The Effect of Climate Regulatory Actions on Credit Allocation: Evidence from the Insurance Industry*

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This version: January 2026

Abstract

We study how climate-change-related regulatory actions affect credit allocation. We use the National Association of Insurance Commissioners (NAIC) Climate Risk Disclosure Survey, which mandates selected insurers to report their climate risk management practices, as a natural experiment. Insurers subject to the disclosure mandate significantly tilt their portfolios away from high-climate-risk corporate bonds. High-climate-risk bonds disproportionately held by mandated insurers experience significant negative returns. The portfolio reallocation is stronger for insurers whose revenues rely more on underwriting than on investment income, a pattern more consistent with regulatory pressure than with updated risk assessment as the primary mechanism. Our results suggest that even soft regulation in the form of disclosure requirements can reshape the portfolio allocation of insurance companies—the largest institutional holders of corporate bonds—and the pricing of corporate credit.

Keywords: Climate change; transition risk; regulation; credit allocation; insurance companies
JEL Codes: G11, G22, G23, G28, Q54

*We thank Monica Barbosa, Scott Frame, Stephen Karolyi (discussant), Mark Jansen (discussant), Kyeonghee Kim, Anil Kumar, Ralf Meisenzahl, Xiao Joyce Lin, Philip Mulder (discussant), Nora Pankratz (discussant), Ahyan Panjwani, Alessio Saretto, Yichen Su, Yi Zhou (discussant) and participants at the ASSA meetings, Federal Reserve System Climate meeting, Federal Reserve Bank of Dallas, Federal Reserve Day Ahead Conference on Financial Institutions, Midwest Finance Associations, and Vietnam Symposium in Banking and Finance for useful discussions. We also thank Rabab Charafeddine, Nina Chen, and Harriette Resnick for providing valuable information on the NAIC Climate Risk Disclosure Survey. The views expressed herein are those of the authors and do not indicate concurrence by the Federal Reserve Bank of Dallas, the principals of the Board of Governors, or the Federal Reserve System. Contact for Ali Ozdagli: Research Department, Federal Reserve Bank of Dallas, ali.ozdagli@dal.frb.org; Victor Wei: Department of Economics, Cornell University, vzw2@cornell.edu.

1 Introduction

A recent report from the Council of Economic Advisers (Boushey et al., 2021) emphasizes that the risks of climate change can be divided into two categories, physical and transition risks: "The physical risks are risks resulting from climatic events, such as wildfires, storms, and floods, whereas transition risks result from policy action taken to transition the economy off of fossil fuels." Transition risk is particularly relevant for financial institutions' investment portfolios, not least because of regulatory pressure to invest in greener industries. The report motivates such regulatory pressure by arguing that "private market actors—including many financial institutions—do not internalize the negative externalities tied to the risks of climate change that are associated with their credit allocation decisions. These decisions include the over-provision of credit to certain activities that exacerbate climate change risks." Therefore, policymakers and financial institutions, as well as other investors and borrowers, need to understand how regulatory actions affect these institutions' credit portfolios. We study this question and its pricing implications for the overall credit market.

Though climate-related regulation is still in its early stages, regulators have ramped up their efforts to identify climate risks through disclosure requirements.[1] In the insurance sector, concern about limited information on climate-risk management led the Federal Insurance Office (FIO) in 2021 to issue a request for information on how to better assess and regulate climate risk in the industry.[2] In contrast, academic research on insurers has so far focused primarily on quantifying their exposure to physical climate risk (e.g., Jung et al., 2023), with

[1] In 2012, the United Kingdom (U.K.) announced a new law that would require publicly listed firms to disclose their greenhouse gas (GHG) emissions. More recently, in the United States, the Securities and Exchange Commission (SEC) proposed a mandate that would require disclosures of climate-related risks and metrics, like a firm's greenhouse gas (GHG) emissions levels. See https://www.sec.gov/news/press-release/2022-46. Moreover, the Federal Reserve has joined the Network for Greening Financial Services, a consortium of central banks and other regulators working on climate scenarios, and announced its own climate scenario analysis.

[2] See https://www.federalregister.gov/documents/2021/08/31/2021-18713/federal-insurance-office-request-for-information-on-the-insurance-sector-and-climate-related.

relatively little attention to regulatory transition risk, even though recent work emphasizes that both physical and transition risks are key components of institutional investors' climate risk exposures (Jung et al., 2024).[3]

We bridge this gap by studying the effect of regulatory climate-change-related disclosure on the corporate bond portfolio of insurance companies, the largest institutional holders of corporate bonds. We use the National Association of Insurance Commissioners (NAIC) Climate Risk Disclosure Survey, which mandates selected insurers to report their climate risk management practices, as a natural experiment. We find that mandated insurers' portfolio share of high-climate-risk corporate bonds decreases by 0.79 percentage points in one year and an additional 1.16 percentage points in the second year, eventually reaching a cumulative reduction of 4 percentage points in seven years after being mandated to participate in the survey.[4]

While our results may appear quantitatively modest relative to the fraction of high-climate-risk bonds in the insurers' total corporate bond portfolio (21%), they represent a large share of insurers' overall climate-related corporate bond investment activity. Indeed, insurance companies, on average, actually increased their high-climate-risk bond holdings by 0.2 percentage points per year during our sample period. Our results suggest that climate regulatory actions, even as simple as mandated disclosure, can impact credit allocation by affecting the investors' portfolio choice.

Our results remain robust when analyzing the life insurance and the property and ca-

[3]At the firm level, Pankratz, Bauer, and Derwall (2023) show that climate shocks and exposure significantly affect operating performance and investor expectations, while Pankratz and Schiller (2024) document how firms adapt to climate risk along global supply chains; we instead focus on how a regulatory climate-risk disclosure intervention reshapes institutional credit portfolios.

