the institution must call several dealers for quotes or subscribe to data vendors like Refinitiv LPC or Markit that broadcast near real-time bid and ask quotes aggregated across contributing dealers. As common for OTC markets, quotes are indicative, not firm.

– Insert Figure 1 around here –

CLOs are structured investment vehicles set up to hold and manage pools of leveraged loans and to a lesser extent high-yield bonds. As CLOs buy loans off banks' balance sheets, they play a central role in mitigating credit risk in the banking sector.[7] In turn, banks face lower capital requirements imposed by financial regulation leading to reduced equity costs. As banks' incentive to sell a loan increases with higher ratings, CLOs are especially important for credit provision to constrained corporations.

CLOs are structured like the better known Collateralized Mortgage Obligations. First, banks (loan originators) grant loans to corporate borrowers. In order to reduce their balance sheet risk, they form a Special Purpose Vehicle (SPV) through securitization. This vehicle or conduit becomes a CLO through buying loans from e.g. the founding bank to create a broad portfolio of credits. The CLO manager achieves sufficient funding through issuing multiple tranches of asset backed securities. The underlying portfolio consists of corporate, mostly syndicated loans and is used as collateral. Asset tranches are served per seniority following the typical waterfall principle; while the AAA tranche receives payments first, the equity tranche is the first to suffer losses. Hence, all obligations of the given-out securities within a tranche need to be redeemed, before the next tranche receives money. This issuance of different credit risk tranches appeals to a diversified institutional investor base. While e.g. pension funds or insurance companies acquire the highest-rated tranches, hedge funds focus on higher yields offered by the riskier tranches (Kundu, 2022a).

In order to avoid risky behavior of CLO managers, equity investors negotiate covenants to align their interests. Hence, covenants are set out to limit risk-taking, forcing them to pay close attention to quality (e.g. rating downgrades within their loan portfolio) and coverage. The latter ensures the presence of enough collateral at all times.[8]

– Insert Figure 2 around here –

[7] Trading allows investors to transform their illiquid loans into liquidity and to profit from risk-sharing with a broader group of investors (Parlour and Winston (2013)). However, secondary markets can also be value-destroying by diluting the monitoring incentives of banks (Gorton and Pennacchi (1995); Parlour and Plantin (2008)).

[8] For more detailed information on CLOs see Kundu (2022a).

Figure 2 shows a schematic life cycle of a CLO. They usually exist around 8 to 10 years. Four main phases can be identified: warehousing, ramping-up, reinvestment and deleveraging. The most relevant phase for the secondary market of leveraged loans is during reinvestment, where the manager actively trades loans with the goal to improve the portfolio quality and performance. Usually, during the first two years, equity holders cannot redeem their investment (non-call period). This makes the resulting stability during the non-call phase one important feature that distinguishes CLOs from mutual loan funds as the latter often allow redemptions on a monthly or even daily frequency. In contrast, CLOs are generally not required to mark-to-market their assets.[9]

This instability of funds has raised concerns in the past, especially when taking into account that leveraged loans are infrequently traded and have long settlement durations. According to Mählmann (2022), in times of loan market stress, fund flows and loan price returns have reinforced each other. This fuels a downward price and liquidity spiral that could cause a "run-on-the-fund" phenomenon as Goldstein et al. (2017) show for bond funds. At the same time, CLOs have stable assets, so that in times when the loan market is cheap and future market returns are high, CLOs use these opportunities to make good deals on the secondary market (Hackenberg and Mählmann (2021)). This makes CLOs asset insulators in the sense of Chodorow-Reich et al. (2021). They can ride out transitory dislocations in market prices and buy up the discounted sales of mutual loan funds. Nevertheless, Irani et al. (2020) describe their inability to categorize CLOs as non-banks with stable or non-stable liability structure due to stability depending on different life cycle phases. We follow the latter and refrain from a general classification as stable non-banks and allow for heterogeneity by incorporating CLO age in our analysis.

The secondary market for leveraged loans presents an ideal setting for our analyses as it shows great importance by simply its size. Their environment and configuration allows CLOs as

[9]Loan mutual funds are typically closed-end or open-end. Closed-end funds are either exchange-traded (ETFs) or continuously offered, implying that investors can buy into these funds each day at the fund's net asset value (NAV) and redemptions are allowed at a monthly or quarterly frequency. Open-end mutual funds are so-called "daily-access" funds into which investors can buy or redeem shares each day at the fund's NAV.

most important players on this market to act independent of short-term pressures and influences of investors, regulators, and the public.

2.2 Economic mechanism and hypotheses

There are several reasons why CLOs might face less challenges in purchasing brown loans when public attention to climate change rises in comparison to other market participants. First, CLOs are non-bank entities which are not in the focus of public attention in contrast to traditional banks. Investors in CLOs are institutional such as banks, insurance companies and pension funds, mutual funds and hedge funds (Kundu, 2022a), whose preferences might be less aligned to the public awareness in comparison to retail investors. Second, in contrast to other entities, CLOs are only short lived with a fixed duration of around 8-10 years (Kundu, 2022a), which allows them to take a shorter time horizon into consideration. Third, as CLOs are non-banks, with a rise in public attention to climate change, they need to worry less about regulation for example concerning exposure to climate risks in comparison to traditional banks (see for example the climate risk stress tests by the ECB as in Dunz et al., 2021). Fourth, CLOs do not need to mark-to-market their assets in contrast to mutual funds and therefore are shielded to a certain extent from price volatility, while benefiting from temporary stable liabilities (see section 2.1).

As Bolton et al. (2021) points out, if all market participants would sell brown assets, somebody had to buy them. Hence, they argue that buyers might hold other opinions on climate change or the state of the world, or assume the role "natural arbitrageurs" who are agnostic about their role in fighting climate change. Considering the above listed characteristics, we expect that CLOs take on the role of arbitrageurs who might detect underpriced assets when public awareness of climate change raises.

Hypothesis 1a: CLOs increase exposure to brown loans when attention to climate change rises.

We hypothesize similarly for the event which we exploit. The PA caused a strong rise in public attention to climate change. It is an ideal laboratory to study the impact of raised public attention to climate change. The reason is that there is no immediate rules or regulations that followed the agreement, but mostly public attention, discussions and awareness towards climate changes. This is important as the rise in awareness is not associated with an immediate threat of downgrading of loans, which could also impact CLOs trading behavior. Hence, for the short time period around the Paris conference observed in this paper, we do not expect a change in short-term credit rating expectations influencing our results. Carbone et al. (2021) confirm our notion by showing that credit risk ratings of climate transition risk exposed U.S. firms do not decline after the PA; only European firms are affected by deteriorating ratings in a long-run study.

Hypothesis 1b: CLOs increase exposure to brown loans after the PA rises attention to climate change.

CLOs have a temporary stable liability structure. After a CLO is set up and closed, a period of around two years allows the manager to reinvest, hence trade, leveraged loans, but investors are excluded from calling on their investment. Afterwards, the investment period continues but without respective call restriction. We expect that CLOs load up on brown loans in particular when they are shielded from investor preferences.

Hypothesis 2: CLOs increase exposure to brown loans during the non-call phase.

Still, CLOs have to adhere to covenants, which should align the incentives of the managers with CLO debt holders' interests. In particular, CLOs have to make sure that they comply with quality as well as coverage covenants (Kundu, 2022a). Among other criteria, the "Weighted Average Rating Factor covenant" demands that the average rating of loans on the CLO's balance sheet must not lie under a certain threshold. As brown issuers compared to non-brown issuers are rated lower on average, we expect CLOs to show a preference for purchasing loans of higher rated issuers in order to keep their portfolio balanced.

Hypothesis 3: CLOs prefer brown loans of issuers with higher ratings.

3 Data and events

Our analyses are based on the main database for CLO trade collection. CLO-i by Creditflux uses trustee reports to aggregate information on CLO transactions. From this database, we identify secondary market transactions and use prices and volumes of CLO sales and purchases on a daily level. As we are largely interested in the treatment of enhanced climate change risks, we need to identify loans issued by polluting firms. We follow Bolton and Kacperczyk (2020) who use firm-level data on greenhouse gas emissions from S&P's Trucost EDX and report the top ten and bottom ten industries (GICS 6) in terms of average emission production. The authors group carbon emissions into three different categories: direct emissions from production (scope 1), indirect emissions from consumption of purchased electricity, heat, or steam (scope 2), and other indirect emissions from the production of purchased materials, product use, waste disposal, outsourced activities, etc. (scope 3). With our categorization, we do not distinguish between these categories but pick the overall industries with high carbon emissions. CLO-i data does not provide the GICS industry classification or matching keys. Hence, we rely on a hands-on approach and choose the industries from our dataset that best match the brown industries defined by Bolton and Kacperczyk. The resulting classification is presented in Table 1. Brown industries are Automobile, Chemicals & Plastics & Rubber, Mining & Steel & Iron & Non-Precious Metals, as well as Oil & Gas. While this categorization has a very practical nature, consider that most firms in our sample are private. Likely, investors do not have additional information on the climate change risk of these firms and also rely on an industry classification. Hence, even though this is just a broad categorization and might understate our findings, it is likely that CLOs use a similar method to understand the carbon footprint of private firms.

We investigate our data over two periods. First, we look at the overall period between 2010 and 2017. CLO development blossomed after the financial crisis of 2008 as they pose a tool to take risk off banks' balance sheet (see Section 2.1). Hence, transaction counts before 2010 are low leading us to exclude this phase. News data is only available to us upon June 2017. Second, we investigate the period around the Conference of the Parties (COP) 21 held from November

30 until December 12, 2015. The resulting Paris Agreement represents a landmark decision on climate change. We compare CLO transactions of brown firms of both pre- and post-event windows. In the baseline analysis, we choose twenty days for these windows. Note that we choose short event windows to mitigate the possibility that loan conditions adapt during the observation period. Additionally, we exclude the possibility of rising brown loan supply from the primary lending market. Table 2 gives precise pre- and post-event definitions. We choose to exclude the whole conference period from our sample to ensure eliminating any possible effect of leaking information.[10]

– Insert Table 2 around here –

Undisputed, the PA represents the first comprehensive and worldwide accord to coordinate actions in the battle against climate change. Its main outcome is the goal to dampen global warming below an average temperature increase of 2 degrees Celsius at a maximum increase of 1.5 degrees. On the one hand, as broadly covered by the media at that time, many politicians and people of international interest, for example, French President François Hollande, UN Secretary-General Ban Kimoon, and Christiana Figueres, Executive Secretary of the UNFCCC, applauded the spirit of the PA. As there was high uncertainty about whether an agreement on a global level can be achieved at the Paris Summit, the extent of the agreement was highly surprising. On the other hand, critical voices, mostly of environmentalists and analysts, expressed less optimism about the pace of climate mitigation and how much the agreement could do for poorer countries. James Hansen, a former NASA scientist and leading climate change expert, for example, voiced anger that most of the agreement consisted of promises or aims rather than firm commitments and called the Paris talks a fraud with no action, just promises.[11] Clearly, this outlines the shortcoming of the PA: instead of international action-taking, it leaves concrete measures to reduce carbon emissions to national sovereignty. However, as all 195 signing nations pledged to

[10] We also test excluding only the day of result presentation (December 12, 2015) and find similar results. Results are not reported but available upon request.

[11] This is according to an article in The Guardian by Oliver Milman on December 12, 2015, available at: `https://www.theguardian.com/environment/2015/dec/12/james-hansen-climate-change-paris-talks-fraud`.

gradually reduce their emissions, the Paris Accords signal a change in climate awareness and politics all over the word. An anticipation effect of markets is unlikely due to low expectation. This makes the PA a valid external shock for our analyses.

