The Spillover Effects of Insurer Climate Supervision into Shadow Markets*

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Abstract

When a firm's climate risk decreases, we find that insurers hold *more* of the firm's debt via bonds, yet hold *less* of the *same* firm's debt via Collateralized Loan Obligations (CLOs). We explain this differential behavior using the staggered rollout of climate supervision for insurance companies. Under increased supervision, insurers lose 1.5% in bond yields as they shift towards greener firms in their outright holdings. Simultaneously, however, these insurers become 13% more likely to invest in CLOs – non-transparent funds that are each comprised of hundreds of high-yield loans. CLO managers receiving this capital launch larger funds that also include browner firms. Finally, we estimate that firms receiving this influx of CLO capital pollute an estimated additional 12.87 pounds of emissions per dollar of total assets.

Keywords— insurance, climate risk, CLOs, shadow investing, corporate bonds, securitization.

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1 Introduction

In 2010, the National Association of Insurance Commissioners (NAIC) adopted an annual Climate Risk Disclosure Survey to increase accountability by insurance companies towards climate-related risk.[1] Subsequent responses showed that over 70% of disclosing insurers consider the impact of climate change in their investment portfolios. This consideration is part of a broader trend for institutional investors, who frequently make investment adjustments in response to the underlying firms' climate risk (Ilhan, Krueger, Sautner, and Starks (2023), Mastouri, Mendiratta, and Giese (2022), Seltzer, Starks, and Zhu (2022), Krueger, Sautner, and Starks (2020)). But monitoring an insurer's portfolio may be complicated by several opaque instruments– the largest of which are Collateralized Loan Obligations (CLOs), which have grown rapidly over the past decade (Figure 1). In 2020, insurers held over $150 billion dollars of CLOs, and yet, there is little understanding of whether insurers consider climate risks in these "shadow markets". We address this gap in this paper. This is an important question not only because CLOs could finance brown projects, but more importantly, as the CLO market continues to grow, the lack of public disclosures in shadow markets makes it challenging for stakeholders to assess climate risk.

We ask two questions in this paper: 1) do insurers respond differently to climate risk in the underlying firm, when that same entity is held directly via CLOs versus indirectly via corporate bonds? 2) how does the capital flow from insurers to CLOs affect CLO managers and the firms they invest in? Previously, we did not have data to answer these questions, because public data on insurance holdings (NAIC Schedule D) do not disclose the underlying components of each CLO investment. By hand-matching data on the hundreds of underlying firms held by each CLO investment to the holdings data, we bring new evidence to bear on these questions.

Our results show a striking differential effect – for the same one s.d. increase in climate risk, on average, insurers *decrease* their holdings by $11,664 if the firm is held directly via bonds, yet they *increase* their holdings by $5,968 (2.8% of the conditional mean) if the firm is held indirectly via

[1] While the surveys officially started in 2009, it only covered and was administered by the state of California in that year. Source: https://www.insurance.ca.gov/0250-insurers/0300-insurers/0100-applications/ClimateSurvey/

CLOs. In this paper, we measure firms' climate risk using climate-related news about the firm, and we interpret each climate-related news as either positive or negative using a measure of investor sentiment from Sautner, Van Lent, Vilkov, and Zhang (2023). As a result, the main measure of climate risk in our analysis is called "Climate Sentiment."[2] Our findings suggest that the incentives for insurers to invest in CLOs versus bonds differ along important dimensions. Cordell, Roberts, and Schwert (2023) show that CLO debt tranches earn higher returns than similarly rated corporate bonds, so changes in CLO investments may reflect insurers reaching-for-yield (Becker and Ivashina, 2015). On the other hand, direct bond investments are easier to monitor, and thus, are more sensitive to regulatory pressures requiring insurers to mitigate climate risk. These two mechanisms do not have to be mutually exclusive. To the best of our knowledge, we are the first to demonstrate a divide in portfolio management *within* the same investor-firm pair.

If climate supervision imposes a binding constraint on the choice of insurers' direct holdings, then insurers may substitute into shadow markets to recoup lost yields. We propose that NAIC's Climate Risk Disclosure Survey imposed such a constraint by requiring some insurers to publicly disclose their position towards climate-related risk in both their assets and liabilities. The surveys were administered in a staggered fashion and received significant attention—they were not only published online by the NAIC for all stakeholders, but survey responses are often promoted by the insurance companies themselves (for example, see the annual disclosures of Pacific Life [3], Berkeley Insurance [4], and Metlife [5]). Furthermore, survey results are regularly part of public discourse by private firms like Deloitte (Deloitte, 2023), nonprofits like Ceres Accelerator (Ceres, 2023), and regulators such as the U.S. Treasury (Treasury, 2023). Finally, the New York Department of Financial Services even used the responses to the NAIC Climate Risk Survey to publicly grade insurers as "Yet to Start," "Early Stage," "Making Progress," or "Good Progress" (NYDFS, 2024).

[2]More specifically, we interpret negative investor sentiment regarding a firm's climate-related news as indicative of positive climate risk for the firm. Alternatively, if we just use exposure to climate related news, without a positive or negative association, we find similar results.

[3]See https://www.pacificlife.com/home/corporate-social-responsibility.html

[4]See https://www.berkley.com/sites/g/files/xkzibx106/files/2023-08/Berkley_ESG_Report%202023.pdf

[5]see https://sustainabilityreport.metlife.com/content/dam/metlifecom/us/sustainability/Sustainability-2024/sustainability-evergreen-microsite/pdf

The report gave the surveys more gravity, because it implied that some agencies may adopt climate responses directly into their examination processes in the future.

Using the staggered rollout of NAIC climate disclosures to insurance companies between 2010 and 2020 as a natural experiment, we trace out the following chain of events: once forced to disclose, the insurance company directs more capital into shadow markets, funding CLO managers with whom the insurer had a previous relationship. Consistent with reach-for-yield behavior, we show evidence of a decrease in yields on direct holdings and increase in yields for indirect holdings after climate supervision. The CLO managers who receive capital injection from insurers subsequently launch new funds, which are more likely to include brown firms in their portfolio. Finally, the capital shock from insurer disclosures transmits to the underlying firms in two ways: firms receiving capital from CLO managers increase future issuance of leveraged loans, and they also subsequently engage in greater polluting activities.

Ultimately, we find that climate supervision successfully *lowers climate risks on net*, by lowering risks in insurers' outright bond portfolios. However, this comes at a cost, as supervision contemporaneously *shifts significant climate risk into opaque shadow markets*, making it hard to monitor and efficiently dis-incentivize the funding of brown projects in the future. This unintended consequence directly contradicts the original intention of the NAIC Climate Risk Disclosure Survey, which is to shed light on how large institutions manage and fund climate-related projects.

We begin our empirical analysis by establishing that insurers react differently in their CLO investments compared to their corporate bond holdings, in response to the same firm's climate-related news. A priori, we might expect insurer evaluations to be similar, irrespective of whether the underlying firm is held directly or indirectly (ie via corporate bonds or via CLOs). Figure 2, however, rejects this idea. Here, we plot the year-over-year change in holdings against climate sentiment, which is a signed proxy for the underlying firm's climate risk. [6] Higher climate sentiment, indicating a positive climate-related outlook by investors, is associated with an increase in direct

[6]The binned scatter plots in Figure 2 absorb variation at both the insurer and year levels. Thus, the difference in behavior between CLO and direct holdings is unlikely to be driven by unobserved cross-sectional differences between large and small insurers, or macroeconomic factors such as the interest rate environment in a particular year.

bond holdings but a decrease in indirectly held CLO tranches. This finding – that insurers appear to be less sensitive to climate risk in their shadow market investments – is stark because it is inconsistent with insurers' own responses to the Climate Risk Disclosure Survey. It also raises a key environmental concern that a growing number of brown projects may receive financing via CLO markets.

A key contribution of our analysis is to hand-collect data that allows us to connect insurers to firms via shadow markets. This link allows us to compare insurers' responses to climate sentiment between direct and CLO holdings, while holding the insurer-firm pair constant. To link insurers to firms within CLO markets, we have to first disaggregate CLO investments from the Insurer×CLO tranche level to the Insurer×Firm level by hand-matching firm-level data to the hundreds of underlying firms held by each CLO. We then regress insurance holdings on lagged climate measures for the underlying firm, interacting this measure with an indicator variable equal to one if the firm is held indirectly in a CLO. We find that this interaction term is negative and strongly significant, confirming the differential investment behavior of insurers. Since our identifying variation is restricted *within* the same Insurer × Firm pair, we may reasonably interpret the differential response as arising from the nature of investment holdings (direct vs. indirect).

Since insurers do not directly control the composition of the CLO portfolio, one may be concerned that the incentives for CLO managers to include a certain firm in their portfolio is wholly disconnected from those of an insurer investing in the same firm. Hence, despite restricting our analysis to the same insurer-firm pair, inherent differences between CLO managers and insurers, independent of climate risk considerations, may explain our result. To address this concern, we utilize a policy shock that changed insurers' incentives but did not affect CLO managers' incentives otherwise: the Climate Risk Disclosure Survey. Figure 3 shows the distribution of insurers' first responses, in which over 70% declared that climate risk is an important consideration in their investment portfolios. If insurers view this supervision as a constraint on the choice of direct holdings, we might expect greater climate risk exposure in their indirect holdings, to recoup lost yields. This would strengthen our hypothesis that climate considerations, rather than different risk preferences between insurers and CLO managers, drive our results.

Figure 4 plots the average climate sentiment of the underlying firms invested by insurers, both leading up and in the years following their first date of disclosure.[7] Indeed, while direct holdings in Figure 4 moved toward greener investments after disclosure (i.e., positive climate sentiment increases in the post-survey period), climate sentiment for indirect holdings decreases after the survey, indicative of an opposing shift toward browner investments. These diverging patterns post-supervision suggest that the differential sensitivity is driven by climate-related constraints imposed on the insurer by climate supervision. We also perform a direct statistical test using a triple difference-in-difference test where the key explanatory variable is Climate Sentiment$_{f,t-1} \times$ Indirect$_{i,f,t} \times$ Disclosing$_{f,t}$. With insurer holdings as the dependent variable, the triple interaction term is negative and strongly significant. Thus, following disclosure, insurers increase their shadow market exposure to brown firms.

To further study the CLO investment behavior of insurers, Figure 5 plots the dynamic coefficients from a regression of (log) total CLO investment against the years relative to the first disclosure. We find a strong increase in CLO investments only in the period following disclosure. Using a regression, we further find that, following disclosure, insurers have a 13 percentage point increase in the probability of holding a CLO, and on average, a $17 million dollar increase in their CLO holding amounts. Since climate supervision was implemented in a staggered fashion across states and time, these results are unlikely to be driven by cofounding factors such as a time trend or insurer characteristics such as size or type.

In our next set of results, we study the propagation of the disclosure shock via shadow markets. We construct two measures that capture shocks to the CLO manager ("CLO manager shock") and the underlying firm ("Firm Shock"). First, we measure the relationship between an insurer and a manager using the amount that the insurer previously invested with the same manager; we find that the probability of an insurer investing in a CLO manager (and the dollar investment amount) significantly increases with the strength of the relationship. Summing across all insurers that each CLO manager has a relationship with, we create *CLO manager shock*, which captures the extent

[7]This analysis has both cross-sectional and time series variation as disclosure requirements were implemented across states in a staggered fashion.

disclosure shocks affect each CLO manager. We find that this measure is associated with greater probability of subsequent CLO fund launches, an increase in the total number of funds launched by the manager, as well as an increase in total dollar amount of future funds. These results support the notion that climate supervision increases the flow of funds to shadow markets. Finally, we show that CLO managers with past relationships are more likely to include browner firms in their portfolio. Thus, the Climate Risk Disclosure Survey may have a significant, unintended consequence of financing brown firms through CLOs.

Finally, we calculate a *Firm Shock* measure based on the total size of past investments between CLO managers who receive a disclosure shock and each firm. Consistent with a story of loosening credit in CLO markets, we find that the *Firm Shock* measure is associated with increased issuance of future leveraged loans. Finally, we study the environmental impact of the firms that receive extra capital flow from insurers via shadow markets. Using the EPA's Toxics Release Inventory data, we find that firms which receive a one s.d. greater shock through the CLO market have an average emission increase of 12.87 pounds per dollar of assets, or a 17% increase from the unconditional average. This striking evidence of the Green Paradox (Jensen, Mohlin, Pittel, and Sterner, 2015), has significant policy implications for climate regulation and the supervision of insurer investments.

Our paper makes three main contributions. First, we show that insurance companies, through their investments in CLO markets, play a significant role in the financing of brown firms. While our results on corporate bond holdings are consistent with emerging evidence showing that institutions mitigate climate risk (Cao, Li, Zhan, Zhang, and Zhou, 2021), our findings on CLOs stand in sharp contrast because CLO investment decisions appear to be dominated by reach-for-yield considerations. Next, by drawing a link from the Climate Risk Disclosure Survey to its effect on insurers' underlying investments, we show that regulation intended to make climate risks more transparent can actually *obfuscate and increase* risks in hard-to-monitor markets. To be clear, insurers' corporate bond holdings are much larger than CLOs, so on net, we still find that climate supervision decreases funding for brown firms. However, as more funding for brown projects moves into opaque markets, it becomes harder for stakeholders to monitor project outcomes and incentivize investments that align with a sustainable future. Finally, we contribute to the climate disclosure

literature which studies the relationship between climate disclosures and future carbon emissions. While research has focused on the impact of underlying firms' climate disclosures on firm value (Matsumura, Prakash, and Vera-Muñoz, 2014), our paper studies the effect of climate disclosures by the institutional *investors* that fund those firms.

2 Related Literature

Our paper relates to three main strands of literature: the financial regulation of insurance, the study of how institutional investors respond to climate risk, and understanding the effect of policies (such as increased disclosure) on climate-related investing.

First, we contribute to a large and growing body of work that studies the financial regulation of insurance companies. On statutory requirements, Becker and Ivashina (2015) show that RBC weights lead insurers to reach for yield within a rating bucket; Koijen and Yogo (2015) show that life policies significantly deviated from fair value to capture regulatory arbitrage on reserve requirements; Koijen and Yogo (2016) show that insurers sold liabilities to shadow re-insurers to avoid regulatory oversight. Unlike banks that are largely regulated at the national level, insurers are regulated by the states they operate in, which allows for heterogeneous frictions arising from the state regulators. Tenekedjieva (2020) and Liu and Liu (2024) find evidence of political frictions at the state level. Focusing on climate risk, Oh, Sen, and Tenekedjieva (2022) find that states with low price regulation subsidize the cost of climate risks from states with high price regulation, and Jung, Engle, Ge, and Zeng (2024) find that insurers operating in states with high climate risks have higher sensitivity to physical risk, requiring different capital shortfalls under various stress testing scenarios. Our study adds to these findings by quantifying the unintended effects of mandatory NAIC climate disclosure laws enforced in a staggered fashion across states.

Second, we study the investment decisions of insurance companies– large institutional investors– regarding climate risk; we provide new evidence that insurers respond to this risk differentially in their direct versus shadow market investments. This contrast speaks to the distinction between *value-based* and *values-based* investing motivations described in Starks (2023). Past literature has shown that institutional investors can influence the climate risk disclosure practices of the under-

lying firms they invest in (Ilhan et al., 2023); institutional investors pay attention to the financial implications of perceived climate risks (Krueger et al., 2020; Berry-Stölzle, Fritzsch, Scharner, and Weiß, 2024); and insurance companies are more likely to sell bonds that are issued by firms which are high carbon emitters (Cao et al., 2021). Perhaps most closely related to this paper, Ivantsova, Kim, and Lin (2021) find that insurers hold fewer carbon-intensive bonds after being required to disclose their views on climate change. Adding to this discussion, we find that incentives for investing in CLOs can differ from those of corporate bonds.

We also add to the emerging literature on disclosure and climate risk, which has had mixed findings. On the one hand, Cohen, Kadach, and Ormazabal (2023) show that investors who are signatories of the CDP (Carbon Disclosure Project), engage more with and divest from polluting firms. On the other hand, Giannetti, Jasova, Loumioti, and Mendicino (2023) show that banks that showcase concern for the environment in their disclosures to investors, lend more to brown industries. They argue that greenwashing by banks is because of zombie lending practices, i.e. banks continue to prop up low-performing firms that are close to financial distress. More broadly, Bartram, Hou, and Kim (2022) show that firms faced with climate regulation in a particular state, shift their emissions to other states where their plants are underutilized. The authors argue that the resulting increase in emissions undermines the effectiveness of climate regulation. Building on these papers, our paper finds that mandated climate disclosure can lead to more capital flow into shadow markets leading to the unintended financing of brown firms. This result speaks to research in environmental economics on the Green Paradox – a situation where climate policies intended to mitigate climate risk have the opposite effect (Jensen et al., 2015).

3 Institutional Details and Data

We combine data from multiple sources to conduct our empirical analysis, and each is described below.

NAIC Insurance Data. First, we obtain insurers' holdings information from annual NAIC Statutory filings, ranging between 2001 and 2020. More specifically, we use Schedule D Part 1 filed

by P&C, Life and Fraternity, as well as Health Insurance companies. In addition to the insurer's name, filing year, and line of business, we also obtain information on the CUSIP, total holding amount, name, effective interest rate and maturity date of each fixed income security held. Since our focus is primarily on the non-financial firms, we filter out government and municipal bonds, asset-backed and mortgage securities, as well as bonds issued by financial institutions from the insurer balance sheets. In Panel A of Table 1, we summarize these insurer holdings: we find that they hold $585,400 of an instrument and roughly 36% of their fixed income holdings are a CLO on average.

To match the NAIC holdings data with the climate database, we found that the most effective match came from linking to Compustat and then matching to the climate data using GVKEY. Matching CUSIP to GVKEY was nontrivial. Since many firms were privately owned without a CUSIP, had CUSIPs that changed over time, or simply had multiple CUSIPs despite being owned by the same parent company–we had to hand match a substantial number of companies based on their name and their parent group.

Insurance Disclosure Data. We gather insurers' public climate disclosures using the NAIC Climate Risk Disclosure Surveys published online from 2010 until 2021. Prior to 2011, only companies with greater than $500 million in direct premiums had to disclose. In 2011, only companies that did business in the state of California with total direct premiums of $300 or more must disclose. The biggest jump in coverage came in 2012, when California, New York, and Washington required all active insurers with premiums of $300 million or more to take the survey and make the results public. In 2013, the premium requirement for filing was lowered to $100 million, and three more states (Connecticut, Minnesota, and New Mexico) mandated participation from their active insurers. While the threshold remained at $100 million, nine more states/jurisdictions mandated survey participation in 2021: Delaware, District of Columbia, Maine, Maryland, Massachusetts, Oregon, Pennsylvania, Rhode Island, and Vermont. NAIC estimates that feedback from the mandated insurers capture nearly 80% of the entire U.S. insurance market in 2021.

The exact questions asked on the survey changes over time and may reflect concurrent issues, such as natural disasters. However, they generally cover the following broad areas: emissions, risk

assessment, and investments. For example, question 5a asks "Has the company considered the impact of climate change on its investment portfolio?" More than half of the insurers responding to the survey are volunteers that are not mandated by any particular state. Yet over 90% of the time, voluntary filings are submitted by companies belonging to a larger insurance group that is required to disclose; often, they submit the exact same response as other insurance companies who are mandated under the same group (Lin, Kim, and Ivantsova 2023).

Figure A1 Panel A shows the distribution of insurance companies that responded to question 5A, based on when we first see them responding in our sample. While many companies started responding from the beginning of our sample, we see the biggest jump in participation in 2012, as the number of participating states increased from just California to include New York and Washington. Panel B shows the average size of disclosing insurers, and while the average sizes shift towards the beginning of the sample—when cutoffs are based on size or distribution in large markets—they remained fairly stable after 2012. Finally, Figure A1 Panel A shows that the fraction of responding insurers that said "yes" to question 5A is generally upward-sloping over time. This suggests that insurers are paying more attention to climate change and adjusting their portfolios more in response to climate change over time.

CLO Data. We use the data on Collateralized Loan Obligations (CLO) from Acuris Creditflux, who source detailed information on fund launches, portfolio holdings and transactions, tranche investments and payouts from more than 45,000 fund trustee reports of CLO funds globally. It contains monthly information on fund capital structure, detailed security holdings, transactions, and monthly covenant tests of 3134 funds launched by 223 managers over the period 2001 through 2020. We hand-match fund and tranche names to the portfolio holdings of insurance companies, obtained from NAIC Schedule D filings to identify investments of insurance companies in CLO funds over the sample period.[8] We identify investments in debt and equity tranches of 2418 funds by 3457 insurance companies.