We present summary statistics of our CLO trade dataset in Table 3 and 4. We only use USD-denominated loan transactions, following Fabozzi et al. (2021), to ensure comparability across loans.[12] Data underlying our first analyses using topic attention is shown in Table 3. We observe 1,297 CLOs over a time period of 90 months. We observe news attention by Bybee et al. (2020) on a monthly level, and hence aggregate transaction data from the loan level to the CLO level on a monthly basis. We calculate monthly averages of prices (a) and volumes (b) per CLO, by purchases/sales and brown/non-brown, respectively. We have 47,698 CLO-month-brown/non-brown observations for purchases and 39,164 for sales. Note that our share of brown loans is smaller than 50%, stating that there are some months in which some CLOs do not trade brown loans. On average, we observe lower/higher transaction prices for brown loans when the CLO is buying/selling. Consider that loan prices are expressed as a percentage of the face value or par amount of the loan. For example, a price of 99 implies that the facility can be purchased at a 1% discount of par on the secondary market. For transaction volumes, we see lower mean amounts for brown loans. The difference is larger for purchases (0.173) than for sales (0.121). Finally, the mean news attention regarding environment is 5.144 stating that about 0.5% of monthly news in the WSJ are allocated to environmental issues. This is slightly lower than average news attention to regulation (about 0.7%). Figure 3 depicts graphically the development of news attention between 2013 and 2016. Attention to environment peaks in December 2015. Although attention to regulation is peaking at the same time, attention to environment reaches not only a local maximum but an almost all time high in December 2015 with the PA.

– Insert Table 3 around here –

– Insert Figure 3 around here –

[12]In fact, the number of brown EUR-denominated transactions that we discard is very limited (<80).

For our second analysis in which we exploit the PA, we present summary statistics in Table 4. Our sample comprises of 6,591 purchases and 4,140 sales from 590 CLOs. The relative share of brown loans is reasonably similar between purchases (12.2%) and sales (12.1%). Mean transaction prices are lower for brown loans, while the difference is more severe for sales (2.989 compared to 1.384). The difference decreases when comparing medians, indicating that there are few observations with very low prices reducing the mean. This is intuitive as loans exhibiting falling prices perform badly and are more likely to be sold off to improve portfolio performance. Intriguingly, CLOs' average purchase price of brown loans is higher than the average sale price. In addition, we find higher standard deviations of brown loan prices. This changes when looking at volumes. Note that the reason for the first could be the lower observation count. Moreover we find average purchase volume (1.124 M USD) to be larger than the average sale volume (0.822 M USD). When only comparing brown transactions, average volumes are close. Finally, part c) breaks down characteristics of purchase volumes. The bulk part of our sample lies between Ba and B ratings by Moodys. We observe brown observation share to gradually increase with declining ratings. Hence, in our sample brown loans have lower credit quality compared to the rest. With rating quality, mean face amounts decline as well.

– Insert Table 4 around here –

4 Empirical Strategy

4.1 Association of attention and trading

In order to assess the association of rising attention to climate change with trading behavior of CLOs, we estimate the following linear regression equation:

$$Y_{i,b,t} = \beta_0 + \beta_1\, environment_t \times brown_b + ... + \beta_x\, X_t + \alpha_i + \alpha_t + \epsilon_{i,b,t} \tag{1}$$

Dependent variable $Y_{i,b,t}$ is (1) number of trades, (2) mean face amount and (3) mean price of purchased loans per CLO (i) per category brown or non-brown (b=1 or b=0, respectively) per year-month (t).[13] As data on attention is only available on a monthly basis, we collapse trading data on the CLO-brown/non-brown- year-month level. $environment_t$ is based on the news indicator by Bybee et al. (2020). We use their measure of news on issues linked to "environment" to measure public attention to the topic of climate change. The indicator is measured on a monthly basis and covers the period January 2010 until June 2017. $brown_b$ classifies loans according to the industry of the issuer into high emission loans ($brown_b$=1) or non-high emission loans ($brown_b$=0). We include the following control variables (X_t): the 3-month LIBOR, the oil price, and the leveraged loan index LLI 100. We use CLO fixed effects α_i and year-month fixed effects α_t. The coefficient of interest is β_1, which captures how the dependent variable changes when attention to climate change rises. The regression also includes the single coefficients for $brown_b$ not reported in equation (1). $environment_t$ drops out due to time fixed effects. Alternatively, we create a binary variable, which equals 1 if *attention* to climate change is above the median of the whole period and 0 otherwise. We use robust standard errors.

We extend the analysis with a further index measuring attention to regulation also derived from Bybee et al. (2020). We expect that the effect of attention towards climate change is

[13] Throughout the analyses, we focus on Purchases, i.e. loans purchased by CLOs. We supplement the analysis with estimations on loans sold, i.e. Sales and attach the results in the appendix. Note, however, that CLOs in the reinvestment phase do purchase and sale loans. However, according to Kundu (2022a), CLOs on average end up with 30% net purchases. Also according to our data, CLOs sales correspond to around 63% of purchases.

attenuated when attention to regulation takes place at the same time, as the threat of tighter regulation linked to climate policies might reduce the incentives to trade brown loans. We estimate the following model:

$$\begin{aligned} Y_{i,b,t} = & \beta_1 \, environment_t \times brown_b \\ & + \beta_2 \, regulation_t \times brown_b \\ & + \beta_3 \, regulation_t \times environment_t \times brown_b \\ & + ... \\ & + \beta_x \, X_t + \beta_0 + \alpha_i + \alpha_t + \epsilon_{i,b,t} \end{aligned} \tag{2}$$

$Regulation_t$ is measured according to news attention to "regulation" in Bybee et al. (2020). We include the following control variables (X_t): the 3-month LIBOR, the oil price, and the LLI 100. We use CLO fixed effects α_i and year-month fixed effects α_t. The coefficients of interests are β_1, which again captures how the dependent variable changes when attention to climate change rises, and β_3, which measures how the effect of attention to climate change is attenuated when at the same time, there is attention to regulation.The regression also includes the single coefficient for $brown_b$ not reported in equation (1). $environment_t$ and $regulation_t$, as well as $regulation_t \times attention_t$ drop out due to time fixed effects. We use robust standard errors.

4.2 Causal analysis

In order to draw conclusion on causal relationship, we employ a difference-in-differences approach with cross sectional data (Lee and Kang, 2006). We estimate the following regression equation:

$$Y_{f,l,t} = \beta_0 + \beta_1 post_t + \beta_2 \, brown_f \times post_t + \beta_x \, X_t + \alpha_f + \epsilon_{f,l,t} \tag{3}$$

Dependent variable $Y_{f,l,t}$ is (1) number of trades, (2) volume of face amount and (3) price, of loan l per issuer f (firm) on day t. Note that we do not have an indicator for loan l, and hence cannot trace loans over time and across CLOs. Every entry in the transaction data hence is considered as a unique l. According to Kundu (2022a), monthly turnover of loans held by CLOs is around 6% and annual turnover around 50%. As we are considering a time period that lasts no longer than 40 days (20 days pre and post and in further analyses we extend the period to 25 and 30 days pre and post), we assume that very few loans are being traded more than once during this time period. $post_t$ equals 0 before the PA and 1 after, excluding the period of 13 days when the conference took place. The coefficient of interest is β_2, which shows changes in trading behavior of loans from brown firms in comparison to loans from other firms pre versus post PA. Loans from the same issuer (firm) might be correlated, or it might even be the same loan traded on several days. Hence, we include issuer (firm) fixed effects α_f. Further, $post_t$ controls for trends over time. $brown_f$ drops out due to issuer fixed effects. We use robust standard errors. Alternatively, we cluster standard errors on the level of the industry of the issuer interacted with time ($post_t$). The reason is that after the PA, observations from industries might be correlated.

We further test for the mechanism that underlies changes in trading behavior. Therefore, we extend equation (3) and interact with indicators concerning CLO or loan characteristics:

$$\begin{aligned} Y_{f,l,t} = &\beta_0 + \beta_1 post_t \\ &+ \beta_2\, brown_f \times post_t \\ &+ ... \\ &+ \beta_3\, brown_f \times post_t \times indicator_l \\ &+ \beta_x\, X_t + \alpha_f + \epsilon_{f,l,t} \end{aligned} \tag{4}$$

As $indicator_l$ we use first, experience of CLOs in trading brown loans, measured according to the average share of brown loans over all trades taking place before the PA in our data. We mark CLOs as experienced brown loan traders if their share is above the median. Second, we use age of CLO, measured according to difference between the current date and the CLO's closing date. Third, we interact with issuer rating. As before, we include issuer (firm) fixed effects α_f. $post_t$ controls for trends over time. $brown_f$ drops out due to issuer fixed effects. Further, the regression includes the terms $indicator_l$, $post_t \times indicator_l$ and $Brown_f \times indicator_l$. We use robust standard errors. Alternatively, we cluster standard errors on the level of the industry of the issuer interacted with time ($post_t$).

4.3 Common trend assumption

As we are estimating a difference-in-differences analysis, we have to ensure that the parallel trend assumption holds, which states that if there was no event, the trends of the outcome variable would not differ across treatment and control group. We can test whether the parallel trend assumption holds in the pre period by estimating the following dynamic difference-in-differences regression equation:

$$\begin{aligned} Y_{f,l,t} = \beta_0 + & \sum_{\tau=Nov10,\tau\neq Nov30}^{Dec31} \beta_{1\tau}\, D_\tau \times \text{brown}_f \\ & + \beta_x\, X_t + \alpha_t + \alpha_f + \epsilon_{f,l,t} \end{aligned} \tag{5}$$

Dependent variable $Y_{f,l,t}$ is the face amount of the purchased loan, which is our main variable of interest throughout the study. We interact our treatment variable $brown_f$ with binary variables for every day preceding 20 days the start of the conference in Paris – hence, the time period starts on November 10, 2015. November 30, 2015, the first day of the conference, serves as the base day. We exclude the period Dec 1 - Dec 12, over which the conference lasted. In the post period, we interact with binary variables for every day lasting until December 31, 2015. We include time fixed effects for every day (α_t) as well as issuer fixed effects (α_f). We cluster standard errors on the issuer industry - post period. We further condition that there are more than five trades per trading day. This condition is not necessary for the main analysis in which we compare pre versus post period.

– Insert Figure 4 around here –

We present results for $\beta_{1\tau}$ in a coefficient plot in in Figure 4. We mark the Paris conference with a red vertical line, leaving out the following 12 days of the conference that are excluded from the regression. Confidence intervals are plotted at the 5% significance level. We show that differences in face amounts of treatment and control group are not statistically different from zero before the start of the Paris conference in comparison to the base day November 30, 2015. From these results we conclude that the parallel trend assumption holds for the pre period.

5 Results

5.1 Association of attention and trading

In this section we present results from estimating equation (1). We consider loans purchased by CLOs.[14] We show results for number of trades as dependent variable in Table 5, mean volume of traded loans in Table 6 and mean prices for traded loans in Table 7.

– Insert Table 5 around here –

Beginning with Table 5, we present results with number of trades, i.e. number of purchases, per CLO per year-month, per category brown or non-brown, over the time period June 2010 until December 2017. We interact a binary variable *brown* with an indicator measuring attention to climate change ($environment_t$), which we derive from Bybee et al. (2020). In columns I - IV, we provide results with the attention index as continuous variable. In columns V-VIII, we use an indicator equaling 1 if attention is above the median, and 0 otherwise, which eases interpretation of coefficients. In column I, the regression includes year-month fixed effects and CLO fixed effects, and in column II we include time varying controls instead of year-month fixed effects.

Our estimations show that as attention to climate change rises ($environment_t$), CLOs purchase more brown loans in comparison to non-brown loans. The relationship is statistically significantly different from zero at the 1% level. In terms of economic magnitude, we can consider column V. Specifically, we find that for periods where attention to climate change is above the median, CLOs increase the number of purchases of brown loans by 1.386. Hence, with the mean count of purchases over the whole time period being 9.379, CLOs increase purchases of brown loans in comparison to non-brown loans by $(1.386/9.379)\times 100 = 14.8\%$. As we are only considering a deviation from the median, an increase of brown loan purchases of 14.8% is a conservative measure. As can be seen in Figure 3, news attention to environmental topics

[14] We also consider loans sold. Results are attached in Appendix A.

fluctuates with strong peaks. When attention soars, the increase of purchases of brown loans grows as well.

Next, we estimate equation (2) to control for the possible attenuating effect of attention to regulation. We present results in Table 5, columns III, IV, VII and VIII. When we additionally control for public attention to regulation, the association between purchasing brown loans while attention to climate change changes (β_1), increases in size. As expected, β_3, is negative. That means, if attention to climate change is accompanied by attention to regulation, then the effect on the number of purchases of brown versus non-brown loans, is attenuated. This results is not surprising since times where public attention is drawn to regulation are mostly associated with regulatory threats causing a change in trading conditions. Hence, CLOs do not react as strongly to increasing climate change awareness when there is also the possibility that the public is considering stronger regulation, or the public draws attention to topics on regulation.

– Insert Table 6 around here –

Next, we assess mean loan volumes of loan purchased by CLOs. In column I and column II in Table 6 we show that using the continuous measure of attention to climate change does not render a result. However, when considering that attention to climate change rises above the median, we find a positive association between attention to climate change and the volume of purchased loans, i.e. face amount, as presented in columns V and VI. In terms of economic magnitude, CLOs increase the mean volume of brown loans purchased in comparison to non-brown loan purchased by 0.041 when attention to climate change is above the median. Considering that the mean of the monthly average face amount is $1.424 M, the change amounts to $(0.041/1.424)\times100=2.9\%$ of the average of mean face amounts.

Similar to previous results on the number of trades per CLO, when we interact attention to climate change with attention to regulation, the association with mean purchase volume is attenuated (see columns II, IV and VII, VIII).

– Insert Table 7 around here –

Finally, we present results on mean prices paid for brown versus non-brown loans in times when attention to climate change rises. In Table 7 we show that mean prices paid by CLOs for brown loans purchased in comparison to non-brown loans are lower the higher the attention to climate change. The association is significantly different from zero at the 1% level in most specifications. In terms of economic magnitude, we consider column V. We find that for periods where attention to climate change is above the median, CLOs pay lower prices for brown loan purchases by 0.396. The mean purchase price over the whole time period is 98.503. Hence, CLOs face lower prices of brown loans in comparison to non-brown loans by $(0.396/98.503)\times 100 = 0.402\%$, i.e. 40 basis points. The effect is lower as soon as there is also attention to regulation, whereby the association is less strong when using binary measures of attention instead of continuous variables.

To summarize, we cannot reject hypothesis 1a, which states that CLOs increase their exposure to brown loans when attention to climate change rises. In fact, we find evidence that CLOs increase trade activity of brown loans at higher face volumes and lower prices when public attention to climate change rises.

5.2 Causal analysis of attention and trading

So far, we can only show an association between public attention to climate change and CLO loan trading behavior. We cannot rule out that there are other variables omitted in the regression, for example government policies that affect both, attention to climate change and CLO trading behavior. Further, we want to rule out that changes in the supply of brown loans on secondary markets bias our results. In fact, according to Kacperczyk and Peydro (2021), banks decrease loan supply to high emission firms when committing to a carbon neutral economy, whereas Mueller and Sfrappini (2021) provide evidence that banks increase lending to high emitters in the U.S. Moreover, Müller et al. (2022) demonstrate that the probability for banks to securitize loans rises with firms' climate change transition risks. In this section, we aim at identifying a causal relationship between public awareness and CLO loan trading by exploiting the PA as an exogenous shock to public attention on climate change. We assess changes in trading behavior of CLOs over tight time corridors, which exclude the possibility of changes in supply of brown loans from the primary market.[15]

The level of analysis is the traded loan, though we cannot trace individual loans over time. We estimate equation (3), which is a difference-in-differences setting on cross sectional data as described in Section 4. We present results in Table 8.

– Insert Table 8 around here –

First, we present results on face amounts of purchased loans as dependent variable. We consider different time periods. In column I and II of Table 8, we show results for the time period +/- 20 days before and after the Paris conference, excluding 13 days when the conference took place. This is the main result of our analysis, and we use this time period in subsequent estimations. We show that CLOs purchase larger face amounts of brown loans after the PA compared to face amounts purchased of non-brown loans. We include issuer (firm) fixed effects and robust standard errors. The effect is statistically significantly different from zero at the 1% level. In column II, we cluster standard errors on the industry-time ($industry \times post$) dimension, which renders similar results. In terms of economic magnitudes, CLOs increase the purchased loan face amount by around $491,000 in comparison to non-brown loans purchased, when attention to climate change spikes due to the PA. This is a considerable increase considering that mean face amount over the whole time period is $1,124,000. We observe similar results when we extend the time period to 25 and 30 days, though the coefficient of interest becomes smaller.

– Insert Table 9 around here –

[15] According to Bruche et al. (2020), the "book-running" process to find investors into potential loan deals in the primary, i.e. syndicated loan market lasts on average a few weeks, and in Bruche et al. (2020)'s sample 46 days. In the following, we assess CLO trading behavior at maximum 30 days after the PA, and changes in loan supply should only materialize after.

Next we assess prices. We report results in Table 9. β_1 is negative across all specifications, though only regressions which use robust standard errors are significantly different from zero. When we cluster standard errors on the $industry \times post$ level, the direction of the effect remains, but statistical significance drops. CLOs purchase brown loans at lower prices in comparison to non-brown loans after the PA. In terms of economic magnitude, when we consider the specification in column 1, we find that CLO purchase brown loans at a price that is by 0.404 lower in comparison to non-brown loans. The magnitude of the effect is similar to the results in Section 5.1. Given that average transaction prices for purchases are 97.299 over the whole time period, CLOs pay (-0.404/97.299)*100= -0.415% lower prices for brown loans, i.e. 42 basis points.

We also test whether number of transactions change after the PA in comparison to before the PA. We do not find any changes in the number of transactions. We report results in the Appendix B. Note here, however, that we have to collapse the data on the CLO - day - brown/ non-brown level and hence have less observations.

To sum up, we find that CLOs trade larger loan amounts of brown loans in comparison to non-brown loans after there is a rise in public attention towards climate change. Further, CLOs pay lower prices on these purchased loans in comparison to prices for non-brown loans. Hence, we cannot reject hypothesis 1b, which states that CLOs increase their trading activity of brown loans after the PA.

5.2.1 CLO heterogeneity

In this Section we test the mechanism underlying changes in trading behavior of CLOs. In particular, we test whether CLO behavior depends on their experience in trading brown loans, on CLO age, and on issuer ratings.

– Insert Table 10 around here –

We test hypothesis 2 and extend equation (3) with a triple interaction, resulting in equation (4). We consider CLOs above the median as experienced in trading brown loans (*indicator* =1). We report results in Table 10. As we are mainly interested in β_2 and β_3 other coefficients are not reported. In columns I and II we present results for face amounts. We observe that CLOs that are experienced in trading brown loans are the sole drivers of the positive effect on face amounts. The coefficient of the interaction term is positive and statistically significantly different from zero at the 1% level. When we include clustered standard errors on the $industry \times post$ level in column II, the coefficient's size is the same, and statistical significance drops to 10%. Our results are in line with Peristiani and Santos (2019) who emphasize the importance of informational advantages for CLO trading behavior. In columns III and IV, we present result with transaction price as dependent. Interestingly, more experienced CLOs trade larger face amounts in brown loans when public attention to climate change rises, but they do not pay lower prices than the average CLO.

– Insert Figure 5 around here –

We expect that trading behavior of CLOs depends on CLO age. As summarized in Section 2.1, CLOs have a temporally stable liability structure during their early reinvestment phase. After the CLO is closed, managers can reinvest without being pressured by investor calls. After this no-call phase follows a call-phase in which investors can exercise their right to end a deal. We assume that CLOs, during their younger age, are shielded from investor calls and hence can act on profit motives without taking investors' preferences info account. We therefore plot histograms of brown and non-brown loan trades before and after the PA in Figure 5. Vertical lines indicate different investment periods, starting with (1) warehousing, (2) ramping up and reinvesting non-call, (3) reinvesting call, and (4) deleveraging. [16] We observe distribution mass for brown trades moves from the call phase, to the non-call phase after Paris. This denotes that CLOs closed for calling drive the effect. To further evaluate this within our methodical setting,

[16]Note that with this categorization we can only approximate the phases CLOs are in. We cannot precisely determine the investment phase of each CLOs as this depends on the individual set up.

we estimate equation (4) with a continuous *indicator* for age measured in 100 days of the CLO. We report the results in Table 11.

– Insert Table 11 around here –

In columns I and II we present results for face amounts. We observe that CLOs purchase larger face amounts of brown loans after the PA in comparison to non-brown loans. However, the older CLOs are, the less pronounced the effect is. The coefficient of the triple interaction, including age, is negative and statistically significant at the 10% in column I and at 5% in column II. Younger CLOs with lower age increase their exposure to brown loans more than older CLOs. From these results we conclude that the stability of the liability structure, which is for example not the case for mutual funds, is important in possibilities for CLOs to benefit from low prices on brown loans when public attention to climate change rises. In column III and IV we show that younger CLOs, however, do not pay lower prices than older CLOs.

5.2.2 Loan heterogeneity

So far we tested for differences across CLO characteristics that could impact CLO behavior. Now we are turning to loan characteristics to test whether CLOs prefer certain loans over others. As we describe in Section 2.1, CLOs need to comply with covenants in order to align manager incentives and debt holders' incentives. One covenant requires that the average loan rating across all loans a CLO holds must not fall below a threshold. We hypothesize hence that CLOs would prefer brown loans with higher ratings. We estimate equation (4) with an *indicator* equaling 1 for loans of issuer with a rating of B1 or better, and one indicator of B2 or better ratings. Note that the median loan over our sample period has a rating of B1. We report results in Table 12.

– Insert Table 12 around here –

We report in columns I and II that there is no statistical significant difference to zero for the triple interaction that includes the indicator for a loan issuer rating of B1 or better. In column III and IV we report results when interacting with the indicator that equals 1 for ratings of B2 or better. Here, the coefficient for the triple interaction is positive and statistically significantly different from zero at the 5% level. CLOs increase purchased face amounts of brown loans of issuers rated B2 or better. They prefer the better ratings when increasingly buying brown to avoid their portfolio quality to deteriorate, and ultimately avoid breaking covenants. Our finding complements Giannetti and Meisenzahl (2022). They show that CLOs and banks have to sell loans with downgrading risk quicker compared to mutual funds or hedge funds due to covenants on loan rating, which CLOs have to adhere to. Within brown loans, CLOs decide for exposure at higher rating.

6 Robustness

In previous chapters, we have shown that CLOs react adversely to the PA as event that increases attention to climate change while regulatory consequences are sparse. It appears that CLOs face competitive advantages as they are neither concerned with regulation nor with increasing public green pressure. Hence, they take the opportunity to increase investments into brown firms at a discount. In the following chapter, we analyze the robustness of our results. We provide placebo estimations for other time periods, we vary the fixed effect structure and control variables, and use a log-linearized version of our main dependent variable $face\ amount$.

Placebo tests. If the PA is a shock event influencing demand through prices and trading volume, we should not find any significant effects when applying our difference-in-difference setting to other dates in our sample. Furthermore, as our shock event includes the year's end period we additionally need to control for year-end effects. For example, it might be that CLOs increase their trade volume in brown loans every December when other market participants shed high emission loans. In addition, as the COP is held every year during the December months, we also test the impact of different conference outcomes. Therefore, we apply our baseline model on CLO loan purchases to the four years following 2015. Event windows are the same as presented for 20 days in Table 2 but for years 2016, 2017, 2018, and 2019.

– Insert Table 13 around here –

We present results in Table 13. For all years tested, we neither find significant $brown_f \times post_t$ coefficients for transaction prices nor for face amount. This not only strengthens our findings of the PA influencing CLO trading behavior of leveraged loans. It furthermore underlines the features of the Paris Accords being a severe climate risk shock that raises public awareness towards climate change. Hence, this analysis confirms our notion that the climate risk related aftermath of the COP in 2015 is by far the strongest.