[8]Our approach is similar to that in Bhardwaj, Ge, and Mukherjee, 2022. However, we cover all insurance companies while they focus only on Life and Property & Casualty insurers.

Figure 1 shows the total CLO holdings reported in Schedule D Part 1 over the sample period. Insurer investments in CLO funds grew manifold over the past two decades. Panel 1a plots the aggregate holding of outstanding debt and equity tranches of CLO funds by insurance companies. It grew from less than $10 billion in 2001 to over $140 billion in 2020. This growth is more evident in Panel 1b, which represents the total holding of CLO funds as a percentage of total insurer assets. Investments in CLO funds represented less than 0.5 percent in 2001, but grew to more than 5 percent of total assets by 2020. In Panel B of Table 1, we further summarize CLO funds: the average CLO fund holds 724 million USD and are highly leveraged (average of 93%). Panel C summarizes the fund managers: on average, they launch a new fund every two years (average is 0.56 funds per year) and the average size of fund launched is about $251 million USD.

Climate Data. Our climate data comes from Sautner et al. (2023). In this data, climate exposure to an issue is the share of conversation during an earnings call transcript that is related to that issue. These measures count the frequency of specific climate change bigrams in a transcript, scaled by the total number of bigrams. They further categorize the sentiment around these bigrams as either positive or negative, based on the tone of the words. Figure A2 gives examples of the largest year over year changes seen in our sample. For instance, one example of a positive sentiment change was when TI Fluid Systems committed to a significant reduction in Scope 1 and 2 CO_2 emissions and more renewable energy projects. Generally, firms with more positive climate-related sentiment are engaging in more green activities. Sautner et al. (2023) document a statistically significant association between the positive climate sentiment and future green investments and green job creation.

Emissions/Reprisk Data. We use facility-level information on the polluting activities of firms from the U.S. Environmental Protection Agency (EPA). The EPA's Toxics Release Inventory (TRI) program tracks emissions of toxic chemicals by industrial facilities, and makes this data publicly available.[9] Panel E of Table 1 summarizes the emissions data at the firm level: on average, each firm emits 221,000 pounds of pollution per chemical, and they release 21 different chemicals on average. There is a lot of variation among firms, and the dataset is skewed by large firms who

[9]https://www.epa.gov/toxics-release-inventory-tri-program/tri-data-and-tools

pollute more. For example, the median firm only emits 9,000 pounds of pollution per chemical and emits 11 different chemicals. For robustness, we also use data from RepRisk, an ESG data science company that specializes in collecting information on climate risk-related incidents. RepRisk screens public sources such as media outlets, regulatory documents etc. for news related to ESG risks. RepRisk classification of pollution incidents include: "climate GHG pollution" "local pollution", "waste issues", "airborne pollutants", "forest burning", "greenhouse gas emissions", and "wastewater management". These incidents are further categorized based on their "severity" and "reach" (i.e. readership in media outlets). The RepRisk dataset has been used by several recently published papers (He, Kahraman, and Lowry, 2023; Graham, Grennan, Harvey, and Rajgopal, 2022).

Debt Origination Data. We obtain data on syndicated loan originations from LPC Dealscan database. It contains details of all syndicated loans issued during our sample period, including origination and amendment dates, size, credit spreads, maturities, and the names of arrangers and lenders, as well as their lending commitments. We match issuing firms in the Dealscan sample to those in the SNL and CLO databases based on their names, yielding a sample of $9,428$ unique borrowers.

We restrict attention to two types of loans : (i) leveraged loans, which are primarily originated to be distributed by financial institutions; and (ii) revolving credit facilities which are typically kept on the books of the underwriting institutions. We define a leveraged loan as senior-secured term-loan facility which has an all-in-drawn spread of at least 125 basis points over the base rate, typically LIBOR. This restriction yields $33,526$ leveraged loans issued by $10,486$ firms over our sample period. A typical syndicated leveraged loan in our sample has an issue amount of $350 million, a maturity of 6 years, and a all-in-drawn spread of 350 basis points over LIBOR. Our sample also includes $58,412$ revolving credit facilities issued by $22,177$ unique firms. A median revolver has a size of $474 million, a credit spread of 150 basis points, and a maturity of 3.67 years. Panel D of Table 1 summarizes information on firm issuances. We find that each firm in our sample has a 6% chance of being included in a CLO fund, and the average loan size is about $67 million USD.

4 Contrast between direct and indirect holdings

In this section, we show how insurance companies react to climate-related news differently in their direct (i.e. bonds) versus indirect (held via CLO funds) holdings. While insurance companies commonly invest in firms through the corporate bond market, they are also one of the largest investors in the collateralized loan obligation (CLO) market, investing almost 160 billion USD as of 2020. Thus, insurers may be indirectly exposed to climate risks of firms through their holdings of CLO fund tranches. To be more precise, we define an indirect holding h_{ijt}^{ind} of firm j by an insurer i at time t as

$$h_{ijt}^{\text{ind}} = \sum_{f \in \mathcal{F}} h_{ift} \cdot w_{fjt} \tag{1}$$

where $h_{i,f,t}$ is the total dollar investment of insurance company i in the debt tranches of a CLO fund f at time t, and w_{fjt} is the weight of firm j in the portfolio of fund f at time t. Since insurers may be indirectly exposed to the same firm j through their holdings of multiple funds $f \in \mathcal{F}$, we sum over all the fund portfolios to arrive at an aggregate indirect exposure measure h_{ijt}^{ind}.

Figure 2 shows that insurers increase their direct holdings of a firms' bonds when their news has more positive climate-related sentiment. In contrast, insurers decrease their indirect holdings of a firms' CLOs when there is positive climate news. The decrease in holdings may be driven by a subsequent decrease in yield opportunities, as there may be a premium for "green" firms (Zerbib 2016). Thus, insurers appear to actively seek firms with negative climate sentiment, motivated by reaching-for-yield. In their direct holdings, however, insurers direct capital towards firms with more positive climate sentiment.

Table 2 formally tests for the difference in direct and indirect holdings by estimating the following regression:

$$h_{ijt} = \alpha_{it} + \alpha_{ij} + \alpha_{jt} + \beta CC_{j,t-1} + \gamma \text{Indirect}_{i,j,t} + \delta CC_{j,t-1} \times \text{Indirect}_{i,j,t} + \xi h_{i,j,t-1} + \varepsilon_{ijt} \tag{2}$$

where $h_{i,j,t}$ is the dependent variable, representing the insurer i's holding of firm j for year t. In columns (1) and (2) the dependent variable h_{ijt} is expressed in the units of \$10,000, while in

columns (3) and (4), the dependent variable is log(1 + dollar holdings). The main explanatory variables include $\text{Indirect}_{i,j.t}$, a dummy for whether a firm j is indirectly held by the insurer i at time t through a CLO; the climate-related sentiment $CC_{j,t-1}$ for firm j in year $t-1$; as well as their interaction, which captures the differential reaction of insurers' to climate-related sentiment for CLOs compared to bonds. Across all specifications, we include insurer-year α_{it} fixed effects to control for time-varying market factors that may affect insurers' holdings overall, and insurer-firm fixed effects α_{ij} to control for insurers' inherent appetite for different firms.

Starting with column 1, if a firm has a one standard deviation increase (0.8) in positive climate-related sentiment ("CC"), insurers increase their direct holdings by \$11,664 or roughly 0.3% of the conditional (i.e. non-zero) average holding of \$3.6 million. This is consistent with insurers actively managing climate risk and choosing to invest in "greener" firms. In contrast, the interaction term with CLO is negative and significant. In the next to last row of the table, we test for the overall effect on indirect holdings, $\text{CC} + \text{Indirect} \times \text{CC}$, - if a firm has a one standard deviation increase in positive climate sentiment, we find that insurers on net *decrease* their indirect holdings by \$5,968. If we consider that the average non-zero holding size for a CLO is \$212,538, then the conditional size of the decrease is roughly 2.8%. Column 3 repeats the analysis using log holdings as the dependent variable and finds consistent results.

In column 2, we tighten our specification by including firm-year fixed effects, to see how an insurer reacts to the same change in climate sentiment for the *same firm* differently, depending on whether that firm is directly or indirectly held. While the coefficient on "CC" is now subsumed by the firm and year fixed effects, consistent and even slightly stronger than previous findings, we find that insurers pull back in their holdings much more if the firm is directly held. The negative interaction term tells us that, if a firm has the same one standard deviation increase in positive climate sentiment, insurers hold \$20,064 less of the firm in their CLO portfolio compared to their bond portfolio. Finally, columns 3 and 4 find similar results using log holdings rather than direct holdings as the dependent variable.

One may argue that the control of insurance companies over their indirect exposures to firms is limited to their investments in the debt tranches of the CLO funds, and they do not directly exert

any influence on the CLO's selection of specific firms. We will address this concern in the next section using the staggered roll-out of climate supervision on insurers. Note that our results suggest that even if insurers are passively holding CLOs, at a minimum, CLO managers actively re-balance their portfolios towards brown firms on the arrival of climate news. We test this hypothesis in the appendix Table A1 using the following specification:

$$h_{fjt} = \alpha_{fj} + \alpha_{ft} + \pi \text{CC}_{j,t-1} + \gamma h_{fjt-1} + \varepsilon_{fjt} \tag{3}$$

We find a strong proclivity of CLO managers for re-balancing their portfolios towards brown firms: our estimates suggest a one standard-deviation decrease in firm climate sentiment $\text{CC}_{j,t-1}$ leads to an increase in CLO holdings of \$10,464, or 0.5% of the mean. Given that there are tight restrictions on diversification and weightage limits in portfolio selection of CLO funds, this change is economically meaningful.

Taken together, the results presented in Figure 2 and Table 2 document a stark differential reaction to positive or negative climate news in the direct and indirect holdings of insurers. In the next section, we test whether this variation is driven by insurers' climate considerations.

5 Climate Risk Disclosure Survey

In this section, we test whether public disclosure motivates the differential treatment of risk in direct and indirect portfolios by insurers. As part of a growing interest by regulators and investors to gauge the climate risk embedded in insurer's large balance sheets, the Climate Risk Disclosure Surveys were collected by the NAIC and published online from 2010 until 2021, covering both insurers' climate risk considerations in their assets as well as liabilities. While there is no official penalty or enforcement actions taken by the NAIC following disclosure, evidence suggests that this disclosure is both salient and costly to insurers, as we find in Table A7 that insurers are more likely to stop doing business in states after they adopt a disclosure rule—especially if they do not do much business in that state.

The public survey results increased scrutiny of insurers' investments in particular, as question

5a asks: "Has the company considered the impact of climate change on its investment portfolio?". If this survey attracts more attention on how insurers manage climate risk in their portfolios, then it may explain why insurers avoid firms with climate risk in their direct holdings– which are easy to see in Schedule D reports– and yet finance firms with high climate risk in their indirect holdings– which are not directly visible in any report, but require tedious hand matching to understand.[10]

To test the effect of disclosures empirically, we take advantage of the staggered timing and regional focus of the surveys. For example, in 2013, California, New York, Washington, Connecticut, Minnesota, and New Mexico required any insurer that underwrote $100 million or more in premiums to disclose their climate considerations through the survey. While the threshold remained at $100 million, nine more states mandated survey participation in 2021: Delaware, District of Columbia, Maine, Maryland, Massachusetts, Oregon, Pennsylvania, Rhode Island, and Vermont.

In Table 3, we estimate the following:

$$\begin{aligned} h_{ijt} = {} & \alpha_{it} + \alpha_{ij} + \alpha_{jt} + \beta CC_{j,t-1} + \gamma \text{Indirect}_{i,j,t} + \delta CC_{j,t-1} \times \text{Indirect}_{i,j,t} \\ & + \beta_2 CC_{j,t-1} \times \text{Disclosing}_{i,t-1} + \gamma_2 \text{Indirect}_{i,j,t} \times \text{Disclosing}_{i,t-1} \\ & + \pi CC_{j,t-1} \times \text{Indirect}_{i,j,t} \times \text{Disclosing}_{i,t-1} + \xi h_{i,j,t-1} + \varepsilon_{ijt} \end{aligned} \tag{4}$$

where the dependent variable $h_{i,j,t}$ is the insurer i's holding of firm j for year t. Similar to Table 2, in columns (1) and (2) the dependent variable h_{ijt} is expressed in the units of $10,000, while in columns (3) and (4), the dependent variable is $\log(1 + \$)$. $CC_{j,t-1}$ measures the climate sentiment of firm j at the end of previous year $(t-1)$, and $\text{Indirect}_{i,j,t}$ is a dummy equal to one if the firm j is held indirectly by insurer i at time t through CLO funds. The new and key explanatory variable of interest is $\text{Disclosing}_{i,t-1}$, which is a dummy equal to one if the insurer i disclosed their climate-risk considerations in the Climate Risk Disclosure Survey. As before, we include insurer-firm and insurer-year fixed effects.

If we believe that the differential treatment of climate risk by insurers in their direct versus

[10]Schedule D only reports the investments of insurance companies in the debt tranches of CLO funds, along with the corresponding yields accruing to them. Indirect exposures of insurers to brown firms will only be observable under additional scrutiny when one maps the fund holdings to their corresponding firms.

indirect portfolios is at least partially driving by monitoring pressures, then we would expect the results from Table 2 to be much stronger for insurance companies that were required to disclose, compared to those that did not. In other words, we would expect the estimate π of the triple interaction term, $CC_{j,t-1} \times \text{Indirect}_{i,j,t} \times \text{Disclosing}_{i,t-1}$, to be negative and significant.

Figure 4 previews our findings in Table 3 by showing the differential effect of disclosure on the average climate sentiment of direct (shown as black line) versus indirect (shown as blue line) holdings over time. We see that prior to the first disclosure date, depicted as year 0, climate sentiment in both sets of insurer holdings was primarily flat and insignificantly different from zero. However, after insurers began to publish their surveys online, the climate-related sentiment in their direct portfolios became significantly more positive and climate-friendly. In contrast, the climate-related sentiment in their indirect portfolios become significantly negative and less climate-friendly.

Given the staggered roll-out of the survey, which is unlikely to be correlated with any climate-related decisions at the firm level, our result suggests that insurers actively manage their holdings by tilting them towards more climate-friendly firms once they face more public scrutiny. In their direct portfolios, which are most salient to regulators and investors, they appear to be consistent with the green values disclosed on the surveys.[11] In contrast, the insurer may seek higher yield or riskier investments in these indirect portfolios, leading to less climate friendly investments in these assets. This can also help offset the lower yields, which is being offered in their greener, directly-held portfolios.

In Table 3, we statistically test these relationships and confirm that the differential treatment of climate risk in the direct and indirect portfolios is largely driven by insurers who faced greater scrutiny by publishing the Climate Risk Disclosure Survey. Looking at column 1, the coefficients on CC and $CC \times$ Indirect are less than a quarter the magnitude of what they were in Table 2. For insurers who did not disclose, a one standard deviation increase in CC only increases direct holdings by 0.9% (calculated as (0.8×4,250)/385,800), and it has no significant effect on indirect holdings (test 1 is insignificant). In contrast, for insurers who disclosed through the climate risk

[11] Almost 80% of all insurers state that they consider climate change in their portfolio decisions

survey, a one standard deviation increase in CC increases direct holdings by about 3% (calculated as $(0.8\times4,060 + 0.8 \times 11,018)/385,800$), and it decreases indirect holdings by 1% (calculated as (0.8×-4,470)/385,800). In column 2, we strengthen our controls by adding firm by year fixed effects, and the results are even more striking. For example, a one standard deviation increase in CC decreases indirect holdings by 2.4% (calculated as (0.8 × 11,620)/385,800). Finally, columns 3 and 4 re-estimate the regression using log holdings as the dependent variable, finding consistent results. [12]

These findings, combined with Figure 4 strongly suggest that insurers who face greater scrutiny to consider climate change are more likely to embrace climate risk in their indirect holdings, perhaps to help counteract the reduction of climate risk and yield in their direct holdings. To further test whether this pattern is driven by reach-for-yield behavior, we next test whether insurers also increase their holdings of CLOs post-disclosure, since CLOs tend to offer higher yields.

5.1 Impact on CLO investments

Previously, we saw that publicly disclosing via the Climate Risk Disclosure Survey pushes insurers to tilt their directly-held portfolios towards companies with more positive climate news, while tilting their indirectly-held portfolios toward firms with less positive climate news. Table A1 provides one channel behind this diverging behavior - the preference of CLO managers for high-yielding brown firms. However, the results presented in Table 3 document a significantly stronger movement in the indirect holdings of disclosing insurers relative to their non-disclosing counterparts. In this section, we further show that a significant part of this difference is driven by insurance companies tilting their portfolios towards more opaque instruments such as CLOs, in response to public disclosure requirements.

Figure 5 plots the dynamic growth in CLO fund investments of insurance companies around their first disclosure date. While insurers generally held a flat level of CLOs prior to disclosure, after their first survey disclosure, they significantly increase their holdings of CLOs for up to the

[12]In the Appendix, A9 also checks and confirms that our findings are still consistent if we use a general exposure measure of climate risk, rather than a sentiment-based measure.

next six years. This figure documents a significant inclination among insurers to invest more in more opaque instruments such as CLOs, perhaps to recover the lower yields in their greener direct portfolios.

We formally test this relationship in Table 4, where we estimate the following:

$$y_{it} = \alpha_i + \alpha_t + \beta \mathbf{1}(\text{Treated})_{it} + X_{it} + \varepsilon_{it} \tag{5}$$

We consider three key outcome variables, y_{it}. In column (1) we use an investment dummy as a dependent variable which assumes a value one if the insurer i invests in a CLO tranche in year t. In column (2) we use the actual dollar value of CLO investments by insurance companies. Finally column (3) of Table 4 reports the dollar value of the tranches newly acquired by the insurance company in year t. The key explanatory variable, Treated_{it}, is an indicator variable which takes the value one for years t after the insurer's first disclosure date. Across all columns, we control for year and insurer fixed effects. If disclosure pushes insurers to invest more in opaque investments, then we would expect the β to be significantly greater than 0.

Looking across Panel A of Table 4, we find that when insurers begin to disclose their stance on climate change, then they have a 12.9 percentage point increase in the likelihood of making a CLO investment; a $17 million increase in their outstanding CLO holdings; and a $6 million increase in new CLO tranches. Overall, the evidence strongly suggest that insurers increase their investments into CLOs post-disclosure, perhaps in order to reach for yield and recoup lost yield opportunities in their directly held portfolio.

One salient concern is that the disclosure shock is more likely to affect big firms that operate in larger markets, especially since the disclosure cutoff rules up until 2012 were based on size and operation in big markets (ie California, New York, and Washington). As shown in Figure A1 Panel B, the average size of the disclosing insurer was significantly larger before 2012, but the size became effectively the same for all years post-2012. Thus, for robustness, in Panel B of Table 4, we repeat the analysis after excluding the insurance companies who started reporting during the period 2010 - 2012. Since these cutoff rules were applied based on geography and not size, this allows us to

check and make sure we are not merely capturing size effects. We find largely consistent results: when firm begins to disclose their stance on climate change, then they have a 8.7 percentage point increase in the likelihood of holding a CLO investment; a 7 million dollar increase in their CLO holdings (conditional on having CLO holdings); and a $2.27 million increase in new CLO tranches.

Since treatment dates are dispersed over time, we also account for heterogeneous treatment effects by using the Callaway and Sant'Anna (2021) estimators in Table A5. In the first three columns, we use the insurers who never disclosed as the control group, while in columns (4) - (6), we use the insurance companies who disclosed later as the control group. In Panel B, we repeat the analysis after excluding the larger insurance companies that started reporting during the period 2010 - 2012, when the disclosure requirement was mainly based on size. Across all of these robustness checks, we find that insurers significantly increase their CLO holdings in both the intensive and extensive margin following disclosure. This result supports our finding that disclosure appears to push insurers' capital into shadow markets.

In Figure A3, we study the heterogeneity of CLO investments across the three major insurer types: life, property and casualty, and health. While all insurer types react to climate disclosure requirements, we find that life insurers have significantly higher CLO investments in the post-disclosure period (Panel A) compared to the other two insurer types (Panel B). This finding is in line with recent evidence on the active role of life insurers in the leveraged loan market (Foley-Fisher, Heinrich, and Verani, 2023).

5.1.1 Reaching For Yield

In the previous section, we documented a significant shift towards greener bonds by insurance companies following implementations of state regulations mandating the disclosure of their climate strategies. At the same time, we observed a marked increase in investments in CLO funds, and hypothesized that investors' reaching-for-yield behavior could account for the substantial growth in CLO investments. In this section, we provide additional evidence supporting this claim.