Confounding events. On December 17, 2015 the FOMC increased the Federal Funds Rate by 25 bps ending a long period of very low rates. Although this event coincides with the PA, there is no reason to believe rising interest rates influence brown and non-brown loans differently. However, we test this by applying our model setting one year later as on December 15, 2016 the Federal Funds Rate increased again by 25 bps. Table 13 shows no significant results for the following year 2016. Furthermore, overall conditions during Q4 in 2015 show commodity prices plummeting. As brown firms are likely to show a higher exposure towards e.g. oil this trend might influence brown firms more than non-brown. With brown firms using more energy and therefore more commodities, we would expect brown firms to profit from declining commodity prices. Nevertheless, we find declining prices of brown firms' loans indicating a loss in value, and not an increase in brown firms' loan prices. In addition, we find a same pattern of plummeting oil prices in Q4 of 2018. We reapply our setting here and do not find significant results, see Table 13, which provides evidence that our results are purely driven by the climate risk shock and not by changing interest rates or declining commodity prices.

Different set of fixed effects and control variables. To further validate our findings from chapter 5, we change fixed effects and control variables included in our model. Table 14 presents five different model specifications. Column I shows our baseline model without controls, only including issuer fixed effects. In model II, we additionally include CLO manager fixed effects in order to control for different strategies, skills, and knowledge among managers (for example Peristiani and Santos, 2019). Although our interaction coefficient shrinks in magnitude, the positive sign remains significant. Including our standard set of control variables (3-month LIBOR, the oil price, and the LLI 100) in column III does not alter our results. In column IV, we remove manager fixed effects and add more time series control variables to our model as well as begin using clustered standard errors on $industry \times post$ level. The additional control variables are from the bond market that many researchers have used in the past (e.g., Fama and French (1989); Fama and Schwert (1977)). These are the term spread (the spread between 10-year Treasury constant maturity and 3-month Treasury constant maturity yields), the 3-

month Treasury-bill yield, and the credit spread (the spread between Moody's Baa corporate bond yields and the 10-year Treasury constant maturity yield). Again, our results remain stable. Lastly, we approximate the model chosen by Fabozzi et al. (2021). They use loan characteristics to build fixed effects as well as controls: issuer type fixed effects, issuer rating fixed effects, and as control time-to-maturity of the loan. Note, that we loose some observations when including issuer rating in our model as not all issuers exhibit rating information. Our coefficient of interest remains positive and significant at the 1% level.

– Insert Table 14 around here –

Log face amounts Our main results concern a shift in traded face amounts of brown loans after the PA. These results should be robust to using the log of face amounts instead. Switching from nominal to logarithmic, we control if outliers drive our results, as logs shift our distribution away from tails closer to normal. We apply our baseline regression setting on the log face amounts. Table 15 provides respective results.

– Insert Table 15 around here –

Our coefficient of interest ($post_t \times brown_f$) are positive and significant for all three time periods (+/- 20 days, +/- 25 days, +/- 30 days).

Mutual loan funds. Our findings so far suggest that CLOs buy larger face amounts of leverage loans after the PA. With CLOs being the largest actor on the leveraged loan market buying, other market participants must be selling off their brown portfolio. In chapter 2.1 we investigate the competitive advantages that CLOs are facing during shock event: First, CLOs are overall confronted with only light regulation as well as little public awareness. Second, CLOs are closed for a long share of their life cycle making them stable investors during this phase. We now look at the second largest participants on the leveraged loan market, which face the opposite background: loan mutual funds. Investors in mutual funds can usually redeem their capital daily. In addition, retail investors buy mutual funds, which places more public and regulatory attention on them.

– Insert Figure 6 around here –

We use the Morningstar Database and retrieve month end holding weights of all US mutual funds invested in bank loans. As fund holdings do not differ among different share classes, we only use one class representative for the whole fund which overall gives us 45 unique US bank loan funds reporting during the fourth quarter of 2015. We exclusively consider loan holdings and therefore discard other asset classes. Loans generally lack a unique identifier. Hence we calculate a similarity score between all loan issuers in our CLO data and the mutual funds holdings for matching. Only issuer matches with a score higher 0.75 are assigned an industry classification. Next, we sum all position weights by their industry classification as brown or non-brown. We plot descriptive statistics for the brown weight portfolio means in Figure 6 together with quintile ranges. The mean weights clearly decline between November 2015 and December 2015. The quintile ranges also suggest an overall tendency of declining brown portfolio weights. This finding matches with previous results that CLOs increase their exposure to brown loans, while other market participants sell their exposures.

7 Conclusion

This paper assesses how non-bank entities, in particular Collateralized Loan Obligations (CLOs) adapt their trading behavior of high emission loans when the public draws attention to climate change. CLOs are major actors on leveraged loan markets and therefore decisive for refinancing opportunities of firms. We show that when climate change gains attention in the public, CLOs take the opportunity to increase their exposure to brown firms at lower prices. We provide evidence that in particular CLOs experienced in trading brown loans, as well as young CLOs drive the effect. CLOs at younger age are shielded from investor redemption and hence can more easily face the opportunity to purchase. Also, we show that CLOs prefer higher rated brown loans over lower rated, reflecting covenants on loan quality, which they have to adhere to.

We conclude from our findings that CLOs assume the role of the arbitrageur who buys brown loans when others are selling due to public attention on climate change. We see two possible explanations for this behavior: First, CLOs might simply not care whether their portfolio consists of brown or green loans as they only focus on firm or loan ratings. CLOs absorb brown loans that other actors, such as mutual funds, sell as CLOs are indifferent on whether loans are brown or not-brown, focusing rather on rating. Or, second, CLOs strategically buy brown loans after an increased climate risk awareness, believing in a temporary under-pricing of brown loans and hence hold a different view on the world than what public attention would suggest.

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Tables

Brown industries	
Automobile	Mining, Steel, Iron, and Non-Precious Metals
Chemicals, Plastics, and Rubber	Oil and Gas

Remaining industries	
Aerospace and Defense	Home and Office Furnishings Houseware
Banking	Hotels, Motels, Inns and Gaming
Beverage, Food and Tobacco	Insurance
Broadcasting and Entertainment	Leisure, Amusement and Entertainment
Buildings and Real Estate	Machinery
Cargo Transport	Personal Transportation
Containers, Packaging and Glass	Personal and Non-Durable Consumer Products
Diversified/Conglomerate Manufacturing	Personal, Food and Miscellaneous Services
Diversified/Conglomerate Service	Printing and Publishing
Ecological	Retail Stores
Electronics	Sovereign and Supranational
Farming and Agriculture	Telecommunications
Finance	Textiles and Leather
Grocery	Utilities
Healthcare, Education and Childcare	

Table 1: Treated and untreated industries

Table 1 categorizes industries used in our analysis into brown (treated) and non-brown (untreated). Note that Buildings and Real Estate only covers non-agriculture, non-construction, and non-electronic. Containers, Packaging and Glass & Personal and Non-Durable Consumer Products is manufacturing only.

Event	Start pre-event	Start event	End event	End post-event
Paris Agreement (20 days)	10-Nov-2015	29-Nov-2015	13-Dec-2015	01-Jan-2016
Paris Agreement (25 days)	05-Nov-2015	29-Nov-2015	13-Dec-2015	06-Jan-2016
Paris Agreement (30 days)	31-Oct-2015	29-Nov-2015	13-Dec-2015	11-Jan-2016

Table 2: Events

Event periods for this paper's results are chosen as shown above. The conference period (13 days) is excluded from our sample.

	Obs.	% Brown	Mean	SD	Median	0.05	0.95
Period 2010 to 2017							
a) CLO transactions: Mean Prices							
USD Purchases (%)	47,698	40.0	98.503	2.299	99.250	94.077	100.250
- Brown	19,063	-	98.300	2.894	99.333	92.150	100.438
- Rest	28,635	-	98.638	1.784	99.182	95.199	100.129
USD Sales	39,164	32.3	97.660	3.955	99.158	89.250	100.565
- Brown	12,654	-	97.666	4.280	99.406	88.450	100.792
- Rest	26,510	-	97.657	3.791	99.061	89.819	100.440
b) CLO transactions: Mean Face amount							
USD Purchases (M USD)	47,698	40.0	1.424	1.239	1.132	0.333	3.263
- Brown	19,063	-	1.320	1.175	1.000	0.250	3.250
- Rest	28,635	-	1.494	1.276	1.222	0.450	3.284
USD Sales (M USD)	39,164	32.3	0.987	1.801	0.715	0.142	2.613
- Brown	12,654	-	0.905	0.917	0.628	0.106	2.603
- Rest	26,510	-	1.026	2.095	0.749	0.169	2.616
c) News attention							
Environment (*1000)	90	-	5.144	0.948	4.917	3.892	6.750
Regulation (*1000)	90	-	7.706	0.955	7.906	6.157	9.134

Table 3: Summary statistics

This table presents summary statistics for our analyses in part I which comprises 1,297 CLOs. Mean prices (a) and face amounts (b) are calculated per CLO, month, and brown. Prices are presented as percentage of the loan nominal. Loan transaction volumes are in M USD. News attention (c) is multiplied with 1000.

	Obs.	% Brown	Mean	SD	Median	0.05	0.95
Paris Agreement (20 days)							
a) CLO transactions: Prices							
USD Purchases (%)	6,591	12.2	97.299	3.668	98.750	89.000	100.000
- Brown	803	-	96.083	4.610	97.630	84.980	100.125
- Rest	5,788	-	97.467	3.484	98.875	89.500	100.000
USD Sales (%)	4,140	12.1	97.336	4.401	99.125	85.750	100.130
- Brown	503	-	94.710	6.365	98.250	83.380	100.130
- Rest	3,637	-	97.699	3.921	99.130	90.000	100.150
b) CLO transactions: Face amount							
USD Purchases (M USD)	6,591	12.2	1.124	1.329	0.606	0.075	3.990
- Brown	803	-	0.778	0.966	0.499	0.021	2.575
- Rest	5,788	-	1.172	1.365	0.657	0.104	4.000
USD Sales (M USD)	4,140	12.1	0.822	1.288	0.474	0.054	2.742
- Brown	503	-	0.815	1.012	0.483	0.060	2.500
- Rest	3,637	-	0.823	1.322	0.470	0.052	2.813
c) Characteristics Purchases							
Issuer Ratings							
- Baa	130	4.6	1.599	1.786	1.000	0.052	5.850
- Ba	2,293	10.1	1.386	1.655	0.800	0.120	5.000
- B	3,772	13.6	0.934	1.008	0.500	0.064	3.000
- Caa	186	15.1	0.784	0.808	0.500	0.064	2.000
- N/R	64	15.6	1.532	1.478	1.042	0.120	5.214
Issue Type							
- Term Loan B	2,826	12.3	1.098	1.245	0.600	0.067	3.800
- Term Loan (Other)	3,765	12.1	1.143	1.389	0.612	0.080	4.000

Table 4: Summary statistics

This table shows summary statistics of individual loan trade prices (a) and face amounts (b) of 590 CLOs used in our main analyses. Prices are presented as percentage of the loan nominal. Loan face values are in M USD. Issuer rating and issue type are portrayed as part of characteristics in c). Ratings are aggregated into groups, e.g. Baa incorporates Baa1, Baa2, and Baa3; Ba incorporates Ba1, Ba2, and Ba3. N/R collects all loans without rating. Issue type is separated into term loan B and rest.