Implicit in our argument is the assumption that a shift towards more climate-friendly investments in their direct bond holdings potentially reduces the yields of insurance companies. Table A3

in the Appendix provides evidence consistent with this argument by estimating:

$$y_{jt} = \alpha_j + \alpha_t + \pi \text{CC}_{j,t-1} + \mathbf{X}_{jt} + \varepsilon_{jt} \tag{6}$$

where the dependent variable y_{jt} is either bond issuance (column 1) or the coupon rate (columns 2 to 4) of firm j in year t. While we don't find any statistically or economically meaningful effect of climate sentiment measure $\text{CC}_{j,t-1}$ on the probability of bond issuance (Column 1), it has a significant impact on bond yields (Columns 2 - 4). Our estimates imply that a one standard-deviation decrease in climate sentiment measure is associated with an approximately 5 to 8 basis points increase in bond coupons issued in the following year. This estimate is robust to additions of progressively more stringent controls, as shown in columns (3) and (4) respectively.

We directly document this shift in yields of insurer bond holdings around the time of first disclosure. Specifically, we estimate a dynamic regression of the form:

$$\text{Yields}_{is(j)t} = \alpha_{ijmr} + \sum_{t=\tau-6}^{\tau+6} \beta_t D_t + \varepsilon_{is(j)t},$$

where the data is at the insurer-security-year level. We consider two important characteristics of the security s issued by firm j : the maturity m, and the credit rating r. The dummy D_t takes a value one for year t relative to the first disclosure period τ, and zero otherwise. To facilitate an even comparison, we include insurer-firm-rating-maturity fixed effects α_{ijmr} to ensure that the dynamic coefficients β_t are estimated off cross-sectional differences of yields of securities with similar rating and maturities. Figure 6 illustrates the dynamic coefficients β_t for the period $[\tau-6, \tau+6]$ relative to the first disclosure period τ, showing that the average yields in insurers' direct portfolios decreased steadily, up to 1.5% lower over the next six years. Conversely, figure 7 shows that the yields earned on insurers' CLO tranches increased steadily up to about one percent in the next six years. Taken together, Figures 6 and 7 provide strong evidence for the main mechanism driving our findings.

This raises the question: how do insurance companies compensate for the reduced yield resulting from a shift toward more climate-friendly companies in their direct investments? They may either increase their allocation to high-yield bonds within their direct portfolio or invest more indirectly

through funds that offer higher yields. The former approach presents two issues: (i) it may heighten investor scrutiny, and (ii) it could lead to an increase in risk-based capital (RBC) requirements for insurers. CLO funds offer a safer investment choice in this regard. As we show below it provides insurers with a higher yield compared to bonds of similar maturity and credit rating. Specifically, we consider the following specification

$$\text{Yields}_{is(mr)t} = \alpha_i + \delta \text{CLO}_{ist} + \alpha_{mrt} + \varepsilon_{is(mr)t}$$

where the dependent variable is the yield offered by the security s of credit-rating r and maturity m held by insurer i at time t. We include insurer fixed effects α_i to absorb insurer-level time-invariant factors, and rating-maturity-year fixed effects α_{mrt} to force the estimation of the coefficient δ off cross-sectional differences in yields offered by different securities of similar rating and maturities at the same time. Table A2 in the Appendix show that CLO tranches provide, on an average, 57 basis points more (96 basis points when we remove the highest AAA rated securities) relative to corporate bonds with similar rating and maturities.

Due to regulatory constraints, we assume that insurers could not simply reach for yield by substituting capital into riskier direct assets, such as lower-quality corporate bonds. CLO tranches—especially those marketed to insurers—are rated within the AAA to A range, which has little impact on insurers' risk-based capital (RBC) charges. Thus, CLO funds provide an attractive alternate investment channel for insurers to earn higher yields without being directly exposed to regulatory risks. If this is true, then an insurer would be more likely to invest in CLO funds if they feel more constrained in terms of their RBC limits. To test this hypothesis, we divide insurance companies into two groups, above- and below median RBC ratio for each year, and look at their relative incentives to shift capital towards CLO after disclosure. We do this by creating an indicator variable Low RBC_{it} which takes a value one if the insurer i has a below-median RBC ratio in year t, and zero otherwise. We then interact this term with the variable Treated_{it} as defined in the regression specification (5), and write

$$y_{it} = \alpha_i + \alpha_t + \beta \text{Treated}_{it} + \gamma \text{Low RBC}_{it} + \pi \text{Treated}_{it} \times \text{Low RBC}_{it} + \varepsilon_{it}$$

where the dependent variable y_{it} denotes the investments of insurance company i into CLO funds in year t, and the indicator variable Treated_{it} assumes a value one if the insurer i has a first disclosure date $\tau < t$, and zero otherwise. We further include insurer and time fixed effects, and cluster the standard errors at the insurer level. Table 5 reports the results of this regression, which confirms our hypothesis. The results presented in column (1) show that relative to an average insurer, insurers with a below-median risk-based capital is 50 percent more likely to invest in a CLO fund in the post-disclosure period. Also as highlighted in columns (2) and (3), more RBC-constrained insurers invest more than double the amount into CLO tranches compared to insurers who are less constrained, especially during the disclosure period.

In sum, we find that after insurers experience greater disclosure and scrutiny, they significantly reduce their holdings of firms with negative sentiment in their bond portfolio.

5.1.2 Matched Pair Regressions

Before closing this section, we address two potential concerns related to our findings : (i) size-based endogeneity concerns, and (ii) concerns about climate exposure on the liability side. The first issue pertains to our key results being influenced by insurer size. Larger insurers, who are also more likely to disclose their climate stance in response to the state mandates, are also more likely to have different investment strategies compared to smaller insurers who also do not disclose. The second potential concern is that insurers' increasing involvement into CLO markets may be driven by climate risks from the liability side. For instance, California, one of the first states to adopt the disclosure mandate, is also prone to recurring natural hazards, like floods and wildfires, often resulting in large insurer outflows. It is possible that the insurers' reaching-for-yield behavior that we documented in the previous section stems from their incentives to manage or mitigate such climate-risk driven losses.

To address these concerns we employ a stacked matching regression. We define an event $e_{i,\tau}$ at the insurer i and first disclosure year τ level. For each such *treatment* insurer, we define a *control* insurer c based on the following criteria : (i) both insurers i and c are in the property and casualty insurance business, (ii) they operate in the same states both in the disclosing year τ and in the

preceding year $\tau - 1$, (iii) the absolute difference in their total premiums across all the states in the year τ must be less than \$100,000, and (iv) the control insurer c must never have filed during the sample period. In essence, we compare firms that are above the size cutoff for reporting with those that are just below the cutoff. If there are multiple matches satisfying all the criteria listed above, then we choose the one with the smallest revenue difference compared to the treatment insurer i. Finally, we create an event-period stacked dataset by including data on the total CLO investments of the treatment insurer i and the control insurer c over an event window spanning 5 years before and after the first disclosure date $[\tau - 5, \tau + 5]$.

Table 6 reports the results from estimating the following specification:

$$y_{it} = \alpha_{e,i} + \alpha_{e,t} + \pi \text{Treatment}_i \times \text{Post}_{e,t} + X_{it} + \varepsilon_{it}, \tag{7}$$

where $\text{Post}_{e,t}$ is an indicator which takes a value one if the year t is after the disclosure year τ for the event $e_{i,\tau}$, and zero otherwise. Similarly, Treatment_i is a dummy which takes the value one for the treatment insurer i for the event $e_{i,\tau}$, and zero for the control insurer c. The dependent variable is defined differently across the columns. In column 1, it is a binary variable $\text{CLO Investment}_{i,t}$ that equals one if insurer i or c has purchased a tranche of CLO debt in year t, and zero otherwise. In column 2, the dependent variable is the total outstanding dollar value of CLO tranches held by the insurers at year t. Finally, in column 3, we use the total dollar value of fresh investments in year t as the dependent variable. Note that the inclusion of insurer-event and event-year fixed effects imply that the baseline coefficients Treatment_i and $\text{Post}_{e,t}$ are not estimated independently.

The key estimates presented in Table 6 helps mitigate concerns outlined at the outset of this section. According to column 1, an insurer which starts disclosing in year τ is 4.9 percentage points, or 70 percent more likely to invest in CLO tranches during the event period $[\tau+1, \tau+5]$ compared to a control insurer c which is almost identical in terms of revenue and geographic coverage, but with a different treatment status. The disclosing insurers also purchase an additional \$4.697 million worth of CLO tranches during the post disclosure period. To put into perspective, note that the average investment in CLO tranches in any given year is around \$1.84 million. Over the same period, their total outstanding holdings increase by \$8.36 million, compared to matched control insurers.

Taken together, our matching regressions document a strong link between climate disclosures and investments into CLO markets.

In the next section, we will trace out the consequences of insurers' funneling more capital to opaque markets like CLOs by looking at how CLO managers react to the increased flow of funding.

5.2 Sensitivity of post-disclosure CLO investments to fund manager relationships

In this section, we explore how sensitive funds supplied by the affected insurers are, to relationships with CLO fund managers. We follow the established literature on bank-firm relationships (see, for instance, Bharath, Dahiya, Saunders, and Srinivasan (2011)) to construct a measure of manager-insurer relationship. Specifically, we define a K-period relationship between insurance company i and fund manager m as

$$\mathcal{R}^{K}_{i,m,t} = \frac{1}{K} \sum_{\tau=t-(K-1)}^{t} \frac{L_{i,m,\tau}}{\text{AUM}_{m,\tau}} \tag{8}$$

where $L_{i,m,\tau}$ is the total investment of insurer i in the debt and equity tranches of funds managed by m at year τ, while $\text{AUM}_{m,\tau}$ is the total dollar value of the manager m's corpus at time τ. The ratio thus measures the relative importance of insurer i as a source of funds. The insurer-manager relationship $\mathcal{R}^{K}_{i,m,t}$ is then defined as the average of this measure over the previous K periods inclusive of the current year. Following the standard practice in the literature, we take $K = 5$. Panel A of Figure A4 plots the evolution of insurer-manager relationships over the sample period. Note that the plot starts at 2005 since we use the initial period $[2000, 2004]$ to define the relationships. As documented in the plot, relationships become progressively stronger over the sample period, with a median insurer accounting for about 5% of the funds under a typical manager's control. However, there is strong dispersion in the data, as evident from the scatter plots of the relationship measure. For instance, the standard deviation of $\mathcal{R}_{i,m,t}$ over the sample period is 0.12, and the 90^{th} percentile value is 0.20. Panel B of Figure A4 plots the number of relationship insurers per \$100 million of assets managed. On an average, a manager with \$100 million in AUM has relationships with around 3 insurers (99^{th} percentile value is 28). The largest (top 1 percentile)

asset managers can have relationships with around 400 insurers in our sample.

We next explore whether managers with past relationships are more likely to receive capital from insurers once they start reporting their climate strategies in state filings. Bhardwaj et al. (2022) document the presence of significant stickiness in insurer-manager relationships. That is, an insurer who has invested with a manager before, is significantly more likely to invest in future funds launched by the same manager. We conjecture that capital flow into CLO markets after climate disclosure is sensitive to the stickiness of insurer-manager relationships. To test our hypothesis we consider the following difference-in-difference specification:

$$y_{i,f(m),t} = \alpha_i + \alpha_f + \alpha_t + \gamma_1 \text{Post}_{i,t} + \gamma_2 \mathcal{R}^5_{i,m,t-1} + \gamma_3 \mathcal{R}^5_{i,m,t-1} \times \text{Post}_{i,t} + \epsilon_{ift} \tag{9}$$

where $y_{i,f(m),t}$ is insurer i's investment in fund f launched by manager m in year t. Here each observation is at an insurer-fund level. Suppose a total set of $\mathcal{I}$ insurers are active in the CLO industry, and denote by $\mathcal{F}$ the total set of funds.[13] For every fund $f \in \mathcal{F}$ launched, we consider investments by any insurer $i \in \mathcal{I}$ in the debt or equity tranches of the fund at its inception. Thus, $y_{i,f(m),t}$ is either the total dollar value of insurer i's investment in the fund f, or 0 otherwise.

Our key independent variable is $\text{Post}_{i,t}$ which assumes a value one if the first reporting year for insurer i is less than year t, and zero otherwise. We allow for a one year lag to mitigate any possibility of reverse bias.[14] To gauge the impact of past relationships in attracting new capital from insurers, especially in the post-disclosure period, we include the relationship variable $\mathcal{R}_{i,m,t-1}$, and its interaction with $\text{Post}_{i,t}$. We further include insurer (α_i), fund (α_f) and year (α_t) fixed effects to absorb any unobservable characteristics from biasing our results. For instance, Fringuellotti and Santos (2021) document that some funds especially cater to insurance companies, and hence attract a larger insurer investment compared to an average fund. The inclusion of fund-fixed effects

[13]The data considered here is essentially $\mathcal{I} \otimes \mathcal{F}$. We label an insurer $i \in \mathcal{I}$ as active if it has made at least one investment in any debt or equity tranche launched by any manager in the previous 5 years. Our estimates remain remarkably stable if we expand the set $\mathcal{I}$ to include all insurers instead.

[14]Suppose we observe a fund launch in the third month of year t, and the first disclosure date of the insurer also falls on year t. Note that disclosure dates and Schedule-D reporting do not provide exact dates, we may falsely classify this as a post-disclosure investment. By classifying the variable *Post* from the next year onward mitigates any possibility of erroneous assignment.

mitigate the impact of such unobservable factors.

Table 7 presents the results of specification (9), and provides evidence supporting our conjecture. In columns (1) and (2), we use a dummy version of the dependent variable $y_{i,f(m),t}$ which assumes a value one of the insurer i invest any positive amount with the fund f, and zero otherwise. In column (1), we find that an insurer i is 0.2 percentage point more likely to invest in a new fund f during the reporting years. To put this into perspective, note that the unconditional investment probability is only 1 percent. Thus, an average insurer is 20 percent more likely invest with a CLO fund when reporting, than when they are not.

More importantly, as shown in column (2) of Table 7, the funds which are most likely to attract new investments from insurers are launched by managers with past relationships. To understand the magnitude and economic significance, consider a one standard deviation increase (.016) in the relationship measure $\mathcal{R}_{i,m,t-1}$. Our estimates indicate that the probability of insurer i investing in a new fund f launched by manager m increases by 0.93 percentage points, or 93 percent relative to the unconditional mean.[15] The statistically significant and economically strong magnitude of γ_2 also captures the stickiness in insurer-manager relationships, and corroborates the finding in Bhardwaj et al. (2022).

In columns (4) through (6) of Table 7, we use the dollar value of tranches bought, conditional on investment, as the dependent variable. Looking at column (6), our estimates indicate that once insurers start reporting, they increase their investments in CLO tranches by $1.8 million, or about 25 percent relative to the unconditional average of $7.09 million. However, for relationship managers, this jump is significantly larger. Post disclosure, a similar one standard deviation increase in the relationship measure increases the insurer investment in a new fund by $8.4 million.[16]

[15]In an unreported alternate specification, we replace the relationship variable $\mathcal{R}_{i,m,t}$ with the indicator variable $1_{\mathcal{R}_{i,m,t}}$. We find, similarly, that an insurer i is 42 percent more likely to invest in the new fund f launched by manager m if it had a prior relationship.

[16]The t-test for the linear combination $\gamma_2 + \gamma_3 = 0$ is rejected at 1% confidence level with a t-statistic of 5.01.

5.3 Insurer Climate Disclosure and CLO Fund Creations

The results presented in Section 5.2 document a pronounced increase in the probability of, and conditional capital flow into CLO fund managers from insurers who report their climate strategy. Furthermore, both these effects increase manifold if the said manager has an existing investing relationship with the insurer. Thus, a manager who is connected to a larger number of reporting insurers receives a considerably bigger cash inflow shock relative to one who have lesser number of such relationships. Moreover, as depicted in Figure 3 Panel A, there is a significant variation in the first reporting dates of insurance companies, while a sizable fraction never report at all. This provides us with important cross-sectional and time-series variation in manager exposures to insurer disclosure shocks. Formally, we define a manager shock as:

$$\lambda_{m,t} = \sum_{i \in \mathcal{I}} \frac{\mathcal{R}^5_{i,m,t}}{\sum_{i \in \mathcal{I}} \mathcal{R}^5_{i,m,t}} \times D_{i,t}, \tag{10}$$

where $\mathcal{R}_{i,m,t}$ is the manager-insurer relationship, as defined in equation 8, and $D_{i,t}$ is a dummy which equals one if the first disclosure year of insurer i is $\tau \leq t$. We normalize the manager shock variable by the total size of insurer-manager relationships $\sum_{i \in \mathcal{I}} \mathcal{R}_{i,m,t}$ so that the manager shock $\lambda_{m,t}$ lies in the interval $[0, 1]$. The extremes correspond to the cases where either all or none of the insurers report in year t. Figure A5 depict the cross-sectional and time evolution of manager shocks in our sample.

We next explore whether an increased exposure to reporting insurers materially impact a manager's fund launches. In particular, we ask whether managers exposed to larger shocks launch more and/or bigger funds in the following year. Also, whether these funds have any differential characteristics compared to other funds launched by managers with smaller shocks. To do so, we run the following regression:

$$Y_{m,t} = \alpha_m + \delta_t + \pi \lambda_{m,t-1} + \nu_{m,t}, \tag{11}$$

where α_m and δ_t respectively denote the manager- and year-fixed effects, to absorb unobserved managerial and aggregate factors which may influence new fund creations.

The results, reported in table 8, document a positive and significant effect of manager shocks $\lambda_{m,t-1}$ on new fund creation. A one-standard-deviation increases fund launch probability next year by 11 percentage points, or by 47 percent relative to its unconditional mean of 0.23. This translates to one extra fund launch roughly every two years, as shown in column (2). The funds launched by managers receiving a larger shock are also considerably bigger. For instance, the estimate expressed in column (3) suggests that a one-standard deviation increase in manager shock increases the total size of funds launched the next year by $186 million - a 70 percent increase over the total corpus size of managers with no shock.

6 Inclusion of Brown Firms in CLO Portfolios

The results reported in subsections 5.2 and 5.3 show that managers who are connected to insurers experience excess capital inflows when these insurance companies start reporting their climate strategy. In turn, these managers launch more, and larger funds. In this section, we focus on the firms that are selected when new funds are launched. We show that brown firms have a higher likelihood of being chosen, especially when they have been a part of the managers' portfolio before. Formally, we define a manager-firm relationship as

$$\mathcal{R}^{5}_{m,j,t} = \frac{1}{5}\sum_{s=t-4}^{t} \frac{L_{m,j,s}}{\sum_{m\in\mathcal{M}} L_{m,j,s}}, \tag{12}$$

where $L_{m,j,s}$ is the outstanding dollar amount of debt of firm j held by CLO manager m at time s, and $L_{j,s} := \sum_{m\in\mathcal{M}} L_{m,j,s}$ is the total outstanding debt of firm j at time s. Thus, firm j has a stronger (weaker) relationship with a manager m, if the manager held a larger (smaller) share of the total outstanding leveraged debt issued by the firm.

To understand which firms are chosen when managers launch new funds, we adopt an approach similar to the one used in specification (9). In particular, we focus on the fund portfolio in the first year of inception. Denote by $\mathcal{J}$ the set of firms which are being held actively by different managers at this time. Which of these firms are included in the portfolio of the new fund f launched by the manager? Let $y_{f(m),j,t}$ be an indicator variable which assumes the value one if the firm $j \in \mathcal{J}$ is

included in the formation-period portfolio of fund f launched by manager m at time t, and zero otherwise. We use the following specification:

$$y_{f(m),j,t} = \alpha_f + \alpha_j + \alpha_t + \gamma_1 \text{CC}_{j,t-1} + \gamma_2 \mathcal{R}^5_{m,j,t-1} + \gamma_3 \text{CC}_{j,t-1} \times \mathcal{R}^5_{m,j,t-1} + \epsilon_{f(m),j,t}. \tag{13}$$

In equation (13), the coefficient γ_2 captures the stickiness of managerial portfolio choices. We also include the last observed climate sentiment measure (γ_1) of the firms to explore whether managers show any particular proclivity towards brown or green firms. Finally, we also include fund-fixed effects α_f, firm-fixed effects α_j, and fund-formation year fixed effects α_t to account fund or firm specific unobservables and aggregate factors.