Dependent: Number of Trades	Continuous				Median			
	I	II	III	IV	V	VI	VII	VIII
Brown×Environment	0.768***	0.760***	6.531***	6.632***	1.386***	1.374***	5.011***	4.807***
	(0.091)	(0.092)	(0.742)	(0.758)	(0.183)	(0.182)	(0.523)	(0.518)
Brown×Regulation			2.740***	2.777***			-0.812*	-0.915*
			(0.495)	(0.501)			(0.478)	(0.475)
Brown×Environment×Regulation			-0.717***	-0.729***			-3.749***	-3.524***
			(0.096)	(0.098)			(0.554)	(0.550)
Brown	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Environment	-	Yes	-	Yes	Yes	-	Yes	-
Regulation	-	Yes	-	Yes	Yes	-	Yes	-
Environment Regulation	-	Yes	-	Yes	Yes	-	Yes	-
Controls	-	Yes	-	Yes	-	Yes	-	Yes
CLO fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-Month fixed effects	Yes	-	Yes	-	Yes	-	Yes	-
N	47,698	47,698	47,698	47,698	47,698	47,698	47,698	47,698
R2	0.349	0.326	0.351	0.327	0.349	0.325	0.35	0.326
Mean Dependent	9.379	9.379	9.379	9.379	9.379	9.379	9.379	9.379
SD Dependent	13.188	13.188	13.188	13.188	13.188	13.188	13.188	13.188

Table 5: Number of trades and news attention

In this table, we present results of the analysis in equation 1 $Y_{i,b,t} = \beta_0 + \beta_1\, environment_t \times brown_b + ... + \beta_x\, X_t + \alpha_i + \alpha_t + \epsilon_{i,b,t}$ and equation 2 $Y_{i,b,t} = \beta_1\, environment_t \times brown_b + \beta_2\, regulation \times brown_b + \beta_3\, regulation \times environment \times brown_b + ... + \beta_x\, X_t + \beta_0 + \alpha_i + \alpha_t + \epsilon_{i,b,t}$. Dependent variable $Y_{i,b,t}$ is mean number of purchases per CLO, brown/non-brown, and month. $brown_f$ is an indicator, which equals 1 for brown loans and 0 for non-brown loans. We use the time period from January 2010 to June 2017. In column I to IV we use the continuous form of environment and regulation attention, in column V to VIII we use an indicator variable which is 1 for environment (regulation) values higher than the median and 0 for lower values. For model I, III, V, and VII we include year-month fixed effects. For model II, IV, VI, and VIII we change to time series control variables instead. Standard errors are reported in parentheses. * marks significance at a 1% level, ** at 5%, and * at 10%.

	Continuous				Median			
Dependent: Face amount	I	II	III	IV	V	VI	VII	VIII
Brown×Environment	-0.008	-0.003	0.201***	0.180**	0.041**	0.048***	0.182**	0.149**
	(0.009)	(0.009)	(0.074)	(0.075)	(0.018)	(0.018)	(0.071)	(0.073)
Brown×Regulation			0.124***	0.105**			0.124***	0.108***
			(0.047)	(0.048)			(0.038)	(0.038)
Brown×Environment×Regulation			-0.026***	-0.023**			-0.156**	-0.111
			(0.009)	(0.009)			(0.074)	(0.075)
Brown	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Environment	-	Yes	-	Yes	Yes	-	Yes	-
Regulation	-	Yes	-	Yes	Yes	-	Yes	-
Environment×Regulation	-	Yes	-	Yes	Yes	-	Yes	-
Controls	-	Yes	-	Yes	-	Yes	-	Yes
CLO fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-Month fixed effects	Yes	-	Yes	-	Yes	-	Yes	-
N	47,698	47,698	47,698	47,698	47,698	47,698	47,698	47,698
R2	0.414	0.394	0.414	0.395	0.414	0.395	0.414	0.395
Mean Dependent	1.424	1.424	1.424	1.424	1.424	1.424	1.424	1.424
SD Dependent	1.239	1.239	1.239	1.239	1.239	1.239	1.239	1.239

Table 6: Purchase volumes and news attention

In this table, we present results of the analysis in equation 1 $Y_{i,b,t} = \beta_0 + \beta_1\, environment_t \times brown_b + ... + \beta_x\, X_t + \alpha_i + \alpha_t + \epsilon_{i,b,t}$ and equation 2 $Y_{i,b,t} = \beta_1\, environment_t \times brown_b + \beta_2\, regulation \times brown_b + \beta_3\, regulation \times environment \times brown_b + ... + \beta_x\, X_t + \beta_0 + \alpha_i + \alpha_t + \epsilon_{i,b,t}$. Dependent variable $Y_{i,b,t}$ is mean volume of loan purchased (face amount) per CLO, brown/non-brown, and month. $brown_f$ is an indicator, which equals 1 for brown loans and 0 for non-brown loans. We use the time period from January 2010 to June 2017. In column I to IV we use the continuous form of environment and regulation attention, in column V to VIII we use an indicator variable which is 1 for environment (regulation) values higher than the median and 0 for lower values. For model I, III, V, and VII we include year-month fixed effects. For model II, IV, VI, and VIII we change to time series control variables instead. Standard errors are reported in parentheses. * marks significance at a 1% level, ** at 5%, and * at 10%.

	Continuous				Median			
Dependent: Mean Transaction Price	I	II	III	IV	V	VI	VII	VIII
Brown×Environment	-0.167***	-0.165***	-1.232***	-1.485***	-0.396***	-0.382***	-0.158	-0.373*
	(0.024)	(0.025)	(0.224)	(0.237)	(0.039)	(0.041)	(0.192)	(0.201)
Brown×Regulation			-0.694***	-0.847***			-0.224**	-0.292***
			(0.139)	(0.146)			(0.103)	(0.104)
Brown×Environment×Regulation			0.135***	0.167***			-0.235	0.004
			(0.028)	(0.030)			(0.196)	(0.205)
Brown	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Environment	-	Yes	-	Yes	Yes	-	Yes	-
Regulation	-	Yes	-	Yes	Yes	-	Yes	-
Environment×Regulation	-	Yes	-	Yes	Yes	-	Yes	-
Controls	-	Yes	-	Yes	-	Yes	-	Yes
CLO fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-Month fixed effects	Yes	-	Yes	-	Yes	-	Yes	-
N	47,698	47,698	47,698	47,698	47,698	47,698	47,698	47,698
R2	0.315	0.217	0.315	0.218	0.315	0.216	0.316	0.217
Mean Dependent	98.503	98.503	98.503	98.503	98.503	98.503	98.503	98.503
SD Dependent	2.299	2.299	2.299	2.299	2.299	2.299	2.299	2.299

Table 7: Purchase transaction prices and news attention

In this table, we present results of the analysis in Equation 1 $Y_{i,b,t} = \beta_0 + \beta_1\, environment_t \times brown_b + ... + \beta_x\, X_t + \alpha_i + \alpha_t + \epsilon_{i,b,t}$ and equation 2 $Y_{i,b,t} = \beta_1\, environment_t \times brown_b + \beta_2\, regulation \times brown_b + \beta_3\, regulation \times environment \times brown_b + ... + \beta_x\, X_t + \beta_0 + \alpha_i + \alpha_t + \epsilon_{i,b,t}$. Dependent variable $Y_{i,b,t}$ is mean transaction prices of loan purchased per CLO, brown/non-brown, and month. $brown_f$ is an indicator, which equals 1 for brown loans and 0 for non-brown loans. We use the time period from January 2010 to June 2017. In column I to IV we use the continuous form of environment and regulation attention, in column V to VIII we use an indicator variable which is 1 for environment (regulation) values higher than the median and 0 for lower values. For model I, III, V, and VII we include year-month fixed effects. For model II, IV, VI, and VIII we change to time series control variables instead. Standard errors are reported in parentheses. * marks significance at a 1% level, ** at 5%, and * at 10%.

	Days: 20		Days: 25		Days: 30	
Dependent: Face amount	I	II	III	IV	V	VI
Post×Brown	0.491***	0.491**	0.363***	0.363*	0.379***	0.379**
	(0.131)	(0.209)	(0.105)	(0.198)	(0.094)	(0.172)
Post	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Issuer FE	Yes	Yes	Yes	Yes	Yes	Yes
Cluster industry-time	-	Yes	-	Yes	-	Yes
N	6,591	6,591	9,020	9,020	10,531	10,531
R2	0.33	0.33	0.301	0.301	0.305	0.305
Mean Dependent	1.124	1.124	1.103	1.103	1.067	1.067
SD Dependent	1.329	1.329	1.276	1.276	1.235	1.235

Table 8: Paris agreement and face amount

In this table, we present results of the difference-in-difference analysis in equation 3: $Y_{f,l,t} = \beta_0 + \beta_1 post_t + \beta_2\, brown_f \times post_t + \beta_x\, X_t + \alpha_f + \epsilon_{f,l,t}$. Dependent variable $Y_{f,l,t}$ is volume of loan purchased (face amount). $brown_f$ is an indicator, which equals 1 for brown loans and 0 for non-brown loans. We use three different time periods: +/-20, +/-25, and +/-30 days before and after the Paris conference. We leave out the period when the Paris conference took place (13 days). In column I, III, and V we use robust standard errors. For column II, IV, and VI we use clustered standard errors at the *industry×post* level. Standard errors are reported in parentheses. * marks significance at a 1% level, ** at 5%, and * at 10%.

Dependent: Transaction Price	Days: 20 I	Days: 20 II	Days: 25 III	Days: 25 IV	Days: 30 V	Days: 30 VI
Post×Brown	-0.404**	-0.404	-0.246*	-0.246	-0.398***	-0.398
	(0.176)	(0.352)	(0.146)	(0.379)	(0.141)	(0.372)
Post	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Issuer FE	Yes	Yes	Yes	Yes	Yes	Yes
Cluster industry-time	-	Yes	-	Yes	-	Yes
N	6,591	6,591	9,020	9,020	10,531	10,531
R2	0.918	0.918	0.902	0.902	0.903	0.903
Mean Dependent	97.299	97.299	97.449	97.449	97.39	97.39
SD Dependent	3.668	3.668	3.591	3.591	3.669	3.669

Table 9: Paris agreement and transaction prices

In this table, we present results of the difference-in-difference analysis in equation 3: $Y_{f,l,t} = \beta_0 + \beta_1 post_t + \beta_2\, brown_f \times post_t + \beta_x\, X_t + \alpha_f + \epsilon_{f,l,t}$. Dependent variable $Y_{f,l,t}$ is transaction price of loans purchased. $brown_f$ is an indicator, which equals 1 for brown loans and 0 for non-brown loans. We use three different time periods: +/-20, +/-25, and +/-30 days before and after the Paris conference. We leave out the period when the Paris conference took place (13 days). In column I, III, and V we use robust standard errors. For column II, IV, and VI we use clustered standard errors at the *industry*×*post* level. Standard errors are reported in parentheses. * marks significance at a 1% level, ** at 5%, and * at 10%.

	Days: 20				
Dependent: Face amount	I	II	III	IV	V
Post×Brown	0.490***	0.238**	0.223**	0.461**	0.568***
	(0.131)	(0.113)	(0.114)	(0.210)	(0.145)
Post	Yes	Yes	Yes	Yes	Yes
Controls	-	-	Yes	Yes	Yes
Time-to-maturity	-	-	-	-	Yes
Issuer FE	Yes	Yes	Yes	Yes	-
CLO Manager FE	-	Yes	Yes	-	
Issue Type FE	-	-	-	-	Yes
Issuer Rating FE	-	-	-	-	Yes
Cluster industry-time	-	-	-	Yes	Yes
Additional controls	-	-	-	Yes	-
N	6,591	6,591	6,591	6,510	6,445
R2	0.329	0.478	0.479	0.339	0.121
Mean Dependent	1.124	1.124	1.124	1.129	1.11
SD Dependent	1.329	1.329	1.329	1.334	1.315

Table 14: Robustness: Varying controls, cluster and fixed effects

In the table above, we present results with our difference-in-difference regression model in equation 3: $Y_{f,l,t} = \beta_0 + \beta_1 post_t + \beta_2\, brown_f \times post_t + \beta_x\, X_t + \alpha_f + \epsilon_{f,l,t}$. Dependent variable $Y_{f,l,t}$ is transaction volume (face amount) of loans purchased. $brown_f$ is an indicator, which equals 1 for brown loans and 0 for non-brown loans. We use +/-20 days before and after the Paris conference. We leave out the period when the Paris conference took place (13 days). From column I to V we gradually increase model complexity according to the control variables listet on the left. Column V includes additional controls, which are control variables from the bond market that many researchers have used in the past (e.g., Fama and French (1989); Fama and Schwert (1977)). These are the term spread (the spread between 10-year Treasury constant maturity and 3-month Treasury constant maturity yields), the 3-month Treasury-bill yield, and the credit spread (the spread between Moody's Baa corporate bond yields and the 10-year Treasury constant maturity yield). Additionally, we include level variables as the 3-month LIBOR, the oil price, and the LLI 100. Columns I to III use robust standard errors, in columns IV and V we use clustered standard errors at the $industry \times post$ level. Standard errors are reported in parentheses. * marks significance at a 1% level, ** at 5%, and * at 10%.