The results from the estimation of equation (13) are reported in Table 9. In column (1) we focus only on the recent climate sentiment of the firm j. According to our estimates, a move from the 99$^{\text{th}}$ percentile to 1$^{\text{th}}$ percentile value (3.47 to -0.76) increases the probability of inclusion by 1.2 percentage points, or 18 percent relative to the unconditional mean. In column (2), we focus on the impact of previous investment relationships on inclusion probability in the new fund launched by the same manager. A one-standard-deviation increase in $\mathcal{R}^5_{m,j,t-1}$ increases the probability of selection by 41 percent. Note that in column (2) we include a stronger firm $\times$ year fixed effects, which controls for firm-level time varying factors orthogonal to firm-manager relationships which impacts firm inclusion probability.[17]

Finally, in column (3) we estimate the joint effect of firm's climate sentiment and past relationships on its probability of being included in the new fund. The baseline coefficient γ_1 is not estimated independently since it is subsumed by the use of firm $\times$ year fixed effects. The coefficient of the interaction term γ_3 is strongly significant and negative, implying managers load up on

[17]Managerial preference for firms that were previously part of their portfolios has also been shown in Bhardwaj et al. (2022). They show that firms which have been held before by the manager are 7 times more likely to be selected in the new fund portfolio. The authors argue that this preference can be related to two primary sources : i) information acquisition costs about firm's debt and default probabilities, and ii) traditional banking relationship between the firms and the funds' underwriting bank. We also find a substantially higher probability, albeit a smaller magnitude compared to the other paper, of being included. The key difference in the results stems from the sets of firms considered. We focus only on public firms since climate data is only available for these firms. While we are agnostic about the exact reason of preferences for existing firms, we note that both these channels are likely to considerably weaker for public firms.

brown firms they have held before when choosing a portfolio for the new fund. Let us consider two simple examples. First, holding the past relationship estimate $\mathcal{R}^5_{m,j,t-1}$ constant, a move from the 99^{th} percentile to 1^{th} percentile value (3.47 to -0.76) increases the probability of inclusion by 86 percent relative to the unconditional mean. Second, if we add a one-standard-deviation increase in the manager-firm relationship measure, the total jump in firm inclusion probability is 121 percent.

Our results suggest a strong predisposition among fund managers towards brown firms which they have held before.[18] When combined with the results presented in subsection 6, this establishes a clear link of capital flow from insurers to firms. Insurance companies who report their climate strategy direct capital towards managers who have an existing relationship with them. These managers in turn purchase a larger quantity of loans from that which they have a relationship with. Combining these two links, we define a firm level shock, similar to the manager-level shocks defined in subsection 5.3, as

$$\theta_{jt} = \sum_{m \in \mathcal{M}} \frac{\mathcal{R}^5_{m,j,t}}{\sum_{m \in \mathcal{M}} \mathcal{R}^5_{m,j,t}} \times \lambda_{m,t} \tag{14}$$

where $\mathcal{R}^5_{m,j,t}$ is the firm-manager relationship as defined in equation (12), and $\lambda_{m,t}$ is the manager shock defined in equation (10). The ratio on the right-hand side of the above equation reflects the strength of the manager-firm relationship. A larger value implies that the manager holds a higher share of the total outstanding debt issued by the firm. Figure A6 depicts the distribution of firm shocks over the period 2012 through 2020. Also note that there is significant cross-sectional variation in the distribution of firm shocks, which we exploit in the next section.

7 Effect of Insurer Disclosure on Firm Capital Raising and Polluting Activity

We have seen that climate supervision results in capital flow from insurance companies to CLO-fund managers, who respond by launching new funds. New fund launches increase demand for leveraged loans. In this section, we explore whether firms with prior manager relationships respond to this excess demand by issuing new loans. To conduct this test, we hand-match the company

[18] Table A6 provides further evidence consistent with this notion.

names in the LPC Dealscan database to the issuer names in the CLO database and Insurance Schedule-D files, and create an annual panel of loan issuances over the sample period. Following standard definitions (see Yago and McCarthy, 2004), we define a leveraged loan as a syndicated, secured term loan with a spread of 125 basis points over the base rate, typically LIBOR.

To identify the impact of firm shocks on future loan issuances, we use the following specification:

$$y_{j,t} = \alpha_j + \alpha_t + \pi\theta_{j,t-1} + \varepsilon_{jt}, \tag{15}$$

where $y_{j,t}$ is an indicator variable which assumes a value one if the firm j issues a leveraged loan in year t, and zero otherwise. The results from this estimation is reported in Table 10. The coefficient π is positive, strongly significant, and economically large, delineating the importance of insurance shocks for future loan market access for firms. A one-standard-deviation (0.325) increase in the firm-level shock $\theta_{j,t-1}$ increases the probability of loan issuance by 1.95 percentage points, or by 28 percent relative to the unconditional mean. In column (2) we replace the year fixed effect α_t by a stronger state-industry-year fixed effects. In this case the coefficient π is estimated off the cross-sectional differences in insurer exposures of firms headquartered in the same state and operating in the same SIC 4 digit industry. In column (3) we add an indicator variable denoting the firm's previous bond market access.[19] Intuitively, the probability of loan issuances are higher for firms which did not historically have access to the bond market. However, the interaction with the firm shock variable is not significantly different from zero. This implies that the impact of insurer exposure shocks works in general, regardless of access to other credit markets.

The firm-shock θ_{jt} captures the exposures of firms to insurance companies through the CLO markets. If our channel is valid, then we should expect no differential impact for other forms of loans not held by the CLO funds. Column (4) addresses this issue by exploring the impact of firm shocks on revolving credit-line issuances. These loans remain in the books of banks and never sold off in the secondary market. As expected, we find no impact on the probability of credit line

[19]To perform this exercise, we using the Dealscan CompanyID-CUSIP linking file provided by Refinitiv, enabling us to cross-match firms in the Dealscan and in the Mergent FISD issuance files. A firm is said to have a bond market access if it has ever issued a bond in the past.

issuance.

Next, we examine how the firm-shock θ_{jt} affects future climate-related activity of the firm in Table 11. We estimate the following:

$$y_{j,t} = \alpha_j + \alpha_t + \pi\theta_{j,t-1} + \epsilon_{jt}, \tag{16}$$

where the dependent variable $y_{j,t}$ is the total emissions of firm j during the period t scaled by total assets of the firm. The key explanatory variable is the firm shock $\theta_{j,t-1}$ as defined in equation (14). To control for natural variation in the pollution-activity of different firms and facilities, we include firm-facility; to account for time-varying trends in pollution activity across sectors, we also include industry-year fixed effects. For data aggregated at facility-chemical-year level, we use a stronger facility-chemical and chemical-industry-year fixed effects. Firm controls include Lagged Assets, Tobin's Q, Profitability, and market leverage. Standard errors, clustered at the facility level, are reported in parentheses.

Starting with columns (1) to (3) of Table 11, which show results at the facility-chemical-year level, we consistently find that firms that receive a positive shock are subsequently more likely to engage in future polluting activity. Using column three as our benchmark, as it has the most stringent controls, a one-standard-deviation (0.32) increase in the firm-level shock $\theta_{j,t-1}$ increases total emissions by 12.87 pounds per dollar of total assets. Compared to the unconditional average of 76.81 pounds, this represents a significant 17% increase. Next, moving to columns (4) and (5) of Table 11, which are aggregated at the facility-year level, we find very similar results. Looking at column (5), which has the most stringent controls, we find that a one-standard-deviation (0.32) increase in the firm-level shock $\theta_{j,t-1}$ increases total emissions by 45.17 pounds per dollar of total assets, or 13% increase from the unconditional mean.

As a robustness check, we finally use a different, news-based measure of pollution and find consistent results in Table A8. To confirm the positive effect of the firm-level shock on future polluting activity, we report the estimates from the following specification:

$$y_{j,t\to t+4} = \alpha_j + \alpha_t + \pi\theta_{j,t-1} + \epsilon_{jt}, \tag{17}$$

where the dependent variable $y_{j,t\to t+4}$ is the relevant environmental impact of firm j over the period $[t, t+4]$. In column (1) the key dependent variable is the number of negative news incidents involving the firm over the interval as reported by Reprisk. If an incident covers multiple firms, then they are labeled as "unsharp" incidents. In column (2) we remove all such cases, and focus only on the news generated by the firm as a standalone entity. In columns (3) - (5), we focus on the pollution incidents. The key corresponding incidents reported by Reprisk are : "climate GHG pollution" "local pollution", "waste issues", "airborne pollutants", "forest burning", "greenhouse gas emissions", and "wastewater management". Each incident is further categorized into 3 "severity" and 3 "reach" levels. In column (3) we focus on the raw pollution variable, while in columns (4) and (5), we weight them according to their severity and reach respectively. Finally in the last 3 columns, we focus on the environmental impact of these polluting incidents. The corresponding Reprisk variables we focus on here are : "impacts on communities", "impacts on landscapes", "health environment issues", "violation of international standards", "violation of national legislation", "waste issues", "economic impact", "health impact", and "water scarcity". We again report the raw numbers, as well as numbers weighted by their severity and reach. The key explanatory variable is the firm shock $\theta_{j,t-1}$ as defined in equation (14). Same as before, we include firm, and year (or state-industry-year) fixed effects and cluster standard errors at the firm level.

Starting with columns (1) and (2) of Table A8 , we see that firms which receive more capital from the CLO market following increased insurance disclosure, are associated with more negative news in the following year. Next, in columns (3) through (5), we see that the firm receives more negative press on pollution-related topics. Finally, in columns (6) through (8), we see that these firms are involved more with news that have negative impacts, including items such as "impacts on communities", "impacts on landscapes", and "health environment issues".

Overall, all evidence is consistent with firms being more emboldened to negatively impact the environment following an increased ability to receive financing via the CLO market. One reason why they do this after receiving CLO funding is that CLO lenders may care less about polluting activity than bond lenders, especially if securitization makes it harder for end investors to monitor each of the underlying firms. Confirming this hypothesis, Table A3 finds that new bond issuances have a much higher coupon if their firms' climate sentiment is low, consistent with heavier polluting

activity–in contrast, Table A4 shows that there is no such penalty when a firm borrows new capital via CLOs. Ultimately, these results are striking, because they show that one effect of climate supervision is increased permission for some firms to conduct polluting activity, the opposite of the disclosures' original intent.

8 Conclusion

In this paper, we find differential insurer responses to a change in climate sentiment for the same underlying firm, performing a tight comparison of the difference in firm's holdings (corporate bonds vs. CLO tranches) within the same insurer-firm pair. Crucial to our analysis, we undertake a hand-matching exercise in order to disaggregate CLO investments from the Insurer×CLO tranche level to the Insurer×Firm level. We find that for the same one s.d. increase in climate risk, insurers *decrease* their holdings if the firm is held directly via bonds, yet *increase* their holdings if the firm is held indirectly via CLOs.

If insurers view climate supervision as a constraint on the choice of their direct holdings, then they are more likely to seek shadow market investments that are hard to monitor, such as CLOs. Indeed, when we study an externally imposed constraint (the NAIC's Climate Risk Disclosure Survey) on insurer capital flows into shadow markets, we find that once required to disclose, insurers are 13% more likely to invest in CLOs and hold $17 million more in CLOs on average.

Tracing the propagation of the insurer disclosure shock via shadow markets, we find that disclosure is associated with greater probability of CLO fund launches, an increase in the number of funds launched by the manager, as well as an increase in total dollar amount of funds for the CLO manager. Furthermore, at the underlying firm level, we find that disclosure is ultimately associated with higher volumes of future leveraged loans as well as increased future polluting activities.

Our paper has three main contributions. First, we show that insurance companies, through their investments in CLO markets, play a significant role in the financing of brown firms. Second, we also show that insurance supervision, intended to mitigate climate risk, can unintentionally support climate risk taking in the subset of firms that borrow from shadow markets. Finally, we add to a growing climate disclosure literature by finding evidence of spillovers into opaque funding

markets. Overall, our findings have natural policy recommendations– tailoring portfolio disclosure to include details of securitized assets may be beneficial. Given the growing investment of insurance companies in CLOs, insurance regulators may need to pay attention to the Green Paradox (Jensen et al., 2015) while designing climate supervision policies.

While we have made one of the first efforts to understand how increased scrutiny affect insurers' behavior in their direct versus indirect portfolios, many more interesting research questions remain. For example, does climate risk naturally present in insurers' liabilities interact with supervision when it comes to their risk-taking activities in their assets? How does a squeeze in financial constraints, such as a large payout by a P&C company after an unexpected natural disaster, affect this spillover? In addition, how do these supervisory pressures affect other, less traditional parts of the insurers' portfolio such as real estate, which carries its own unique set of climate risks?

References

Bartram, S. M., K. Hou, and S. Kim (2022): "Real effects of climate policy: Financial constraints and spillovers," *Journal of Financial Economics*, 143, 668–696.

Becker, B. and V. Ivashina (2015): "Reaching for yield in the bond market," *The Journal of Finance*, 70, 1863–1902.

Berry-Stölzle, T. R., S. Fritzsch, P. Scharner, and G. Weiss (2024): "Insurers' climate change risk management quality and natural disasters," *Journal of Risk and Insurance*.

Bharath, S. T., S. Dahiya, A. Saunders, and A. Srinivasan (2011): "Lending relationships and loan contract terms," *The Review of Financial Studies*, 24, 1141–1203.

Bhardwaj, A., S. Ge, and S. Mukherjee (2022): "The Effect of Investor Demand on Loan Securitization and Firm Financing," *SSRN Electronic Journal*.

Callaway, B. and P. H. Sant'Anna (2021): "Difference-in-differences with multiple time periods," *Journal of econometrics*, 225, 200–230.

Cao, J., Y. Li, X. Zhan, W. Zhang, and L. Zhou (2021): "Carbon emissions, institutional trading, and the liquidity of corporate bonds," *Available at SSRN*, 3881497.

Ceres (2023): "Climate Risk Management in the U.S. Insurance Sector," .

Cohen, S., I. Kadach, and G. Ormazabal (2023): "Institutional investors, climate disclosure, and carbon emissions," *Journal of Accounting and Economics*, 76, 101640.

Cordell, L., M. R. Roberts, and M. Schwert (2023): "CLO performance," *The Journal of Finance*, 78, 1235–1278.

Deloitte (2023): "The growing importance of the insurance industry's Climate Risk and Disclosure Survey," .

Foley-Fisher, N., N. Heinrich, and S. Verani (2023): "Are US life insurers the new shadow banks?" *Available at SSRN 3534847*.

Fringuellotti, F. and J. A. Santos (2021): "Insurance companies and the growth of corporate loans' securitization," *FRB of New York Staff Report*, 975.

Giannetti, M., M. Jasova, M. Loumioti, and C. Mendicino (2023): ""Glossy green" banks: the disconnect between environmental disclosures and lending activities," *Banks: The Disconnect between Environmental Disclosures and Lending Activities (December, 2023). ECB Working Paper*.

Graham, J. R., J. Grennan, C. R. Harvey, and S. Rajgopal (2022): "Corporate culture: Evidence from the field," *Journal of financial economics*, 146, 552–593.

He, Y. E., B. Kahraman, and M. Lowry (2023): "ES risks and shareholder voice," *The Review of Financial Studies*, 36, 4824–4863.

Ilhan, E., P. Krueger, Z. Sautner, and L. T. Starks (2023): "Climate risk disclosure and institutional investors," *The Review of Financial Studies*, 36, 2617–2650.

Ivantsova, A., K. Kim, and X. Lin (2021): "Climate risk disclosure and institutional investors: Evidence from the insurance industry," *Available at SSRN 3984467*.

Jensen, S., K. Mohlin, K. Pittel, and T. Sterner (2015): "An introduction to the green paradox: the unintended consequences of climate policies," *Review of Environmental Economics and Policy*.

Jung, H., R. Engle, S. Ge, and X. Zeng (2024): "Physical Climate Risk Factors and an Application to Measuring Insurers' Climate Risk Exposure," in *FRB of New York Staff Report No. 1066*.

Koijen, R. S. and M. Yogo (2015): "The cost of financial frictions for life insurers," *American Economic Review*, 105, 445–475.

——— (2016): "Shadow insurance," *Econometrica*, 84, 1265–1287.

Krueger, P., Z. Sautner, and L. T. Starks (2020): "The importance of climate risks for institutional investors," *The Review of Financial Studies*, 33, 1067–1111.

Lin, X., K. Kim, and A. Ivantsova (2023): "Insights from the mandatory insurer climate risk disclosure survey in the United States," *Risk Management and Insurance Review*, 26, 107–118.

Liu, J. and W. Liu (2024): "The effect of political frictions on the pricing and supply of insurance," *The Review of Financial Studies*, 37, 1149–1189.

Mastouri, A., R. Mendiratta, and G. Giese (2022): "Corporate Bonds and Climate-Change Risk," *The Journal of Portfolio Management*.

Matsumura, E. M., R. Prakash, and S. C. Vera-Muñoz (2014): "Firm-value effects of carbon emissions and carbon disclosures," *The accounting review*, 89, 695–724.

NYDFS (2024): "An Analysis of NAIC Climate Risk Disclosure Survey Responses and Other Reporting," .

Oh, S., I. Sen, and A.-M. Tenekedjieva (2022): "Pricing of climate risk insurance: Regulation and cross-subsidies," *Available at SSRN 3762235*.

Sautner, Z., L. Van Lent, G. Vilkov, and R. Zhang (2023): "Firm-level climate change exposure," *The Journal of Finance*, 78, 1449–1498.

Seltzer, L. H., L. Starks, and Q. Zhu (2022): "Climate regulatory risk and corporate bonds," Tech. rep., National Bureau of Economic Research.

Starks, L. T. (2023): "Presidential address: Sustainable finance and esg issues—value versus values," *The Journal of Finance*, 78, 1837–1872.

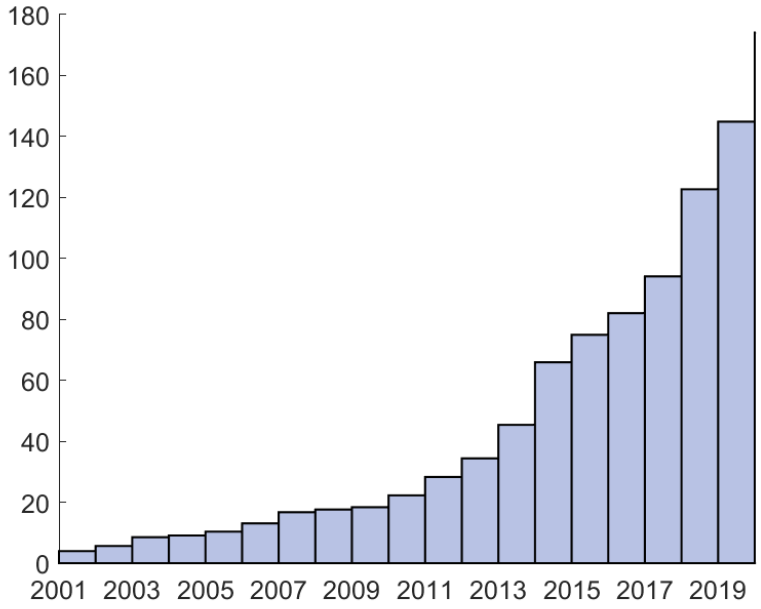
Tenekedjieva, A.-M. (2020): "The revolving door and insurance solvency regulation," Ph.D. thesis, The University of Chicago.

Treasury, U. (2023): "Climate Risk Financial Oversight Workstream," .

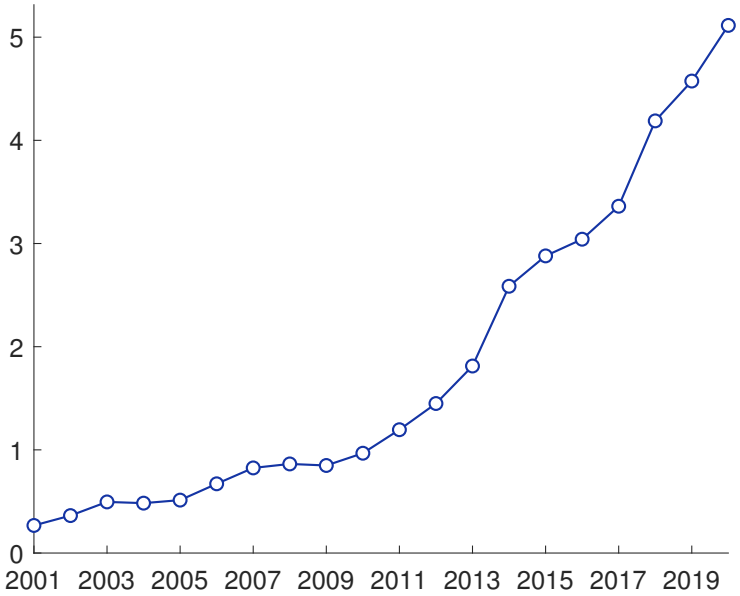
Yago, G. and D. McCarthy (2004): *The US leveraged loan market: A primer*, Milken Institute Santa Monica, CA.

Zerbib, O. D. (2016): "Is There a Green Bond Premium? The yield differential between green and conventional bonds," *Published in the Journal of Banking and Finance*, 98, 39–60.

Figure 1: Insurance Companies Investments in CLO funds.



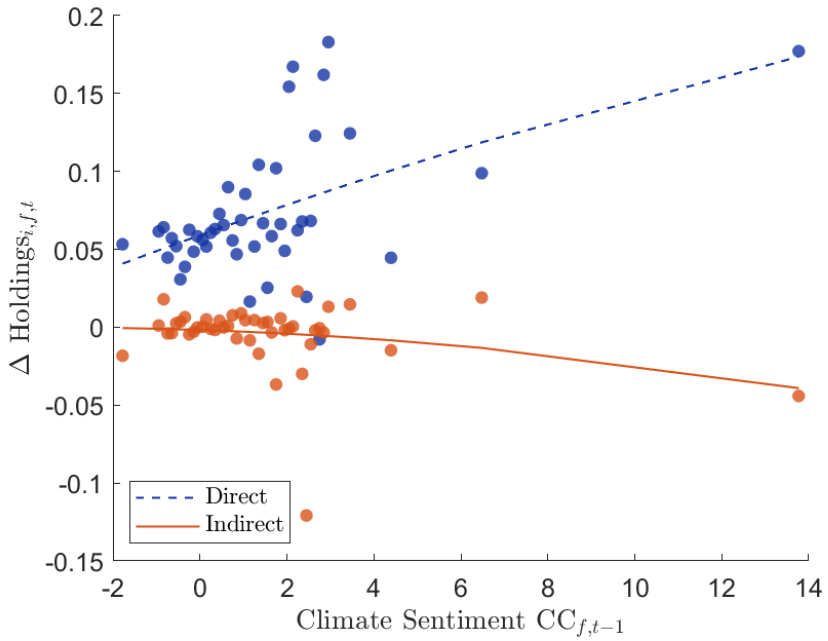
(a) Aggregate Holdings in $ Billions



(b) Percentage of Portfolio

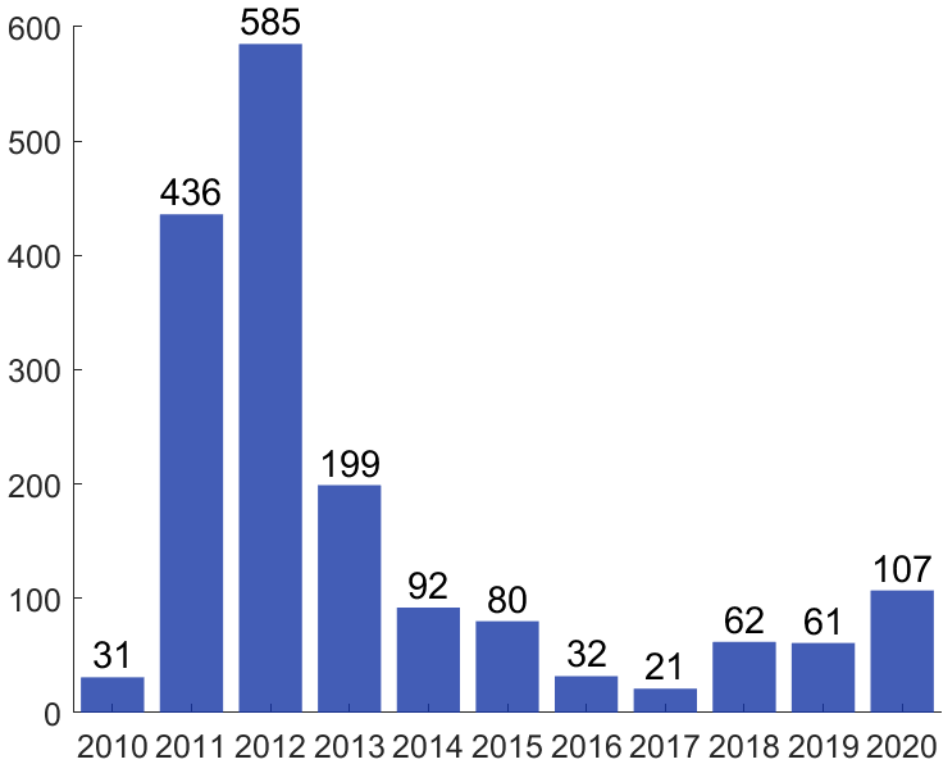
Note: This figure plots the aggregate holdings of the debt tranches of Collateralized Loan Obligations (CLO) by the Insurance companies over the sample period 2001 through 2020. Data on CLO tranches comes from Acuris Creditflux, and data on insurance portfolios come from NAIC Schedule D files. We hand match the insurance company holdings to the CLO information to create a mapping. Panel A plots the aggregate dollar holdings of insurance companies, while in Panel B, we plot the aggregate portfolio weight as a fraction of non-government fixed income.

Figure 2: Contrasting behavior of direct versus CLO holdings



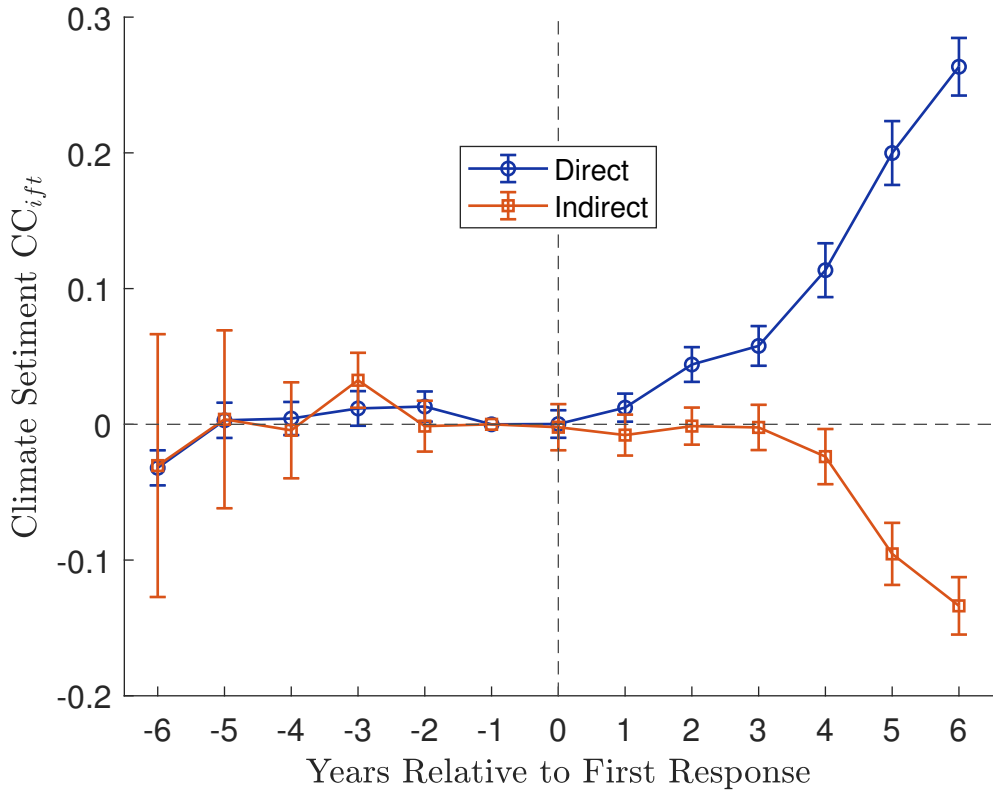
Notes: This graph plots the YoY change in holdings against a lagged measure of investor sentiment measured from climate-related discussions in earnings transcripts. Holdings data comes from NAIC schedule D filings, and the climate data comes from Sautner et al. (2023). The data sample covers years 2001 to 2020. Higher climate sentiment indicates a positive outlook of investors. The plot shows that positive climate sentiment is associated with an increase in direct bond holdings but a decrease in investment held indirectly (via CLO tranches). The binned scatter plots absorb variation at the insurer and year levels.

Figure 3: Insurance Company Climate Disclosures



Notes: The figure above plots the distributions of first response dates of climate survey disclosures of insurance companies. The data comes from NAIC climate disclosure survey results published online and shared with us.

Figure 4: Climate Sentiment in Direct and Indirect (CLO) Holdings of Insurance Companies Around Disclosure Dates.

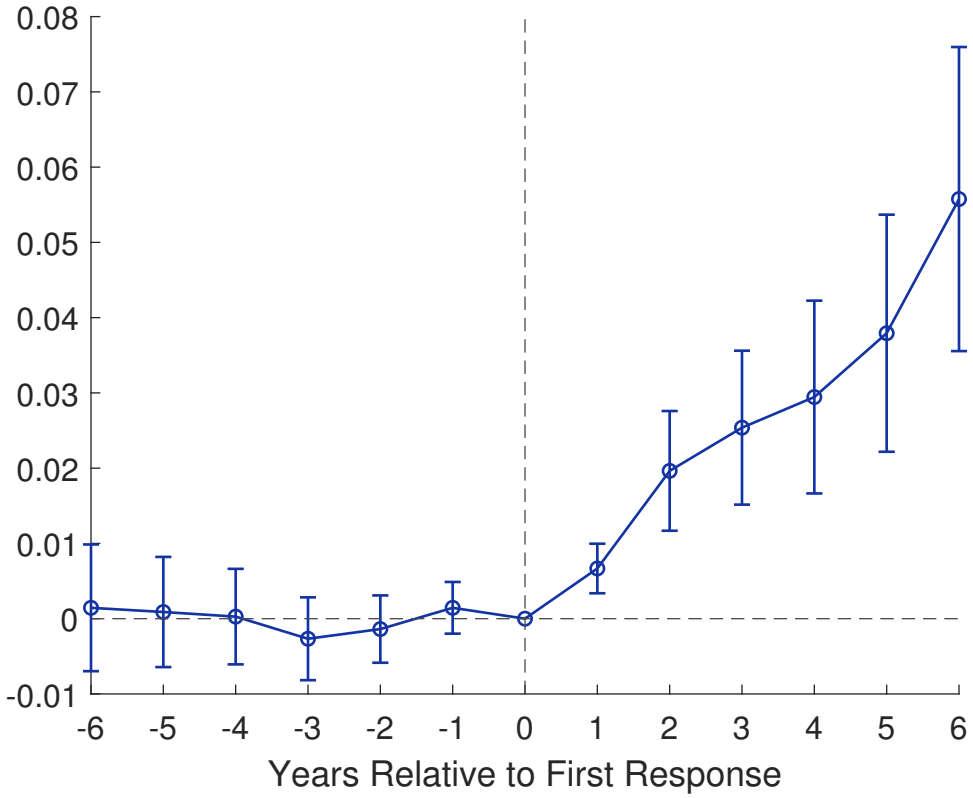


Notes: This figure plots CLO fund investments of insurance companies around the disclosure date. Specifically, the figure plots the β_t coefficients from the following regression:

$$\text{Sentiment}_{it} = \alpha_i + \alpha_y + \sum_{t=\tau-7}^{\tau+7} \beta_t D_{i,t} \times \text{CLO}_{it} + X_{it} + \varepsilon_{it}$$

where Sentiment_{it} is the aggregate direct or indirect climate sentiment measure of an insurance company i at time t. Aggregate sentiment measures at an insurer-level is calculated as the weighted average of climate sentiment measure, computed separately for direct and indirect holdings. Higher (lower) values represents more positive (negative) climate-related news. τ represents the year when the insurance company first started disclosing, among other things, their investment strategy related to climate risk, and $D_{i,t-\tau}$ is an indicator which assumes the value 1 for year t, and zero otherwise. We focus on the time period $[\tau-6, \tau+6]$ around the first disclosure date. X_{it} is the natural logarithm of total insurance company i's assets in year t. We also include insurer fixed effects α_i and cluster the standard errors at the insurer level. Insurance holdings data comes from NAIC schedule D, disclosure dates come from the published NAIC climate surveys, CLO data comes from Acuris Creditflux, and climate sentiment measures come from Sautner et al. (2023). Sample period runs from 2001 to 2020.

Figure 5: Insurance Companies Investments in CLO funds Around Disclosure Dates.

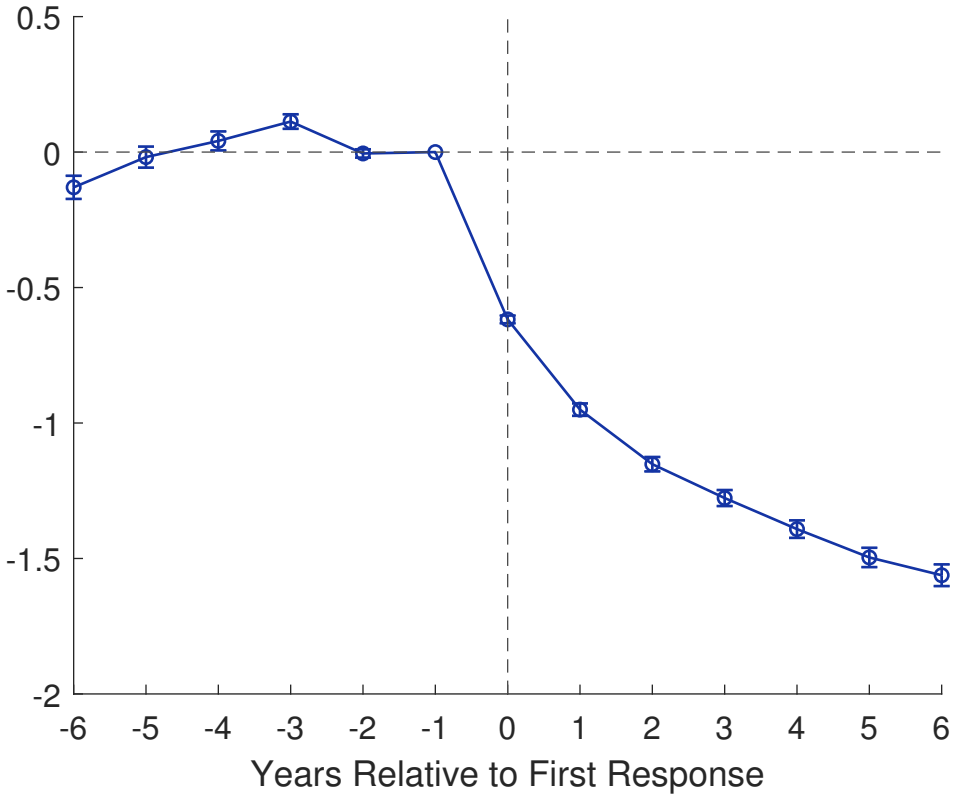


Notes: This figure plots CLO fund investments of insurance companies around the disclosure date. Specifically, the figure plots the β_t coefficients from the following regression:

$$y_{it} = \alpha_i + \sum_{t=\tau-6}^{\tau+6} \beta_t D_{i,t} + X_{it} + \varepsilon_{it}$$

where $y_{it} = \log(1+CLO_{it})$ is the natural logarithm to total investment of insurance company i in CLO debt tranches in year t. τ represents the year when the insurance company first started disclosing, among other things, their investment strategy related to climate risk, and $D_{i,t-\tau}$ is an indicator which assumes the value 1 for year t, and zero otherwise. We focus on the time period $[\tau-6, \tau+6]$ around the first disclosure date. X_{it} is the natural logarithm of total insurance company i's assets in year t. We also include insurer fixed effects α_i and cluster the standard errors at the insurer level. Insurance holdings data comes from NAIC schedule D, disclosure dates come from the published NAIC climate surveys, CLO data comes from Acuris Creditflux, and climate sentiment measures come from Sautner et al. (2023). Sample period runs from 2001 to 2020.

Figure 6: Yields on Insurer's Direct Holdings Around Disclosure Dates.

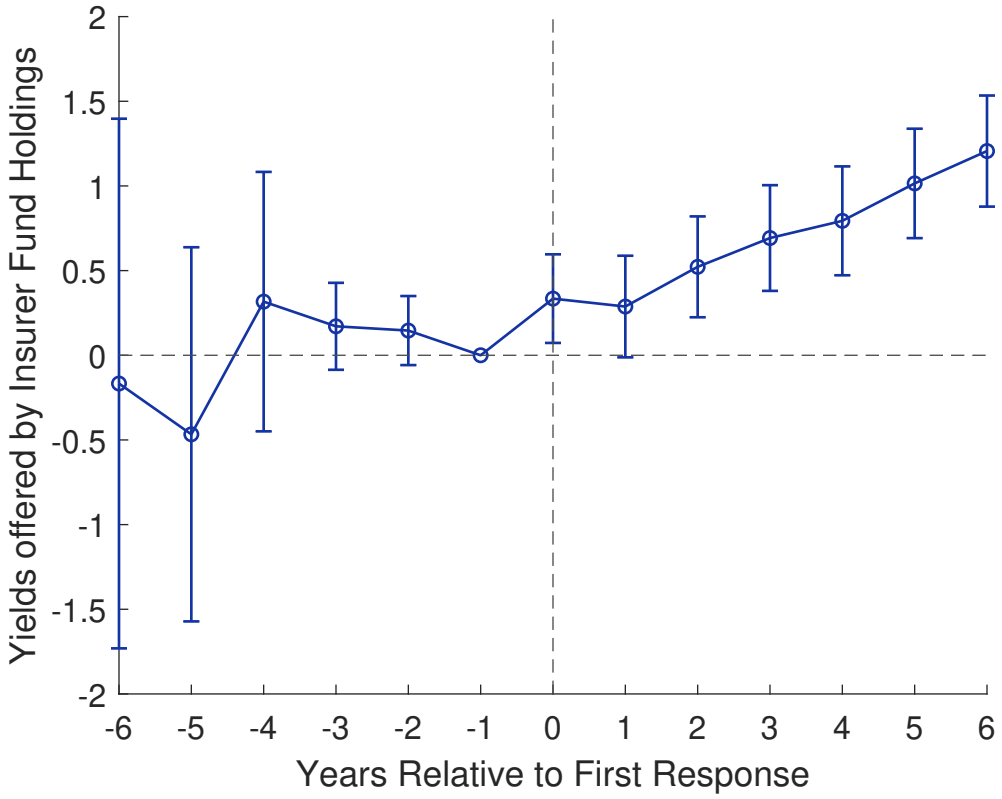


Notes: This figure illustrates the yields of insurance companies' direct investments consisting of holdings in various corporate bonds. Specifically, we plot the β_t coefficients from the following regression:

$$\text{Yields}_{is(j)t} = \alpha_{ijmr} + \sum_{t=\tau-6}^{\tau+6} \beta_t D_t + \varepsilon_{ist}$$

where s denotes a security held by insurer i at time t. We further index the firm issuing the security s by j, and denote the maturity by m, and the credit rating by r. We focus on the time period $[\tau - 6, \tau + 6]$ around the first disclosure date. We include insurer-firm-maturity-rating fixed effect α_{ijrm}. We cluster the standard errors at the insurer and firm level. Insurance holdings data comes from NAIC schedule D, disclosure dates come from the published NAIC climate surveys, and bond data comes from Fixed Income Securities Database (FISD). Sample period runs from 2001 to 2020.

Figure 7: Yields on Insurer's CLO Holdings Around Disclosure Dates.



Notes: This figure illustrates the yields offered by the CLO tranches that insurance companies invest in around the disclosure period. Specifically, we plot the β_t coefficients from the following regression:

$$\text{Yields}_{is(f)t} = \alpha_{ifmr} + \sum_{t=\tau-6}^{\tau+6} \beta_t D_t + \varepsilon_{ist}$$

where s denotes a security held by insurer i at time t. We further index the CLO fund issuing the tranche security s by f, and denote the maturity by m, and the credit rating by r. We focus on the time period $[\tau - 6, \tau + 6]$ around the first disclosure date. We include insurer-firm-maturity-rating fixed effect α_{ifrm}. We cluster the standard errors at the insurer and firm level. Insurance holdings data comes from NAIC schedule D, disclosure dates come from the published NAIC climate surveys, and CLO data comes from Acuris Creditflux. Sample period runs from 2001 to 2020.