	Share of brown			
	Dependent: Face amount		Dependent: Transaction Price	
	I	II	III	IV
Post×Brown	-0.029	-0.029	-0.670**	-0.67
	(0.192)	(0.239)	(0.283)	(0.460)
Post×Brown×Indicator	0.654***	0.654*	0.335	0.335
	(0.240)	(0.356)	(0.304)	(0.286)
Post	Yes	Yes	Yes	Yes
Indicator	Yes	Yes	Yes	Yes
Post×Indicator	Yes	Yes	Yes	Yes
Brown×Indicator	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Issuer FE	Yes	Yes	Yes	Yes
Cluster industry-time	-	Yes	-	Yes
N	6,591	6,591	6,591	6,591
R2	0.332	0.332	0.918	0.918
Mean Dependent	1.124	1.124	97.299	97.299
SD Dependent	1.329	1.329	3.668	3.668

Table 10: CLO experience in brown trading

In this table, we present results of the extended difference-in-difference analysis in equation 4: $Y_{f,l,t} = \beta_0 + \beta_1 post_t + \beta_2\, brown_f \times post_t + ... + \beta_3\, brown_f \times post_t \times indicator_l + \beta_x\, X_t + \alpha_f + \epsilon_{f,l,t}$. Dependent variables $Y_{f,l,t}$ are volume of loan purchased (face amount) and transaction price. $brown_f$ is an indicator, which equals 1 for brown loans and 0 for non-brown loans. $indicator_l$ equals 1 if CLO is above the median in the share of brown loan transactions in the whole time period that we observe in the CLO-i data, and 0 otherwise. We use +/-20 days before and after the Paris conference. We leave out the period when the Paris conference took place (13 days). In column I and III we use robust standard errors. For column II and IV we use clustered standard errors at the $industry \times post$ level. Standard errors are reported in parentheses. * marks significance at a 1% level, ** at 5%, and * at 10%.

	Age			
	Dependent: Face amount		Dependent: Transaction Price	
	I	II	III	IV
Post×Brown	0.669***	0.669***	-0.611**	-0.611
	(0.184)	(0.196)	(0.265)	(0.389)
Post×Brown×Indicator	-0.029*	-0.029**	0.027	0.027
	(0.016)	(0.014)	(0.020)	(0.020)
Post	Yes	Yes	Yes	Yes
Indicator	Yes	Yes	Yes	Yes
Post×Indicator	Yes	Yes	Yes	Yes
Brown×Indicator	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Issuer FE	Yes	Yes	Yes	Yes
Cluster industry-time	-	Yes	-	Yes
N	6,486	6,486	6,486	6,486
R2	0.339	0.339	0.917	0.917
Mean Dependent	1.129	1.129	97.302	97.302
SD Dependent	1.331	1.331	3.669	3.669

Table 11: Age of a CLO

In this table, we present results of the extended difference-in-difference analysis in equation 4: $Y_{f,l,t} = \beta_0 + \beta_1 post_t + \beta_2\, brown_f \times post_t + ... + \beta_3\, brown_f \times post_t \times Indicator_l + \beta_x\, X_t + \alpha_f + \epsilon_{f,l,t}$. Dependent variable $Y_{f,l,t}$ is volume of loan purchased (face amount). $brown_f$ is an indicator, which equals 1 for brown loans and 0 for non-brown loans. $Indicator$ is CLO age (in days) starting from closing date to December 12, 2015 divided by 100. We use +/-20 days before and after the Paris conference. We leave out the period when the Paris conference took place (13 days). In column I and III we use robust standard errors. For column II and IV we use clustered standard errors at the $industry \times post$ level. Standard errors are reported in parentheses. * marks significance at a 1% level, ** at 5%, and * at 10%.

Dependent: Face amount	Rating B1 or better I	II	Rating B2 or better III	IV
Post×Brown	0.493***	0.493**	-0.079	-0.079
	(0.185)	(0.220)	(0.292)	(0.224)
Post×Brown×Indicator	-0.148	-0.148	0.606**	0.606**
	(0.198)	(0.240)	(0.297)	(0.231)
Post	Yes	Yes	Yes	Yes
Indicator	Yes	Yes	Yes	Yes
Post×Indicator	Yes	Yes	Yes	Yes
Brown×Indicator	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Issuer FE	Yes	Yes	Yes	Yes
Cluster industry-time	-	Yes	-	Yes
N	6,378	6,378	6,378	6,378
R2	0.327	0.327	0.326	0.326
Mean Dependent	1.106	1.106	1.106	1.106
SD Dependent	1.313	1.313	1.313	1.313

Table 12: Issuer rating

In this table, we present results of the extended difference-in-difference analysis in Equation 4: $Y_{f,l,t} = \beta_0 + \beta_1 post_t + \beta_2\, brown_f \times post_t + ... + \beta_3\, brown_f \times post_t \times indicator_f + \beta_x\, X_t + \alpha_f + \epsilon_{f,l,t}$. Dependent variable $Y_{f,l,t}$ is volume of loan purchased (face amount). $brown_f$ is an indicator, which equals 1 for brown loans and 0 for non-brown loans. $indicator_f$ equals 1 if issuer rating is B1 or better in columns I and II, and equals 1 if issuer rating is B2 or better in columns III and IV, and 0 otherwise. We use +/-20 days before and after the Paris conference. We leave out the period when the Paris conference took place (13 days). In column I and III we use robust standard errors. For column II and IV we use clustered standard errors at the $industry \times Post$ level. Standard errors are reported in parentheses. * marks significance at a 1% level, ** at 5%, and * at 10%.

	2016		2017		2018		2019	
Dependent:	TP	FA	TP	FA	TP	FA	TP	FA
Post×Brown	-0.174	-0.134	-0.158	0.056	0.223	0.132	0.161	0.118
	(0.144)	(0.125)	(0.121)	(0.159)	(0.189)	(0.085)	(0.382)	(0.082)
Post	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Issuer FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cluster industry-time	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	13,419	13,419	19,354	19,354	26,874	26,874	25,004	25,004
R2	0.909	0.223	0.853	0.454	0.891	0.470	0.930	0.405
Mean Dependent	99.034	1.173	99.487	1.306	98.006	0.895	98.089	0.686
SD Dependent	2.412	1.174	1.853	1.749	2.643	1.231	3.599	0.888

Table 13: Placebo tests for following years

In this table, we present results of placebo tests for years 2016, 2017, 2018, and 2019 with our baseline regression model in equation 3: $Y_{f,l,t} = \beta_0 + \beta_1 post_t + \beta_2\, brown_f \times post_t + \beta_x\, X_t + \alpha_f + \epsilon_{f,l,t}$. Dependent variable $Y_{f,l,t}$ is transaction price (TP) and face amount (FA) of loans purchased. $brown_f$ is an indicator, which equals 1 for brown loans and 0 for non-brown loans. We use +/-20 days before and after the Paris conference. We leave out the period when the Paris conference took place (13 days). In all columns we use clustered standard errors at the *industry*×*post* level. Standard errors are reported in parentheses. * marks significance at a 1% level, ** at 5%, and * at 10%.

	Days: 20		Days: 25		Days: 30	
Dependent: Face amount (log)	I	II	III	IV	V	VI
Post×Brown	0.714***	0.714**	0.478***	0.478**	0.483***	0.483**
	(0.134)	(0.306)	(0.101)	(0.207)	(0.094)	(0.198)
Post	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Issuer FE	Yes	Yes	Yes	Yes	Yes	Yes
Cluster industry-time	-	Yes	-	Yes	-	Yes
N	6,416	6,416	8,730	8,730	10,174	10,174
R2	0.38	0.38	0.332	0.332	0.341	0.341
Mean Dependent	-0.468	-0.468	-0.477	-0.477	-0.518	-0.518
SD Dependent	1.164	1.164	1.165	1.165	1.180	1.180

Table 15: Paris agreement and face amount in logs

In this table, we present results of the difference-in-difference analysis in equation 3: $Y_{f,l,t} = \beta_0 + \beta_1 post_t + \beta_2\, brown_f \times post_t + \beta_x\, X_t + \alpha_f + \epsilon_{f,l,t}$. Dependent variable $Y_{f,l,t}$ is the log of volume of loans purchased (face amount). $brown_f$ is an indicator, which equals 1 for brown loans and 0 for non-brown loans. We use three different time periods: +/-20, +/-25, and +/-30 days before and after the Paris conference. We leave out the period when the Paris conference took place (13 days). In column I, III, and V we use robust standard errors. For column II, IV, and VI we use clustered standard errors at the *industry×post* level. Standard errors are reported in parentheses. * marks significance at a 1% level, ** at 5%, and * at 10%.

Figures

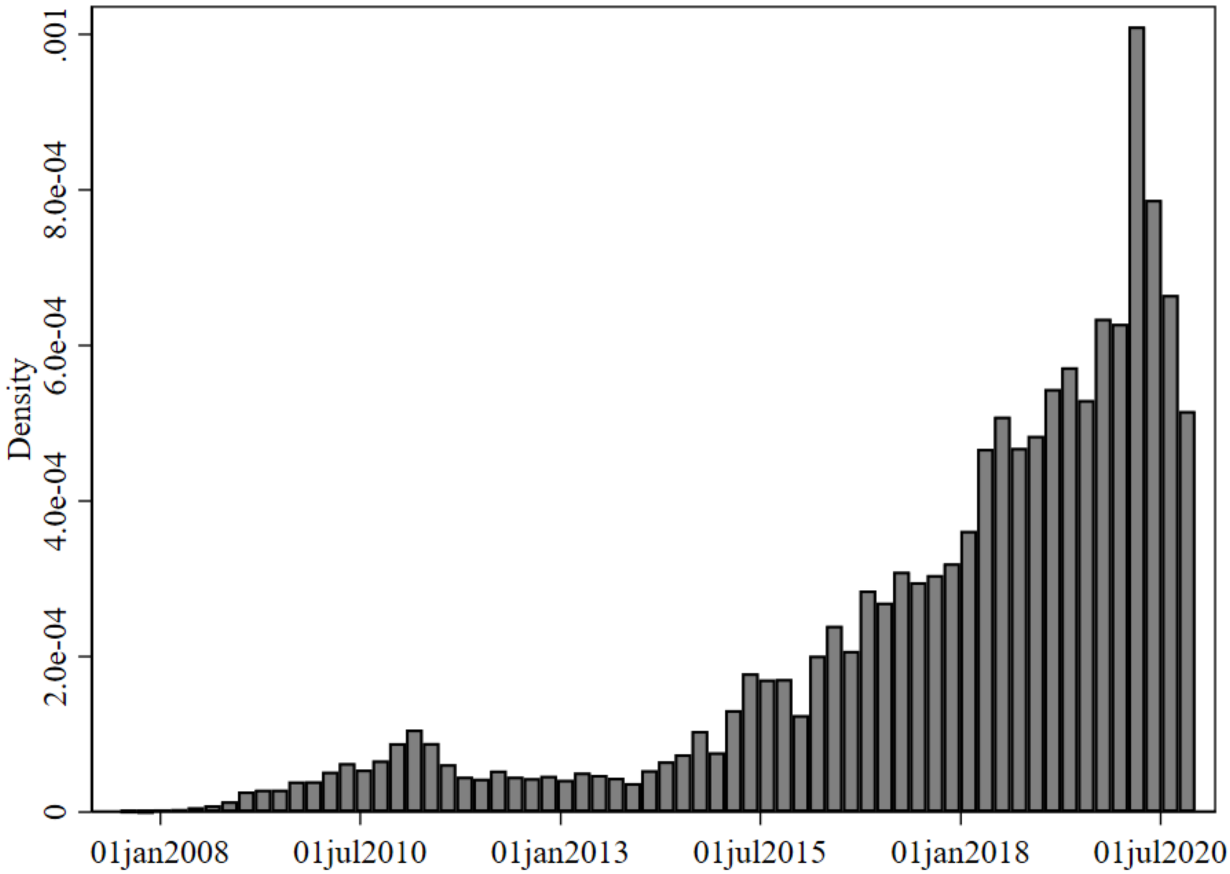

Figure 1: Histogram of CLO trades between 2008 and 2020

Figure 1 shows the growing importance of CLOs on the secondary market for leveraged loans through plotting the number of CLO trades in our data between 2008 and 2020 within our CLO-i dataset. Note that after the global financial crisis CLOs' trading of loans began. After stabilizing between 2011 and 2014, CLOs' trading entered a strong growth phase lasting until 2020.