Table 1: Summary Statistics

	Mean	Std. Dev.	P5	Median	P95
Panel A : Insurers					
Insurer Holdings ($, '0,000s)	58.54	247.17	0.00	0.00	300.00
$CC_{f,t}$ (Direct)	0.22	0.80	-0.24	0.02	1.16
$CC_{f,t}$ (Indirect)	0.19	0.81	-0.25	0.00	1.00
Insurance CLO Investment Dummy	0.36	0.48	0.00	0.00	1.00
CLO Tranche Purchase ($, Millions)	1.94	10.76	0.00	0.00	5.00
Insurer Direct (non-zero) Holdings ($,'0,000s)	361.04	523.33	5.8	100	1750
Insurer Indirect (non-zero) Holdings ($,'0,000s)	21.25	91.32	0.07	1.98	84.92
Panel B : CLO Funds					
CLO Fund Balance ($, Millions)	724.32	380.72	355.50	607.00	1431.05
Fund Leverage (%)	92.58	6.14	87.11	92.00	100.00
No. of Portfolio Firms	481.64	219.37	186.00	449.00	883.00
Fund Holdings ($, '0,000s)	193.99	156.64	28.63	151.82	498.12
Avg. Loan Maturity	5.20	1.51	2.50	5.50	7.00
Avg. Loan. Rating Score	11.22	1.75	9.00	11.00	14.00
Panel C : Fund Managers					
Prob. CLO Tranche Investment	0.56	7.48	0.00	0.00	0.00
Prob. (Insurer-Manager Relationship $\mathcal{R}^5_{i,m,t} > 0$)	0.05	0.21	0.00	0.00	0.00
$\mathcal{R}^5_{i,m,t}$ (Conditional on Relationship)	8.78	21.52	0.08	1.37	45.30
Manager Shock $\lambda_{m,t}$	0.19	0.37	0.00	0.00	0.97
Prob. Fund Launch	0.23	0.42	0.00	0.00	1.00
No. of Annual Fund Launches	0.56	1.40	0.00	0.00	3.00
Launch Size ($ Millions)	250.93	635.49	0.00	0.00	1625.50
Panel D : Firm Issuance					
Prob. Firm Included in Fund Portfolio	0.06	0.24	0.00	0.00	1.00
Prob. of Manager-Firm Relationship ($\mathcal{R}^5_{m,j,t} > 0$)	0.12	0.32	0.00	0.00	1.00
$\mathcal{R}^5_{m,j,t}$ (Conditional on Relationship)	8.11	16.08	0.34	3.15	33.09
Firm Shock $\theta_{j,t}$	0.14	0.32	0.00	0.00	0.93
Firm Issued Leveraged Loan Dummy	0.07	0.26	0.00	0.00	1.00
Loan Size ($ Millions)	66.56	515.71	0.00	0.00	250.00
All-in-Drawn Spread (bps)	383.88	161.60	161.84	374.07	675.00
Firm Issued Revolver Loan Dummy	0.07	0.25	0.00	0.00	1.00
Panel E : Firm Emissions					
Total Emissions in 000 lbs. (Per Chemical)	221.12	894.57	0.00	9.23	833.11
Number of Chemicals Released	21.42	32.77	1.00	11.00	80.00
Scaled Emissions (Per Chemical over Lagged Asset)	70.82	784.26	0.00	0.37	133.09
Total Emissions in 000 lbs. (Per Facility)	1273.70	4125.79	0.00	28.64	8442.97
Scaled Emissions (Per Facility over Lagged Asset)	354.67	2237.53	0.00	1.64	943.44

Notes: This table summarizes the summary statistics for the five main datasets in our sample. Insurance holdings data comes from NAIC schedule D, disclosure dates come from the published NAIC climate surveys, CLO data comes from Acuris Creditflux, and climate sentiment measures come from Sautner et al. (2023). Sample period runs from 2001 to 2020.

Table 2: Climate News and Insurer Portfolios

	Holdings in USD '0,000s		Log(1 + Dollar Amount)	
	(1)	(2)	(3)	(4)
$CC_{j,t-1} \times \text{Indirect}_{i,j,t}$	-2.204***	-2.508***	-0.100***	-0.099***
	(0.158)	(0.232)	(0.004)	(0.006)
Indirect Dummy	-46.845***	-47.495***	-0.915***	-0.928***
	(2.939)	(2.989)	(0.032)	(0.033)
$CC_{j,t-1}$	1.458***		0.049***	
	(0.112)		(0.002)	
Obs	20,257,613	20,256,241	20,257,613	20,256,241
R^2	0.79	0.79	0.61	0.66
Unconditional Average Holding Amount $\overline{y}$	58.55	58.55	2.88	2.88
Conditional Holding Amount (Direct)	361.04	361.04	13.91	13.91
Conditional Holding Amount (Indirect)	21.25	21.25	9.96	9.96
Insurer-Firm FE	Yes	Yes	Yes	Yes
Insurer-Year FE	Yes	Yes	Yes	Yes
Firm-Year FE	No	Yes	No	Yes
CC + Indirect× CC	-0.746***	-2.508***	-0.051***	-0.099***
SE	(.063)	(.232)	(.002)	(.006)

Notes: This table reports the results of the specification

$$h_{ijt} = \alpha_{it} + \alpha_{ij} + \alpha_{jt} + \beta CC_{j,t-1} + \gamma \text{Indirect}_{i,j,t} + \delta CC_{j,t-1} \times \text{Indirect}_{i,j,t} + \xi h_{i,j,t-1} + \varepsilon_{ijt}$$

where the dependent variable $h_{i,j,t}$ is the insurer i's holding of firm j for year t. In columns (1) and (3) the dependent variable h_{ijt} is expressed in the units of \$10,000, while in columns (2) and (4), the dependent variable is $\log(1+\$)$. CC is the key explanatory variable and measures the firm-level climate sentiment. We differentiate between the direct and indirect (held though the CLO) holdings of the same firm by insurer i using the indicator variable $\text{CLO}_{i,j,t}$ which assumes the value one if the firm j is held indirectly through the CLO funds at time t, and zero otherwise (for directly held firms). α_{ij} and α_{it} denote insurer-firm and insurer-year fixed effects respectively. We cluster the standard errors at the insurer level, and reported in the parentheses. Insurance holdings data comes from NAIC schedule D, CLO data comes from Acuris Creditflux, and climate sentiment measures come from Sautner et al. (2023). Sample period runs from 2001 to 2020.

Table 3: Effect of Disclosures on Insurers' Climate Exposures

	Holdings in USD '0,000s		Log(1 + Dollar Amount)	
	(1)	(2)	(3)	(4)
$CC_{j,t-1} \times Disclosing_{i,t} \times Indirect_{i,j,t}$	-1.214***	-0.972***	-0.101***	-0.054***
	(0.182)	(0.186)	(0.008)	(0.008)
$CC_{f,t-1} \times Disclosing_{i,t}$	0.811***	0.531***	0.035***	0.012**
	(0.156)	(0.154)	(0.005)	(0.006)
$CC_{j,t-1} \times Indirect_{i,j,t}$	-0.469***	-0.721***	-0.057***	-0.075***
	(0.089)	(0.142)	(0.005)	(0.007)
$Indirect_{i,j,t} \times Disclosing_{i,t}$	-11.018***	-10.250***	0.240***	0.079
	(1.129)	(1.125)	(0.053)	(0.050)
$Indirect_{i,j,t}$	-27.055***	-27.934***	-0.769***	-0.693***
	(1.193)	(1.186)	(0.048)	(0.046)
$CC_{j,t-1}$	0.425***		0.032***	
	(0.073)		(0.003)	
Obs	14,016,570	14,015,527	14,016,570	14,015,527
R^2	0.71	0.73	0.58	0.64
$\overline{y}$	38.58	38.58	3.23	3.23
Insurer-Firm FE, Insurer-Year FE	Yes	Yes	Yes	Yes
Firm-Year FE	No	Yes	No	Yes
Test1	-0.045	-0.721***	-0.025***	-0.075***
SE1	(.035)	(.142)	(.003)	(.007)
Test2	-0.447***	-1.162***	-0.092***	-0.117***
SE2	(.054)	(.152)	(.004)	(.008)

Notes: This table reports the results of the specification

$$\begin{aligned} h_{ijt} = \alpha_{it} + \alpha_{ij} + \beta CC_{j,t-1} + \gamma \text{Indirect}_{i,j,t} + \delta CC_{j,t-1} \times \text{Indirect}_{i,j,t} \\ + \beta_2 CC_{j,t-1} \times \text{Disclosing}_{i,t-1} + \gamma_2 \text{Indirect}_{i,j,t} \times \text{Disclosing}_{i,t-1} \\ + \pi CC_{f,t-1} \times \text{Indirect}_{i,j,t} \times \text{Disclosing}_{i,t-1} + \xi h_{i,j,t-1} + \varepsilon_{ijt} \end{aligned}$$

where the dependent variable $h_{i,f,t}$ is the insurer i's holding of firm f for year t. In columns (1) and (3) the dependent variable h_{ift} is expressed in the units of \$10,000, while in columns (2) and (4), the dependent variable is $\log(1+\$)$. CC is the key explanatory variable and measures the firm-level climate sentiment. We differentiate between the direct and indirect (held though the CLO) holdings of the same firm by insurer i using the indicator variable $\text{CLO}_{i,f,t}$ which assumes the value one if the firm f is held indirectly through the CLO funds at time t, and zero otherwise (for directly held firms). α_{if} and α_{it} denote insurer-firm and insurer-year fixed effects respectively. We cluster the standard errors at the insurer level, and reported in the parentheses. Finally, we report the results of two F-tests,

$$\begin{aligned} &\text{Test}_1 : CC_{j,t-1} + CC_{j,t-1} \times \text{Indirect}_{i,j,t} \\ &\text{Test}_2 : CC_{j,t-1} + CC_{j,t-1} \times \text{Indirect}_{i,j,t} + CC_{j,t-1} \times \text{Disclosing}_{i,t-1} + \\ &\qquad \text{Indirect}_{i,j,t} \times \text{Disclosing}_{j,t-1} + CC_{j,t-1} \times \text{Indirect}_{i,j,t}\text{Disclosing}_{i,t-1} \end{aligned}$$

along with their standard errors. Insurance holdings data comes from NAIC schedule D, disclosure dates come from the published NAIC climate surveys, CLO data comes from Acuris Creditflux, and climate sentiment measures come from Sautner et al. (2023). Sample period runs from 2009 to 2020.

Table 4: Effect of Disclosures on Insurers' CLO Investments

	(1) Probability of CLO investment	(2) CLO Investment in $ Millions	(3) New CLO Flow in $ Millions
		Panel A: All Insurers	
Post First Response	0.129***	17.284***	6.054***
	(0.009)	(1.397)	(0.465)
Obs	71,883	71,883	71,883
R^2	0.21	0.57	0.44
$\overline{y}$	.11	6.23	1.94
Insurer FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
	Panel B: Excluding Size Based Disclosures (excl 2010-2012)		
Post First Response	0.087***	6.807***	2.266***
	(0.015)	(1.525)	(0.516)
Obs	53,760	53,760	53,760
R^2	0.12	0.33	0.24
$\overline{y}$	.08	1.88	.65
Insurer FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes

Notes: This table reports the results of the specification

$$y_{it} = \alpha_i + \alpha_t + \beta \mathbf{1}(\text{Treated})_{it} + X_{it} + \varepsilon_{it}$$

In column (1) we use an investment dummy as a dependent variable which assumes a value one if the insurer i invests in a CLO tranche in year t. In column (2) we use the actual dollar value of CLO investments by insurance companies. Finally in column (3) reports the dollar value of the tranches newly acquired by the insurance company in year t. The key explanatory variable, Treated_{it}, is an indicator variable which takes the value one for years t after the insurer's first disclosure date. We also include insurer fixed effects α_i, year-fixed-effects α_t. In Panel B, we repeat the analysis after excluding the insurance companies who started reporting during the period 2010 - 2012. Since these cutoff rules are based on size, the disclosing companies are larger compared to the ones who don't. Standard errors are clustered at insurer level, and reported in the parentheses. Insurance holdings data comes from NAIC schedule D, disclosure dates come from the published NAIC climate surveys, CLO data comes from Acuris Creditflux, and climate sentiment measures come from Sautner et al. (2023). Sample period runs from 2001 to 2020.

Table 5: Effect of Insurer's Constraints on Post-Disclosure CLO Investments

	Probability of Investing	Investment Volume in $ Millions	CLO Holding Amount in $ Billions
	(1)	(2)	(3)
Treated × Low RBC	0.037**	9.543***	0.027***
	(0.017)	(2.276)	(0.006)
Post First Response	0.004	0.511	0.001
	(0.018)	(1.554)	(0.004)
Low RBC	0.018*	-3.169***	-0.009***
	(0.009)	(1.005)	(0.003)
Obs	22,888	22,888	22,888
R^2	0.31	0.44	0.54
$\overline{y}$	.17	8.49	.02
Insurer FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes

Notes: This table considers the effect of insurer portfolio constraints on their CLO investments around the disclosure period. We employ the specification

$$y_{it} = \alpha_i + \alpha_t + \gamma_1 \text{Post}_{it} + \gamma_2 \text{Low RBC}_{it} + \gamma_3 \text{Low RBC}_{it} \times \text{Post}_{it} + \varepsilon_{it}$$

where y_{it} is the insurer i's investment strategy in CLO funds in year t. We consider three variations of the dependent variable : i) an investment dummy which equals one if the insurer i invests in CLO funds in year t, and zero otherwise (columns 1); ii) the dollar value of the insurer's investment in the CLO funds in year t (column 2); and (iii) the total amount of outstanding investments of insurer i in CLO funds in year t expressed in $ billions (column 3). $\text{Post}_{i,t}$ is an indicator variable which assumes one if the insurer i's first disclosure filing occurs before year t, and zero otherwise. The indicator variable Low RBC_{it} takes a value one if the risk-based capital (RBC) of insurer i, expressed as a percentage of total insurer assets is below the median in year t, and zero otherwise. We also include insurer (α_i), and year (α_t) fixed effects. Standard errors are clustered at the insurer level. Insurance holdings data comes from NAIC schedule D, disclosure dates come from the published NAIC climate surveys, CLO data comes from Acuris Creditflux, and climate sentiment measures come from Sautner et al. (2023). Sample period runs from 2001 to 2020.

Table 6: Robustness with Matched Insurer Control Group

	Probability of CLO investment (1)	CLO Investment in $ Millions (2)	New CLO Flow in $ Millions (3)
Treatment × Post	0.049***	8.359***	4.697***
	(0.006)	(1.140)	(0.686)
Obs	56,080	56,080	56,080
R^2	0.67	0.75	0.73
$\overline{y}$	.07	3.41	1.84
Event-Insurer FE	Yes	Yes	Yes
Event-Year FE	Yes	Yes	Yes

Notes: This table reports the results of the matched specification

$$y_{it} = \alpha_{e,i} + \alpha_{e,t} + \pi \text{Treatment}_i \times \text{Post}_{e,t} + X_{it} + \varepsilon_{it},$$

Treated and control insurers in this regression are matched based on: line of business, states of operation, and size of total premiums collected. In column (1) we use an investment dummy as a dependent variable which assumes a value one if the insurer i invests in a CLO tranche in year t. In column (2) we use the dollar value of outstanding CLO investments by insurance companies. Finally column (3) reports the dollar value of the tranches newly acquired by the insurance company in year t. The data is stacked at the insurer-event-year level, where the event $e_{i,\tau}$ is defined as a tuple including the disclosing insurer i and the first disclosure date τ. The key explanatory variable, Treatment_i, is an indicator variable which takes the value for the disclosing (treatment) insurer i, and zero for the matched control insurer c. The dummy variable $\text{Post}_{e,t}$ takes a value one if the observation year t is after the first disclosure date τ, defined at the event level $e_{i,\tau}$. We include insurer-event fixed effects $\alpha_{e,i}$, year-fixed-effects α_t or event-year fixed effects $\alpha_{e,t}$ as described in the table. Standard errors are clustered at insurer-event level, and reported in the parentheses. Insurance holdings data comes from NAIC schedule D, disclosure dates come from the published NAIC climate surveys, CLO data comes from Acuris Creditflux, and climate sentiment measures come from Sautner et al. (2023). Sample period runs from 2001 to 2020.

Table 7: Insurer Investments in CLO Tranches Around Disclosure Events

	Probability of Investing			Dollar Investment Volume		
	(1)	(2)	(3)	(4)	(5)	(6)
Post First Response	0.002***		0.001***	0.029***		0.018***
	(0.000)		(0.000)	(0.003)		(0.003)
Insurer-Mgr Rel $\mathcal{R}^5_{i,m,t-1}$		0.583***	0.235***		7.112***	2.504***
		(0.020)	(0.034)		(0.275)	(0.533)
$\mathcal{R}^5_{i,m,t-1}\times$ Post Response			0.396***			5.240***
			(0.040)			(0.627)
Obs	2,906,871	2,906,871	2,906,871	2,906,871	2,906,871	2,906,871
R^2	0.06	0.06	0.07	0.05	0.06	0.06
$\overline{y}$	.01	.01	.01	.06	.06	.06
Insurer FE	Yes	Yes	Yes	Yes	Yes	Yes
CLO FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table shows that the probability of insurer investments in CLO funds increase substantially after they start disclosing their climate change strategy. We employ the specification

$$y_{if(m)t} = \alpha_i + \alpha_f + \alpha_t + \gamma_1 \text{Post}_{it} + \gamma_2 \text{Relationship}_{i,m,t-5\to t-1} + \gamma_3 \text{Post}_{it} \times \text{Relationship}_{i,m,t-5\to t-1} + \varepsilon_{ifmt}$$

where $y_{if(m)t}$ is the insurer i's investment strategy for fund f launched by the fund-manager m in year t. We consider two variations of the dependent variable : i) an investment dummy which equals one if the insurer i invests in the fund j, and zero otherwise (columns 1, and 2); and ii) the dollar value of the insurer's investment in the fund f (columns 3, and 4). $\text{Post}_{i,t}$ is an indicator variable which assumes one if the insurer i's first disclosure filing occurs before year t, and zero otherwise. Insurers who have invested with a fund manager m before may have more information about the manager m's success and investing style, and may thus be more inclined to invest with her again. We capture this notion with the variable $\text{Relationship}_{i,m,t-5\to t}$, as defined in equation (8). The key explanatory variable is the interaction between past relationship and post disclosure, captured by the coefficient γ_3. We also include insurer (α_i), fund (α_f) and year (α_t) fixed effects. Standard errors are clustered at the fund level. Insurance holdings data comes from NAIC schedule D, disclosure dates come from the published NAIC climate surveys, CLO data comes from Acuris Creditflux, and climate sentiment measures come from Sautner et al. (2023). Sample period runs from 2001 to 2020.

Table 8: Manager Shocks and New Fund Launches

	(1) Fund Launch Dummy	(2) No. of Funds Launched	(3) Total Manager Balance
Manager Shock $\lambda_{m,t-1}$	0.285***	1.012***	490.077***
	(0.024)	(0.100)	(52.279)
Obs	5,650	5,650	5,650
R^2	0.45	0.52	0.49
$\overline{y}$	.23	.56	264.71
SD($\lambda_{m,t-1}$)	.38	.38	.38
Manager FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes

Notes: This table reports the effects of insurer supply shocks in year $(t-1)$ on manager fund creation in the following year t, estimated from equation (11). The dependent variable is the probability of a fund launch in column (1), the total number of funds launched in year t in column (2), and the natural logarithm of the total corpus of new funds launched in year t in column (3). The key explanatory variable is the manager level exposure to insurer disclosure shocks, as defined in equation (10). All regressions include manager- and year-fixed effects. The standard errors are clustered at the manager level, and reported in the parentheses. Insurance holdings data comes from NAIC schedule D, disclosure dates come from the published NAIC climate surveys, CLO data comes from Acuris Creditflux, and climate sentiment measures come from Sautner et al. (2023). Sample period runs from 2001 to 2020.

Table 9: Climate Sentiment, and Stickiness in Fund Manager Portfolio

	Dependent Variable : Is Firm Included		
	(1)	(2)	(3)
$CC_{j,t-1}$	-0.003***		
	(0.000)		
Firm-Manager-Relationship $\mathcal{R}^5_{m,j,t-1}$		0.464***	0.467***
		(0.014)	(0.014)
$CC_{j,t-1} \times \mathcal{R}^5_{m,j,t-1}$			-0.014***
			(0.005)
Obs	4,489,216	4,489,209	4,489,209
R^2	0.24	0.31	0.31
$\overline{y}$	.07	.07	.07
Fund FE	Yes	Yes	Yes
Year FE	Yes	No	No
Firm FE	Yes	No	No
Firm-Year FE	No	Yes	Yes

Notes: This table reports the estimates from the following specification:

$$y_{f(m),j,t} = \alpha_f + \alpha_j + \alpha_t + \gamma_1 CC_{j,t-1} + \gamma_2 \mathcal{R}^5_{m,j,t-1} + \gamma_3 CC_{j,t-1} \times \mathcal{R}^5_{m,j,t-1} + \epsilon_{f(m),j,t},$$

where the dependent variable $y_{f(m),j,t}$ is a dummy which assumes a value one if the firm $j \in \mathcal{J}$ is included in the initial portfolio of fund f launched by manager m at time t. The key explanatory variables include the firm's climate sentiment from the previous year, $CC_{j,t-1}$, previous investment relationship between firm j and manager m, $\mathcal{R}_{m,j,t-1}$, and their interaction. The relationship variable is formally defined in equation (12). We also include find, firm, and year fixed effects. Additionally, we control for the rating and maturity of the outstanding loans of firms being traded in the secondary market. Standard errors, clustered at the fund level, are reported in the parentheses. Insurance holdings data comes from NAIC schedule D, disclosure dates come from the published NAIC climate surveys, CLO data comes from Acuris Creditflux, and climate sentiment measures come from Sautner et al. (2023). Sample period runs from 2001 to 2020.

Table 10: Firm Shock and Loan Issuances

	Leveraged Loan Issuance			Revolver Issuance	
	(1)	(2)	(3)	(4)	(5)
Sample	All		Public Firms	All	Public Firms
Firm Shock $\theta_{j,t-1}$	0.060***	0.066***	0.072***	-0.005	0.014
	(0.004)	(0.007)	(0.011)	(0.007)	(0.011)
Obs	126,320	48,040	22,060	48,040	22,060
R^2	0.23	0.41	0.43	0.44	0.44
$\overline{y}$	.07	.08	.08	.08	.12
Firm FE	Yes	Yes	Yes	Yes	Yes
Industry-Year FE	Yes	No	No	No	No
State-Industry-Year FE	No	Yes	Yes	Yes	Yes

Notes: This table reports the estimates from the following specification:

$$y_{j,t} = \alpha_j + \alpha_{skt} + \pi\theta_{j,t-1} + \epsilon_{jt},$$

where the dependent variable $y_{j,t}$ is a dummy which assumes a value one if the firm j issues a leveraged loan(columns 1 and 2) or a revolving line of credit (column 3) in year t. The key explanatory variable is the firm shock $\theta_{j,t-1}$ as defined in equation (14). We also include firm, and year (or state-industry-year) fixed effects. Standard errors, clustered at the firm level, are reported in the parentheses. Insurance holdings data comes from NAIC schedule D, disclosure dates come from the published NAIC climate surveys, CLO data comes from Acuris Creditflux, and climate sentiment measures come from Sautner et al. (2023). Sample period runs from 2001 to 2020.

Table 11: Firm Shock and Emission Activities

Dependent Variable : Total Emissions in Pounds Scaled by Total Assets					
	Facility-Chemical-Year Level			Facility-Year Level	
	(1)	(2)	(3)	(4)	(5)
Firm Shock $\theta_{j,t-1}$	45.440***	44.132***	40.234***	145.203***	141.143***
	(12.404)	(13.772)	(12.910)	(50.521)	(49.968)
Obs	182,386	155,464	150,994	37,120	36,000
R^2	0.12	0.83	0.84	0.82	0.82
$\overline{y}$	72.90	77.8	76.81	352.22	345.48
Facility FE	Yes	No	No	Yes	Yes
Industry-Year FE	Yes	No	No	Yes	Yes
Facility-Chemical FE	No	Yes	Yes	No	No
Industry-Chemical-Year FE	No	Yes	Yes	No	No
Firm Controls	No	No	Yes	No	Yes

Notes: This table reports the estimates from the following specification:

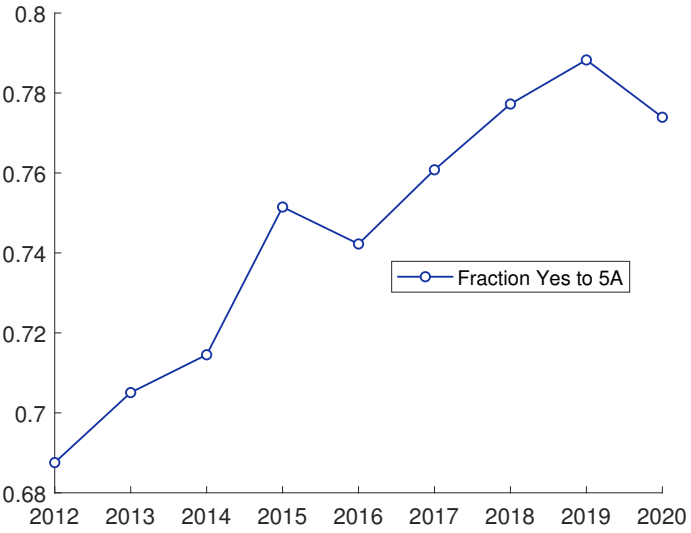
$$y_{j,t} = \alpha_j + \alpha_t + \pi\theta_{j,t-1} + \epsilon_{jt},$$

where the dependent variable $y_{j,t}$ is the total emissions of firm j during the period t scaled by total assets of the firm. The key explanatory variable is the firm shock $\theta_{j,t-1}$ as defined in equation (14). We also include firm-facility, and industry-year fixed effects. For data aggregated at facility-chemical-year level, we use a stronger facility-chemical and chemical-industry-year fixed effects. Firm controls include Lagged Assets, Tobin's Q, Profitability, and market leverage. Standard errors, clustered at the facility level, are reported in the parentheses. Insurance holdings data comes from NAIC schedule D, disclosure dates come from the published NAIC climate surveys, CLO data comes from Acuris Creditflux, and climate sentiment measures come from Sautner et al. (2023). Sample period runs from 2001 to 2020.

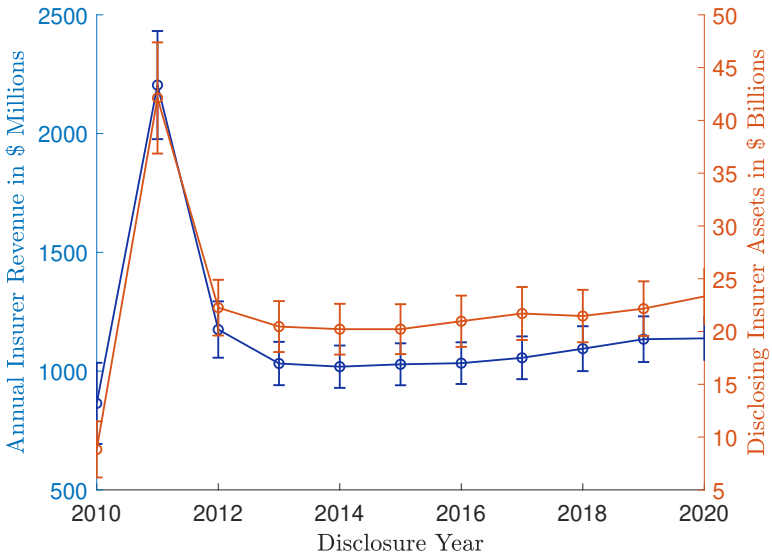
Internet Appendix
The Spillover Effects of Insurer Climate Supervision into Shadow Markets

A Additional Tables and Figures

Figure A1: Insurance Company Climate Disclosures



(a) Response to Question 5A in the Disclosure Survey



(b) Size Distributions of Disclosing Insurers

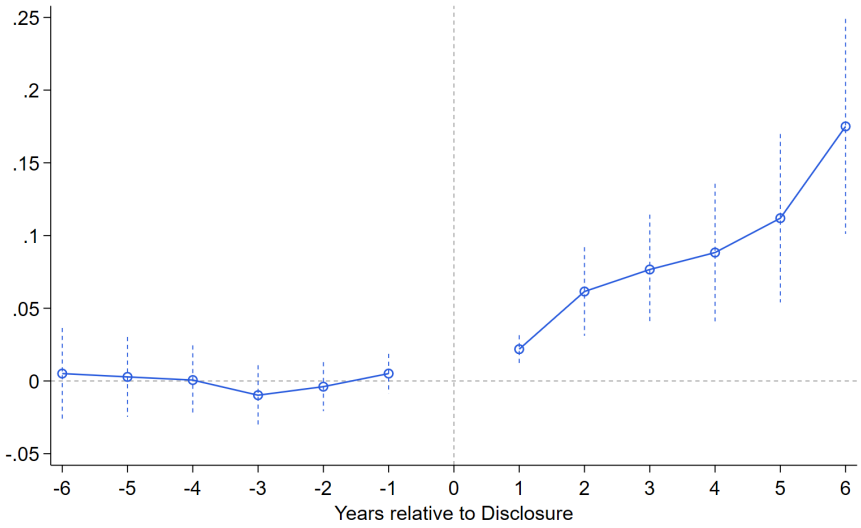
Notes: Panel A above shows the fraction of insurance companies that responded yes to Question 5A in the climate disclosure survey. Question 5a asks "Has the company considered the impact of climate change on its investment portfolio?". Panel B shows the average annual revenue in $ millions of the insurers who disclose their climate strategy in response to the state imposed mandates. The distribution is relatively stable across the years, especially after 2012, suggesting that size effects are unlikely to drive our results (especially those excluding 2010 to 2012). In 2011, only California insurers were surveyed, which added several large insurers to our sample. In subsequent years, the survey was expanded to other states, which added smaller insurers and lowered the overall average.

Figure A2: Examples of Positive and Negative Climate-related Sentiment

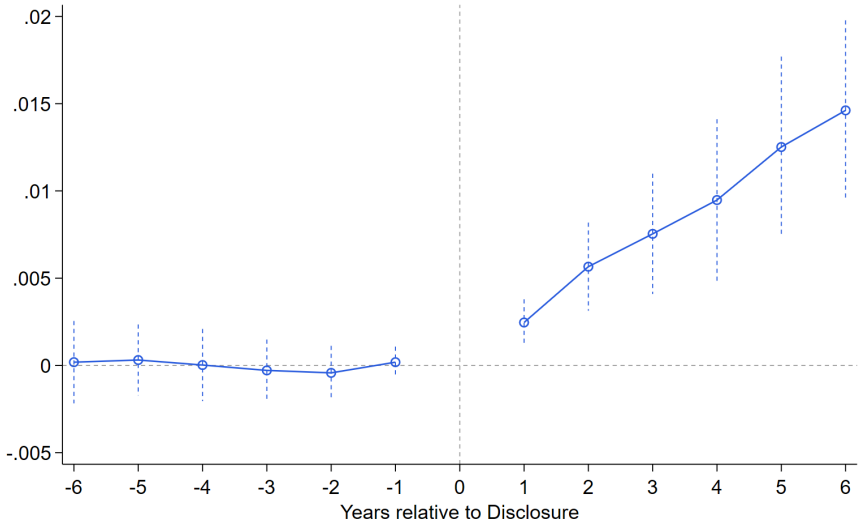
Type of Sentiment	Firm Name	Year	ISIN	Related News Report
Positive	TI Fluid Systems	2021	GB00BYQB9V88	In 2021, the company committed to a 37.5% reduction in Scope 1 and 2 CO2e emissions by 2039, through increased use of renewable electricity together with energy efficiency projects.
Negative	Northern Power Systems	2016	CA66561Y1079	Northern Power Systems sells its utility-scale turbine operations – including technology, patents, and engineers.
Positive	AquaVenture	2017	VGG0443N1078	'Seven Seas Water' desalination plants exited the 2017 floods in Peru and two Category 5 hurricanes in the Caribbean with minimal damage and many coming back online within 72 hours of the storms' passing.
Negative	Suncorp-Metway	2020	AU000000SUN6	Suncorp must manage more than 70,000 insurance claims following several large natural hazard events.
Positive	Ackermans & Van Haaren	2021	BE0003764785	Several Belgian industrial groups and research centres on Friday said they had formed a consortium to promote the production of "green hydrogen" in the Dutch-speaking Flanders region to help industries lower their carbon footprint.
Negative	EGL	2006/2007	US2684841024	Transportation and logistics firm EGL Inc. said Wednesday that the private firm [General Atlantic] set to buy the bulk of EGL's stock [...] pulled out of the $1.2 billion deal, citing concerns about EGL's impending 2006 earnings report.

Notes: The figure shows examples of both positive and negative climate-related sentiment from the Sautner et al. (2023) data.

Figure A3: Heterogeneity in CLO Investments Across Life, PC and Health Insurers



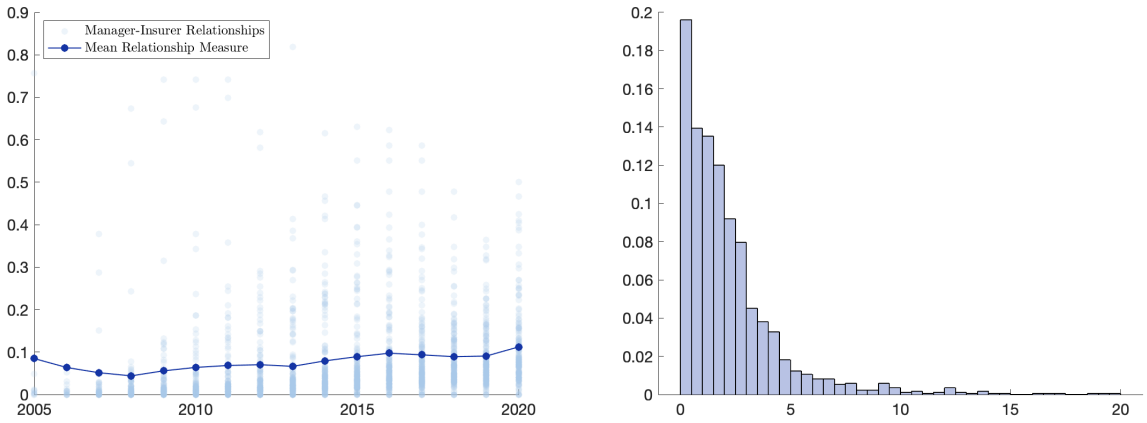
(a) CLO investments of life insurers around disclosure



(b) CLO investments of PC and Health insurers around disclosure

Notes: This figure plots CLO fund investments across insurer types around disclosure dates, following the analysis in Figure 5. The difference between Panels A and B shows that life insurers have larger investments in CLO funds compared to other insurer types. We also include insurer fixed effects α_i and cluster the standard errors at the insurer level. Insurance holdings data comes from NAIC schedule D, disclosure dates come from the published NAIC climate surveys, CLO data comes from Acuris Creditflux, and climate sentiment measures come from Sautner et al. (2023). Sample period runs from 2001 to 2020.

Figure A4: Distribution of Insurer-Manager Relationships

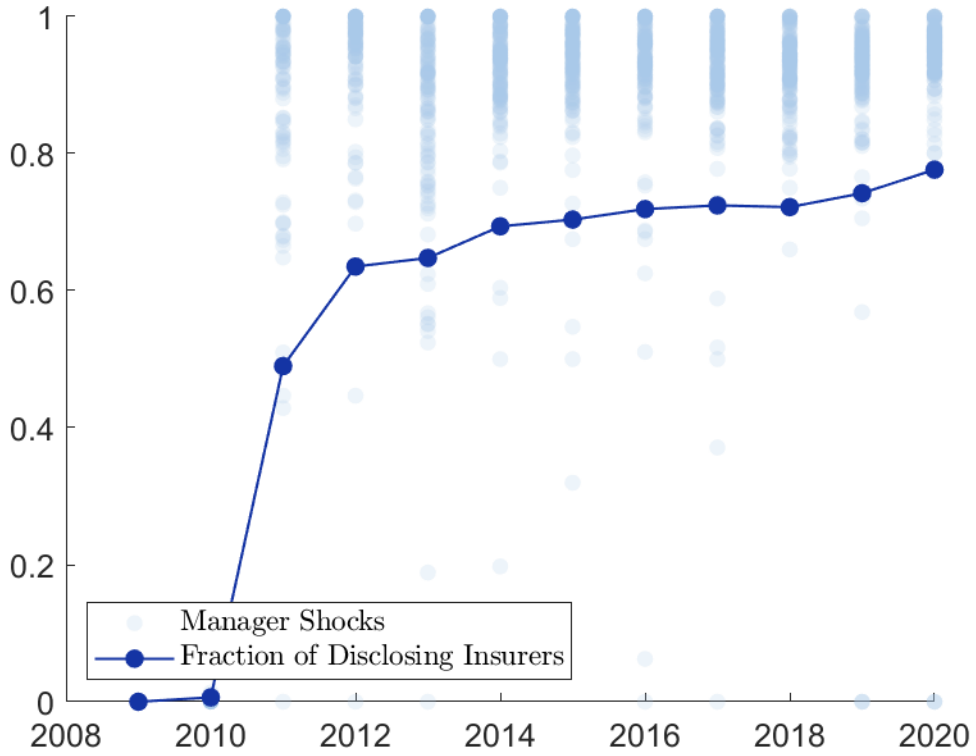


(a) Time Series of Relationships

(b) Histogram of Relationship Insurers

Notes: The figure plots the time series of manager-insurer relationships (panel a) and the histogram of relationships (panel b).

Figure A5: Distribution of Manager Shocks.

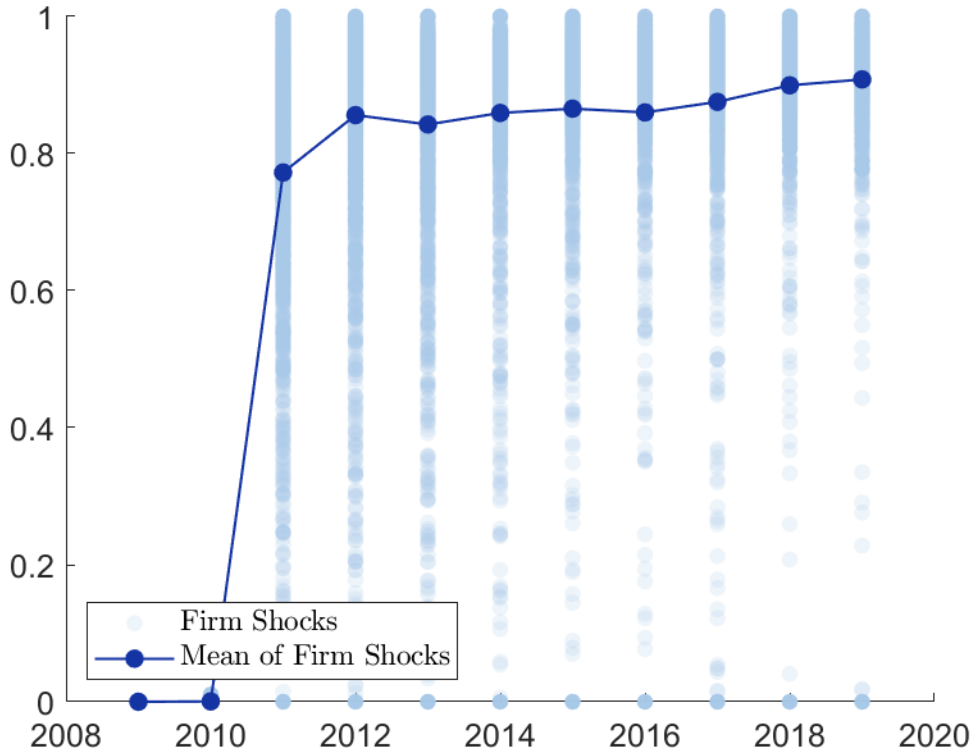


Notes: The figure above shows the average distribution over time of the manager level exposure to insurer disclosure shocks $\lambda_{m,t}$, as shown in equation (10), reproduced below:

$$\lambda_{m,t} = \sum_{i \in \mathcal{I}} \frac{\mathcal{R}^5_{i,m,t}}{\sum_{i \in \mathcal{I}} \mathcal{R}^5_{i,m,t}} \times D_{i,t},$$

where $\mathcal{R}_{i,m,t}$ is the stickiness of the manager-insurer relationship, for insurer i in year t with manager m as defined in equation 8, and $D_{i,t}$ is a dummy which equals one if the first disclosure year of insurer i is $\tau \leq t$. Insurance holdings data comes from NAIC schedule D, disclosure dates come from the published NAIC climate surveys, and CLO data comes from Acuris Creditflux. Sample period runs from 2001 to 2020.