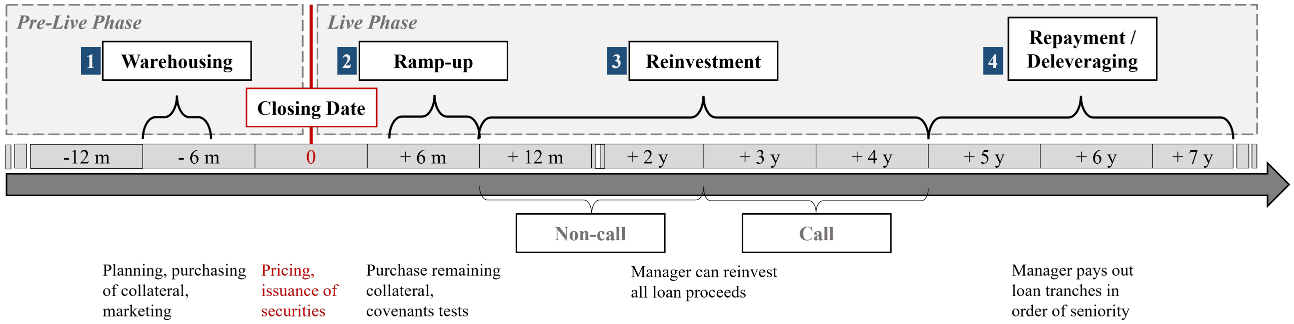

Figure 2: CLO lifecycle

This Figure shows a schematic timeline of an exemplary CLO. Age count starts with the closing date. As CLOs can be called anytime after the non-call period ends, CLOs can be redeemed before their natural maturity date. Source: Kundu (2022a) and Kollmorgen and Oh (2022), authors' own illustration.

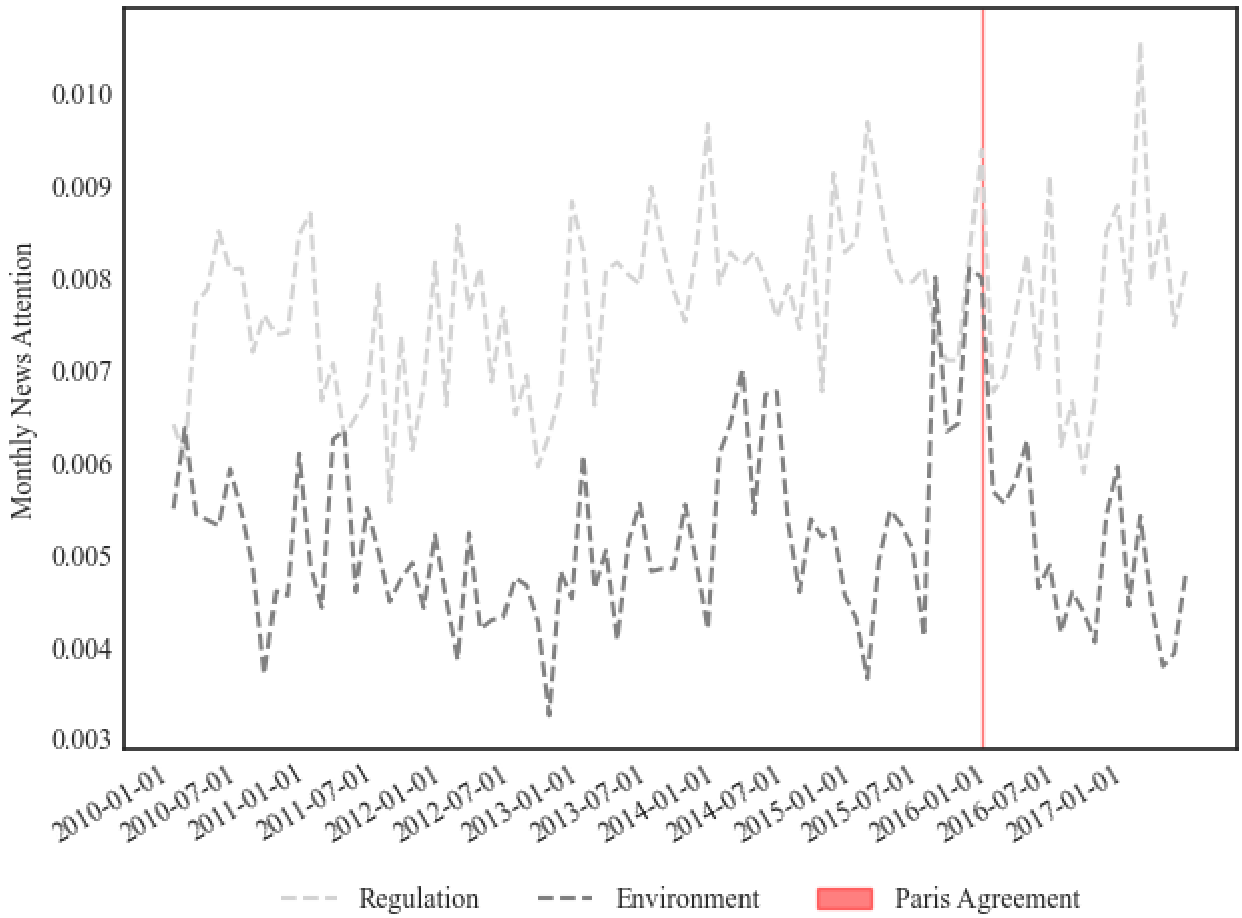

Figure 3: News attention allocation of the WSJ to the topics environment and regulation

This figure was created using monthly topic attention data of Bybee et al. (2020). The scale can be interpreted as the share of news allocated to a specific topic. Hence, attention on all topics adds up to 1. We observe news attention to regulation an environment to be peaking in December 2015 during the Paris Agreement.

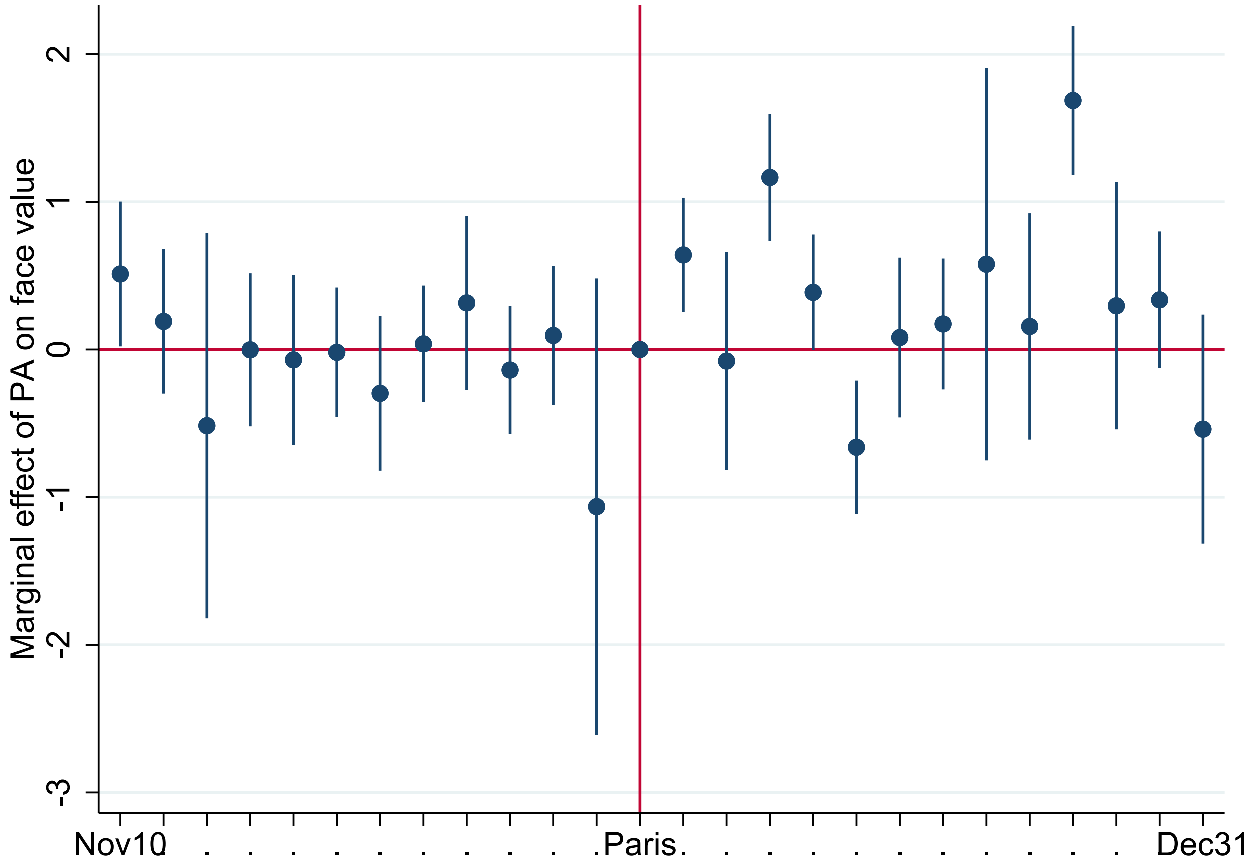

Figure 4: Common trend assumption

This figure shows the coefficient plot for $\beta_{1\tau}$ from estimating the following regression equation: $Y_{f,l,t} = \beta_0 + \sum_{\tau=Nov10,\tau\neq Nov30}^{Dec31} \beta_{1\tau}\ D_\tau \times \text{brown}_f + \beta_x\ X_t + \alpha_t + \alpha_f + \epsilon_{f,l,t}$. Dependent variable is face amount of loans purchased. The regression model is build up as in column II of Table 8. The red vertical line shows the period of the Paris conference. We use the first day of the conference as base day, and further condition on a minimum of five trades per day.