Figure A6: Distribution of Firm Level Shocks.



Notes: The figure above shows the average distribution over time of the firm level exposure to insurer disclosure shocks θ_{jt}, as shown in equation (14), reproduced below:

$$\theta_{jt} = \sum_{m \in \mathcal{M}} \frac{\mathcal{R}^5_{m,j,t}}{\sum_{m \in \mathcal{M}} \mathcal{R}^5_{m,j,t}} \times \lambda_{m,t}$$

where $\mathcal{R}^5_{m,j,t}$ represents the affinity of manager m to pick firm j in year t as defined in equation (12), and $\lambda_{m,t}$ is the manager shock defined in equation (10). Insurance holdings data comes from NAIC schedule D, disclosure dates come from the published NAIC climate surveys, and CLO data comes from Acuris Creditflux. Sample period runs from 2001 to 2020.

Table A1: Climate News and CLO Fund Portfolios

	Fund Holdings in $ '0,000s	Log (1 + $) Holdings
	(1)	(2)
$CC_{j,t-1}$	-1.315***	-0.134***
	(0.199)	(0.011)
Obs	1,099,346	1,099,346
R^2	0.64	0.55
$\overline{y}$	101	6.99
Fund-Firm FE	Yes	Yes
Fund-Year FE	Yes	Yes

Notes: This table reports the results of the specification

$$h_{fjt} = \alpha_{ft} + \alpha_{fj} + \pi CC_{jt-1} + \gamma h_{f,j,t-1} + \varepsilon_{fjt}$$

where the dependent variable $h_{i,f,t}$ is the fund i's holdings of firm f for year t. In columns (1) and (3) the dependent variable h_{ift} is expressed in the units of \$10,000, while in columns (2) and (4), the dependent variable is $\log(1+\$)$. In columns (1) and (2) is the CC measures the total climate exposure measure, while in columns (3) and (4), we use the firm level climate sentiment as the key explanatory variable. α_{if} and α_{it} denote fund-firm and fund-year fixed effects respectively. Standard errors, clustered at the fund level, are reported in the parentheses. Insurance holdings data comes from NAIC schedule D, disclosure dates come from the published NAIC climate surveys, CLO data comes from Acuris Creditflux, and climate sentiment measures come from Sautner et al. (2023). Sample period runs from 2001 to 2020.

Table A2: Yields Offered by Corporate Bonds and CLO Securities

	All Securities			Except AAA
	(1)	(2)	(3)	(4)
CLO Tranche Dummy	0.569***	0.744***	0.888***	0.959***
	(0.060)	(0.037)	(0.041)	(0.038)
Obs	4686542	4686257	4686257	4594410
R^2	0.56	0.67	0.68	0.68
$\overline{y}$	4.73	4.73	4.73	4.76
Insurer FE	Yes	Yes	Yes	Yes
Rating-Year FE	Yes			
Maturity-Rating-Year FE		Yes	Yes	Yes
Bond Controls			Yes	Yes

Notes: This table reports the results of the specification

$$y_{ist} = \delta_{rt} + \beta \text{CLO Tranche Dummy}_s + \Gamma \mathbf{X}_{st} + \varepsilon_{ist}$$

where the dependent variable y_{ist} is the effective yield offered by security s held by insurer i at time t. The securities s held by insurers are of primarily two types : corporate bonds, and CLO tranches. The key independent variable CLO Tranche Dummy$_s$ assumes a value one if the security is a CLO tranche, and zero if it is a corporate bond. We collect yield and maturity data for all securities directly from the NAIC Schedule-D Part-1 files. We collect rating time series on corporate bonds from the Mergent Fixed Income database, and rating information on CLO tranches from the Creditflux CLO database. Control variables included in the vector $\mathbf{X}$ include the outstanding dollar amount of the security s at time t. We also include security rating-year fixed effects δ_{rt} in column (1), and a stronger maturity-rating-year fixed effect δ_{rmt} in columns (2) - (4). In columns (1) - (3), we focus on all securities held by insurers over the period 2001-2020, while in column (4) we exclude the AAA-rated securities.

Table A3: Effect of Climate Sentiment on New Bond Issuances

	Prob. Bond Issuance	Bond Coupon		
	(1)	(2)	(3)	(4)
$CC_{j,t-1}$	0.001	-0.078***	-0.065***	-0.066***
	(0.004)	(0.024)	(0.022)	(0.020)
Obs	38,553	10,790	8,921	7,956
R^2	0.32	0.70	0.72	0.72
$\overline{y}$	.3	4.96	5.04	4.97
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Bond Controls			Yes	Yes
Firm Controls				Yes

Notes: This table reports the results of the specification

$$y_{jt} = \alpha_j + \alpha_{rmt} + \pi \text{CC}_{j,t-1} + \Gamma \mathbf{X}_j + \varepsilon_{jt}$$

where the dependent variable y_{jt} is an outcome variable related to the bond issuance of firm j at time t. In column (1), we use an indicator variable which assumes a value one if the firm j issued a bond at time t, and zero otherwise. In columns (2) - (4), we use the coupon on the new bond issued, conditional on issuance, as the dependent variable. The key independent variable is the climate sentiment $\text{CC}_{j,t-1}$ of firm j in year $(t-1)$. We control for firm fixed effects α_j, and year fixed effects in columns (1) and (2). In columns (3) and (4), we employ a more stringent maturity rating year fixed effect α_{rmt}. We collect rating time series on corporate bonds from the Mergent Fixed Income database, and the first available rating of the bond as our rating measure. Control variables included in the vector $\mathbf{X}$ include control dummies for whether the bond was issued through a private 144A placement, and whether the bond is backed by an asset. Firm level controls also include the natural logarithm of total assets, Tobin's Q, return on assets, market leverage, and cash over assets. Standard errors are clustered at firm level, and reported in parentheses. Insurance holdings data comes from NAIC schedule D, disclosure dates come from the published NAIC climate surveys, CLO data comes from Acuris Creditflux, and climate sentiment measures come from Sautner et al. (2023). Sample period runs from 2001 to 2020.

Table A4: Effect of Climate Sentiment on New Leveraged Loan Issuances

	Prob. Loan Issuance	Loan Spread		
	(1)	(2)	(3)	(4)
$CC_{j,t-1}$	0.018	-2.108	-2.919	0.306
	(0.039)	(3.242)	(3.263)	(3.155)
Obs	20,948	5,442	5,374	4,372
R^2		0.60	0.60	0.60
$\overline{y}$	.19	302.81	302.39	293.11
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Loan Controls			Yes	Yes
Firm Controls				Yes

Notes: This table reports the results of the specification

$$y_{jt} = \alpha_j + \alpha_{mt} + \pi \text{CC}_{j,t-1} + \Gamma \mathbf{X}_j + \varepsilon_{jt}$$

where the dependent variable y_{jt} is an outcome variable related to the leveraged loan issuance of firm j at time t. In column (1), we use an indicator variable which assumes a value one if the firm j issued a leveraged loan at time t, and zero otherwise. In columns (2) - (4), we use the all-in-drawn spread (AISD) on the new loan issued, conditional on issuance, as the dependent variable. The key independent variable is the climate sentiment $\text{CC}_{j,t-1}$ of firm j in year $(t-1)$. We control for firm fixed effects α_j, and year fixed effects in columns (1) and (2). In columns (3) and (4), we employ a more stringent maturity-year fixed effect α_{mt}. Control variables included in the vector $\mathbf{X}$ include loan size, the natural logarithm of total assets, Tobin's Q, return on assets, market leverage, and cash over assets. Standard errors are clustered at firm level, and reported in parentheses. Insurance holdings data comes from NAIC schedule D, disclosure dates come from the published NAIC climate surveys, CLO data comes from Acuris Creditflux, and climate sentiment measures come from Sautner et al. (2023). Sample period runs from 2001 to 2020.

Table A5: Robustness : Disclosures and Insurers' CLO Investments

	Prob of Investment	Investment in $ 10 millions	Tranche Purchase	Prob of Investment	Investment in $ 10 millions	Tranche Purchase
Control Group	Never Disclosed			Not-yet Disclosed		
	(1)	(2)	(3)	(4)	(5)	(6)
	Panel A : All Insurers					
ATT	0.174***	0.926***	1.859***	0.162***	0.900***	1.833***
	(0.015)	(0.072)	(0.116)	(0.013)	(0.067)	(0.116)
	Panel B : Removing Size-Based Disclosing Insurers (i.e. excl 2010-2012)					
Control Group	Never Disclosed			Not-yet Disclosed		
	(1)	(2)	(3)	(4)	(5)	(6)
ATT	0.209***	0.379***	0.753***	0.201***	0.360***	0.731***
	(0.018)	(0.066)	(0.104)	(0.018)	(0.060)	(0.103)

Notes: This table reports the results of the specification

$$y_{it} = \alpha_i + \alpha_t + \beta \mathbf{1}(\text{Treated})_{it} + X_{it} + \varepsilon_{it}$$

In column (1) we use an investment dummy as a dependent variable which assumes a value one if the insurer i invests in a CLO tranche in year t. In column (2) we use the actual dollar value of CLO investments by insurance companies. Finally in column (3) reports the dollar value of the tranches newly acquired by the insurance company in year t. The key explanatory variable, Treated_{it}, is an indicator variable which takes the value one for years t after the insurer's first disclosure date. We also include insurer fixed effects α_i, year-fixed-effects α_t. Since treatment dates are dispersed over time, we account for heterogeneous treatment effects by using the Callaway and Sant'Anna (2021) estimators. In the first three columns, we use the insurers who never disclosed as the control group, while in columns (4) - (6), we use the insurance companies who disclosed later as the control group. In Panel B, we repeat the analysis after excluding the insurance companies who started reporting during the period 2010 - 2012. Since these cutoff rules are based on size, the disclosing companies are larger compared to the ones who don't. Insurance holdings data comes from NAIC schedule D, disclosure dates come from the published NAIC climate surveys, CLO data comes from Acuris Creditflux, and climate sentiment measures come from Sautner et al. (2023). Sample period runs from 2001 to 2020.

Table A6: Manager Shocks and Fund Climate Sentiment

	Fund Climate Exposure		
	(1)	(2)	(3)
Manager Shock $\lambda_{m,t-1}$	-0.023***	-0.022***	-0.019***
	(0.003)	(0.003)	(0.003)
Obs	702,727	685,851	682,878
R^2	0.81	0.81	0.81
$\overline{y}$	.27	.27	.27
Year FE	Yes	Yes	Yes
Manager-Firm FE	Yes	Yes	Yes
Rating FE	No	Yes	Yes

Notes: This table reports the results of the specification

$$CC_{ift} = \alpha_{im} + \alpha_t + \beta\lambda_{m,\tau-1} + X_{it} + \varepsilon_{ift}$$

where the dependent variable CC_{ift} is the climate sentiment of firm i belonging to fund f at time t. The fund f is launched by manager m at time τ. The key independent variable is the manager m's shock $\lambda_{m,\tau-1}$ for the year before the fund launch, $(\tau - 1)$. In columns (2) and (3) we also include firm-rating fixed effects. Additional controls included in the regression reported in column (3) include natural logarithm of fund balance, and firm yield. Standard errors are clustered at fund level, and reported in parentheses. Insurance holdings and RBC data come from the NAIC, disclosure dates come from the published NAIC climate surveys, and climate sentiment measures come from Sautner et al. (2023). Sample period runs from 2001 to 2020.

Table A7: Climate Disclosure and Insurer Supply by State

	Dummy=100 if Insurer Drops from State				
	(1)	(2)	(3)	(4)	(5)
Disclosure Dummy	0.047***	0.033***	-0.253***		-0.360***
	(0.010)	(0.010)	(0.054)		(0.094)
Low Premium Dummy		-0.729***	-2.242***	-2.203***	-2.276***
		(0.018)	(0.042)	(0.042)	(0.044)
Disclosure × Low Premium		0.207***	0.807***		0.774***
		(0.033)	(0.064)		(0.097)
New Disclosure Dummy				-0.308***	
				(0.086)	
New Disclosure × Low Premium				0.578***	
				(0.099)	
Lagged Disclosure					0.133
					(0.102)
Lagged Disclosure × Low Premium					0.085
					(0.107)
Total Premiums(mil USD)			0.864***	0.849***	0.884***
			(0.109)	(0.108)	(0.111)
Log Total Premiums(000s)			-0.312***	-0.312***	-0.316***
			(0.007)	(0.007)	(0.008)
Obs	10,859,022	10,859,022	1,565,755	1,565,755	1,533,161
R^2	0.043	0.043	0.064	0.064	0.066
$\overline{y}$	0.455	0.455	0.960	0.960	0.960
Insurer-State Fixed Effects	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes

Notes: This table reports the results of the specification

$$\text{Drop}_{ist} = \alpha_{is} + \alpha_t + \gamma_1 \text{Disclosure}_{st} + \gamma_2 \text{Low Premium}_{ist} + \gamma_3 \text{Disclosure x Low Premium}_{ist} + \gamma_4 X_{ist} + \varepsilon_{ist}$$

where the dependent variable $Drop_{ist}$ is equal to one if an insurer i is no longer actively selling in state s at time t, but it was actively selling in this state in the previous year. Independent variables include "Disclosure," a dummy equal to one if the state s had a disclosure requirement in year t; "Low Premium," a dummy equal to one if insurer i collected fewer than one million USD in total premiums in state s and year t (ie less than the approximate median amount of premiums); and the interaction of these two dummies, which measures if insurers respond differently when they are asked to disclose in a state where they do not do a lot of business. X_{ist} represents additional controls: total premiums collected in the state and log total premiums. Column 4 replaces the disclosure dummy with a dummy equal to one only if it is the first year that state s adopted a climate disclosure rule. Finally, column 5 adds a lagged disclosure variable to test if it took more than a year for insurers to react to disclosure rules. Insurance premiums data comes from NAIC schedule D and disclosure dates come from the published NAIC climate surveys. Standard errors are clustered at the insurer and state level, and reported in parentheses. Sample period runs from 1996 to 2022.

Table A8: Firm Shock and Polluting Activities

	News	Sharp News	Pollution (Weighted by)			Impact (Weighted by)		
			Raw	Severity	Reach	Raw	Severity	Reach
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Firm Shock $\theta_{j,t-1}$	2.341**	2.032***	3.500**	4.944**	5.946***	4.572**	6.309*	7.974**
	(1.005)	(0.777)	(1.390)	(2.144)	(2.136)	(2.281)	(3.815)	(3.362)
Obs	2,595	2,595	2,595	2,595	2,595	2,595	2,595	2,595
R^2	0.02	0.02	0.03	0.03	0.03	0.02	0.02	0.02
$\overline{y}$	5.91	4.51	8.55	12.68	13.32	12.87	19.89	19.53
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table reports the estimates from the following specification:

$$y_{j,t\to t+4} = \alpha_j + \alpha_t + \pi\theta_{j,t-1} + \epsilon_{jt},$$

where the dependent variable $y_{j,t\to t+4}$ is the relevant environmental impact of firm j over the period $[t, t+4]$. In column (1) the key dependent variable is the number of negative news incidents involving the firm over the interval as reported by Reprisk. However, in some incidents covering multiple firms, it is difficult to assign responsibilities. Reprisk terms them unsharp incidents. In column (2) we remove all such cases, and focus only on the news generated by the firm as a standalone entity. In columns (3) - (5), we focus on the pollution incidents. The key corresponding incidents reported by Reprisk are : "climate GHG pollution" "local pollution", "waste issues", "airborne pollutants", "forest burning", "greenhouse gas emissions", and "wastewater management". Each incident is further categorized into 3 "severity" and 3 "reach" levels. In column (3) we focus on the raw pollution variable, while in columns (4) and (5), we weight them according to their severity and reach respectively. Finally in the last 3 columns, we focus on the environmental impact of these polluting incidents. The corresponding Reprisk variables we focus on here are : "impacts on communities", "impacts on landscapes", "health environment issues", "violation of international standards", "violation of national legislation", "waste issues", "economic impact", "health impact", and "water scarcity". We again report the raw numbers, as well as numbers weighted by their severity and reach. The key explanatory variable is the firm shock $\theta_{j,t-1}$ as defined in equation (14). We include year fixed effects. Standard errors, clustered at the firm level, are reported in the parentheses.

Table A9: Robustness : Measuring Risk using Climate Exposures instead of Sentiment

	Holdings in USD '0,000s		Log(1 + Dollar Amount)	
	(1)	(2)	(3)	(4)
$CC_{j,t-1} \times Disclosing_{i,t} \times Indirect_{i,j,t}$	-0.388***	-0.308***	-0.029***	-0.012***
	(0.070)	(0.073)	(0.003)	(0.003)
$CC_{j,t-1} \times Disclosing_{i,t}$	0.125**	0.081	0.009***	0.003
	(0.061)	(0.058)	(0.002)	(0.002)
$CC_{j,t-1} \times Indirect_{i,j,t}$	-0.619***	-0.766***	-0.056***	-0.060***
	(0.059)	(0.086)	(0.002)	(0.003)
$Indirect_{i,j,t} \times Disclosing_{i,t}$	-10.870***	-10.157***	0.249***	0.078
	(1.118)	(1.115)	(0.053)	(0.050)
$Indirect_{i,j,t}$	-26.435***	-27.185***	-0.716***	-0.639***
	(1.176)	(1.161)	(0.048)	(0.047)
$CC_{j,t-1}$	0.459***		0.035***	
	(0.040)		(0.002)	
Obs	14,016,570	14,015,527	14,016,570	14,015,527
R^2	0.71	0.73	0.58	0.64
$\overline{y}$	38.58	38.58	3.23	3.23
Insurer-Firm FE	Yes	Yes	Yes	Yes
Insurer-Year FE	Yes	Yes	Yes	Yes
Firm-Year FE	No	Yes	No	Yes
Test1	-0.161***	-0.766***	-0.021***	-0.060***
SE1	(.035)	(.086)	(.002)	(.003)
Test2	-0.424***	-0.994***	-0.041***	-0.069***
SE2	(.045)	(.094)	(.002)	(.004)

Notes: This table replicates our main specification, Table 3 in the main paper, but replaces the signed measure of Climate Sentiment with a Climate Exposure measure instead Sautner et al. (2023). More specifically, this table reports the results of the specification

$$\begin{aligned} h_{ijt} = \alpha_{it} + \alpha_{ij} + \beta CC_{j,t-1} + \gamma \text{Indirect}_{i,j,t} + \delta CC_{j,t-1} \times \text{Indirect}_{i,j,t} \\ + \beta_2 CC_{j,t-1} \times \text{Disclosing}_{i,t-1} + \gamma_2 \text{Indirect}_{i,j,t} \times \text{Disclosing}_{i,t-1} \\ + \pi CC_{f,t-1} \times \text{Indirect}_{i,j,t} \times \text{Disclosing}_{i,t-1} + \xi h_{i,j,t-1} + \varepsilon_{ijt} \end{aligned}$$

where the dependent variable $h_{i,f,t}$ is the insurer i's holding of firm f for year t. In columns (1) and (3) the dependent variable h_{ift} is expressed in the units of \$10,000, while in columns (2) and (4), the dependent variable is $\log(1 + \$)$. CC is the key explanatory variable and measures the firm-level climate exposure. We differentiate between the direct and indirect (held though the CLO) holdings of the same firm by insurer i using the indicator variable $\text{CLO}_{i,f,t}$ which assumes the value one if the firm f is held indirectly through the CLO funds at time t, and zero otherwise (for directly held firms). α_{if} and α_{it} denote insurer-firm and insurer-year fixed effects respectively. We cluster the standard errors at the insurer level, and reported in the parentheses. Finally, we report the results of two F-tests,

$$\begin{aligned} &\text{Test}_1 : CC_{j,t-1} + CC_{j,t-1} \times \text{Indirect}_{i,j,t} \\ &\text{Test}_2 : CC_{j,t-1} + CC_{j,t-1} \times \text{Indirect}_{i,j,t} + CC_{j,t-1} \times \text{Disclosing}_{i,t-1} + \\ &\qquad \text{Indirect}_{i,j,t} \times \text{Disclosing}_{j,t-1} + CC_{j,t-1} \times \text{Indirect}_{i,j,t}\text{Disclosing}_{i,t-1} \end{aligned}$$

along with their standard errors. Insurance holdings data comes from NAIC schedule D, disclosure dates come from the published NAIC climate surveys, CLO data comes from Acuris Creditflux, and climate sentiment measures come from Sautner et al. (2023). Sample period runs from 2009 to 2020.