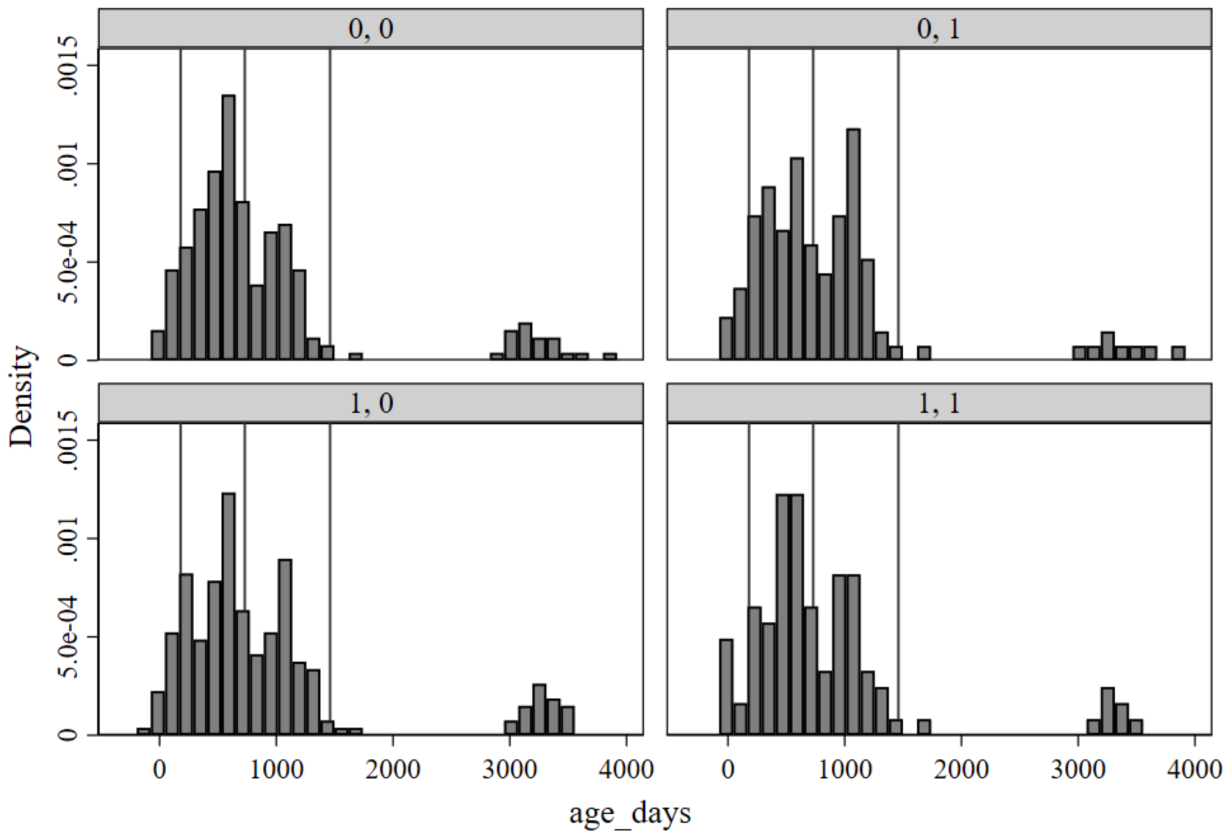

Figure 5: Histogram of CLO age and loan purchases

This figure shows a histogram of CLO age in days before (0) and after (1) the Paris Agreement when purchasing non-brown (0) loans and brown (1), i.e. (Time, Brown). Vertical lines indicate life cycle phases of CLOs: First, warehousing (<0 days), second, ramping and non-call investment phase (0 to 730 days), third, call phase (730 to 1460 days), and fourth, deleveraging (> 1460 days).

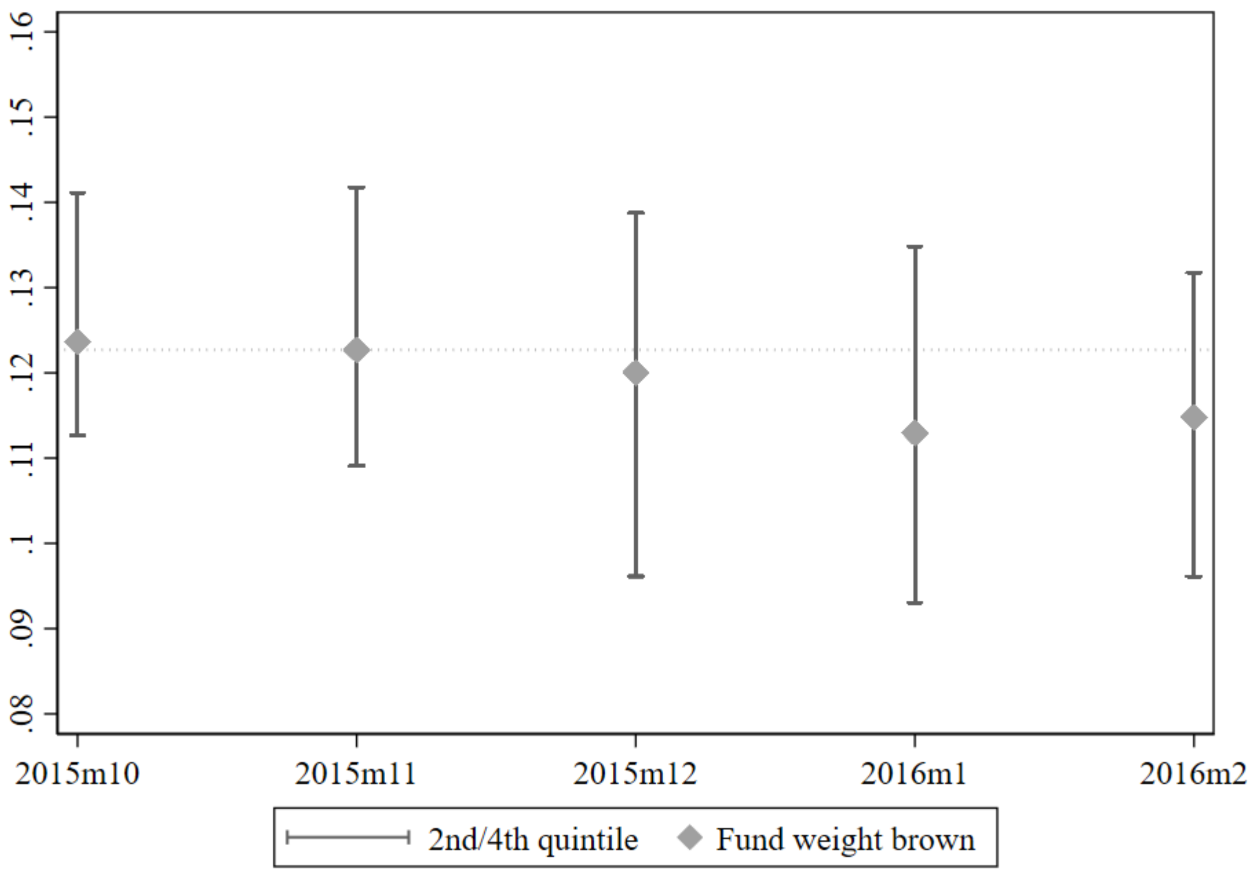

Figure 6: Average share of brown loans held by mutual bank loan funds

This is a descriptive statistics plot showing the monthly mean share of brown loans held by US mutual bank loan funds at the end of the month. Bars depict the lowest and highest value within the second / fourth quintile.

A Results for sale side

	Days: 20		Days: 25		Days: 30	
Dependent: Face amount	I	II	III	IV	V	VI
Post×Brown	0.264*	0.264	0.157	0.157	0.114	0.114
	(0.154)	(0.289)	(0.111)	(0.187)	(0.105)	(0.086)
Post	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Issuer FE	Yes	Yes	Yes	Yes	Yes	Yes
Cluster industry-time	-	Yes	-	Yes	-	Yes
N	4,140	4,140	5,618	5,618	7,422	7,422
R2	0.159	0.159	0.182	0.182	0.174	0.174
Mean Dependent	0.822	0.822	0.767	0.767	0.727	0.727
SD Dependent	1.288	1.288	1.19	1.19	1.102	1.102

Table 16: Paris agreement and volumes sold

In this table, we present results of the difference-in-difference analysis in equation 3: $Y_{f,l,t} = \beta_0 + \beta_1 post_t + \beta_2\, brown_f \times post_t + \beta_x\, X_t + \alpha_f + \epsilon_{f,l,t}$. Dependent variable $Y_{f,l,t}$ is volume of loan sold (face amount). $brown_f$ is an indicator, which equals 1 for brown loans and 0 for non-brown loans. We use three different time periods: +/-20, +/-25, and +/-30 days before and after the Paris conference. We leave out the period when the Paris conference took place (13 days). In column I, III, and V we use robust standard errors. For column II, IV, and VI we use clustered standard errors at the *industry*×*post* level. Standard errors are reported in parentheses. * marks significance at a 1% level, ** at 5%, and * at 10%.

Dependent: Transaction Price	Days: 20 I	Days: 20 II	Days: 25 III	Days: 25 IV	Days: 30 V	Days: 30 VI
Post×Brown	-0.387	-0.387	-0.757***	-0.757	-0.582***	-0.582
	(0.259)	(0.457)	(0.266)	(0.519)	(0.216)	(0.431)
Post	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Issuer FE	Yes	Yes	Yes	Yes	Yes	Yes
Cluster industry-time	-	Yes	-	Yes	-	Yes
N	4,140	4,140	5,618	5,618	7,422	7,422
R2	0.929	0.929	0.905	0.905	0.898	0.898
Mean Dependent	97.336	97.336	96.982	96.982	97.126	97.126
SD Dependent	4.401	4.401	4.769	4.769	4.607	4.607

Table 17: Paris agreement and prices of sales

In this table, we present results of the difference-in-difference analysis in equation 3: $Y_{f,l,t} = \beta_0 + \beta_1 post_t + \beta_2\, brown_f \times post_t + \beta_x\, X_t + \alpha_f + \epsilon_{f,l,t}$. Dependent variable $Y_{f,l,t}$ is transaction price of loans sold. $brown_f$ is an indicator, which equals 1 for brown loans and 0 for non-brown loans. We use three different time periods: +/-20, +/-25, and +/-30 days before and after the Paris conference. We leave out the period when the Paris conference took place (13 days). In column I, III, and V we use robust standard errors. For column II, IV, and VI we use clustered standard errors at the *industry×post* level. Standard errors are reported in parentheses. * marks significance at a 1% level, ** at 5%, and * at 10%.

	Days: 20		Days: 25		Days: 30	
Dependent: Number of trades per CLO	I	II	III	IV	V	VI
Post×Brown	0.123	0.06	0.236	0.209	0.370***	0.369
	(0.202)	(0.329)	(0.149)	(0.299)	(0.131)	(0.327)
Post	Yes	Yes	Yes	Yes	Yes	Yes
Controls	-	Yes	-	Yes	-	Yes
Issuer FE						
CLO FE	Yes	Yes	Yes	Yes	Yes	Yes
N	2,140	2,140	2,884	2,884	3,765	3,765
R2	0.159	0.169	0.176	0.186	0.197	0.201
Mean Dependent	1.76	1.76	1.802	1.802	1.859	1.859
SD Dependent	1.33	1.33	1.402	1.402	1.574	1.574

Table 18: Paris agreement and number of sales per CLO

In this table, we present results of the difference-in-difference analysis in equation 3: $Y_{f,l,t} = \beta_0 + \beta_1 post_t + \beta_2\, brown_f \times post_t + \beta_x\, X_t + \alpha_f + \epsilon_{f,l,t}$. Dependent variable $Y_{f,l,t}$ is number of loans sold. $brown_f$ is an indicator, which equals 1 for brown loans and 0 for non-brown loans. We use three different time periods: +/-20, +/-25, and +/-30 days before and after the Paris conference. We leave out the period when the Paris conference took place (13 days). In column I, III, and V we use robust standard errors. For column II, IV, and VI we use clustered standard errors at the *industry*×*post* level. Standard errors are reported in parentheses. * marks significance at a 1% level, ** at 5%, and * at 10%.

B Further results

	Days: 20		Days: 25		Days: 30	
Dependent: Number of trades	I	II	III	IV	V	VI
Post×Brown	-0.276	-0.336	-0.177	-0.233	-0.216	-0.243
	(0.289)	(0.286)	(0.222)	(0.215)	(0.190)	(0.186)
Post	Yes	Yes	Yes	Yes	Yes	Yes
Controls	-	Yes	-	Yes	-	Yes
Issuer FE	-	-	-	-	-	-
CLO FE	Yes	Yes	Yes	Yes	Yes	Yes
N	3,338	3,338	4,628	4,628	5,479	5,479
R2	0.022	0.022	0.039	0.039	0.049	0.049
Mean Dependent	2.003	2.003	1.971	1.971	1.943	1.943
SD Dependent	3.615	3.615	3.455	3.455	3.224	3.224

Table 19: Paris agreement and number of purchases per CLO

In this table, we present results of the difference-in-difference analysis in equation 3: $Y_{f,l,t} = \beta_0 + \beta_1 post_t + \beta_2\, brown_f \times post_t + \beta_x\, X_t + \alpha_f + \epsilon_{f,l,t}$. Dependent variable $Y_{f,l,t}$ is number of loans purchased. $brown_f$ is an indicator, which equals 1 for brown loans and 0 for non-brown loans. We use three different time periods: +/-20, +/-25, and +/-30 days before and after the Paris conference. We leave out the period when the Paris conference took place (13 days). In column I, III, and V we use robust standard errors. For column II, IV, and VI we use clustered standard errors at the *industry*×*post* level. Standard errors are reported in parentheses. * marks significance at a 1% level, ** at 5%, and * at 10%.