[4]High-climate-risk corporate bonds are bonds issued by firms in sectors identified as particularly exposed to climate policy, emissions intensity, or physical climate risk (e.g., fossil fuels, heavy industry, transportation, and agriculture). We use existing industry-based classifications rather than firm-level scores because, unlike industry-based classifications, various firm-level scores have little correlation with each other (Berg et al. 2022).

sualty (P&C) insurance industries separately. These results are also robust to alternative identification strategies, including (i) the dynamic two-way fixed effects approach discussed in Sun and Abraham (2021), (ii) restricting the treatment sample to firms that have been mandated in 2012 and the control sample to never-treated firms (Baker et al. 2022) and (iii) focusing on firms in a window around the mandating threshold in a regression discontinuity design. Moreover, while we classify high-climate-risk bonds using the U.S. Commodity Futures Trading Commission (CFTC) industry classification, which is an objective external U.S.-based classification consistent with earlier public and private sector reports, we obtain similar results when employing an alternative classification widely used by European regulators (Battiston et al. 2017).[5] Finally, our results are not driven by the boom-bust cycle in oil prices in 2010s as the results remain strong after excluding coal, oil and gas industries from the sample.

Turning to spillovers to the broader corporate bond market, we find that high-climate-risk bonds more widely held by mandated insurers experience larger cumulative return declines following the mandate. Quantitatively, a high-climate-risk bond held exclusively by mandated insurers exhibits roughly 3 percentage points lower cumulative returns than a comparable bond not held by these insurers. This effect is both economically and statistically significant, indicating that the mandate-induced reallocation of insurers' portfolios has measurable consequences for borrowers' cost of capital.

Our findings indicate that insurance companies adjust their portfolios in response to climate change disclosure mandates, despite lacking legal repercussions for disregarding climate risks. This adjustment can be explained through two mechanisms: regulatory pressure/anticipation and risk (re)assessment. Under the regulatory pressure channel, insurers

[5]While relatively new, the CFTC list is in line with earlier governmental reports on greenhouse gas emissions (Truitt, 2008, from EPA) and climate change disaster risk (Lavell et al., 2012, from IPCC) as well as private sector reports (PWC 2010, Climate Disclosure Project), which were circulating around before widespread adoption of NAIC disclosure survey in early 2010s.

may voluntarily adjust their portfolios to maintain a good relationship with the regulators or to minimize disruptions from anticipated future regulations. Under the risk assessment channel, disclosure mandates may prompt insurers to conduct a more comprehensive assessment of their climate-related risks and thereby modify their portfolios to mitigate such risks.

To better understand the mechanism underlying our results, we examine insurers' reliance on insurance premiums versus investment income. Under the regulatory pressure channel, insurers that rely more on insurance premiums may adjust their portfolios more after the mandate because their ability to generate premiums depends directly on remaining in good standing with regulators. Under the risk-assessment channel, insurers that rely more on investment income may be more inclined to conduct climate risk assessments to avoid potential investment losses and adjust their portfolios accordingly. We find that the mandates have a stronger effect among insurers that are more reliant on insurance premiums. While the two channels are certainly not mutually exclusive, this evidence is more consistent with the regulatory pressure channel. This finding also aligns with the notion that "disclosure is widely recognized as a soft form of regulation, incentivizing changes in corporate behavior" (Harper Ho, 2020).

Related Literature — Our work contributes to the emerging literature on how investors incorporate climate-related information into their portfolios. More specifically, there have been multiple studies that investigate the portfolio management of institutional investors around natural disasters (Massa and Zhang 2021, Liu 2018, Huynh and Xia 2023). There have also been studies that examine how firms manage their portfolio following climate policy shocks (Ramelli et al., 2021), and self commitment to responsible investing (Gibson et al. 2022, Meisenzahl 2023). We differ from studies of investor self-commitments and ESG pledges by exploiting a regulatory shock, rather than voluntary initiatives, to identify the impact of climate risk disclosure on institutional investment decisions.

Our work also contributes to the literature on the impact of mandatory climate disclosure. Much of the current literature studies the effect of disclosures on publicly traded firms, while our study focuses on institutional investors. Krueger (2015) studies the effect of a U.K. law that mandates publicly traded firms to disclose their greenhouse gas (GHG) emissions, and finds that firms that are heavily affected by the new regulation experience significant positive valuation effects. Utilizing the same U.K. law, Jouvenot and Krueger (2019) find that firms reduce their GHG emissions by 16% following the new regulation that mandates carbon disclosure. Ilhan et al. (2023) show that investors demand climate risk disclosures and influence their portfolio firms for improvements.[6] Méssonier and Nguyen (2020) examine a French law that requires non-bank institutional investors to report their climate-related exposure and mitigation policy and found evidence that these investors lowered their financing of fossil energy companies compared to French banks and other institutional investors in the euro area. We complement this literature by (i) studying an investor-side disclosure requirement targeted at U.S. insurers—the largest institutional holders of corporate bonds—in a setting with a sharply defined variation across insurers that allows a very clean identification; (ii) showing how such regulation affects both portfolio allocation and the pricing of the corporate bonds insurers hold; (iii) considering a broad set of high-climate-risk sectors rather than fossil energy alone; and (iv) providing evidence on the mechanism underlying the portfolio reallocation by distinguishing between regulatory pressure and risk-assessment channels. As such, our work also complements Jha, Karolyi, and Muller (2025) that shows that environmental regulatory interventions can have first-order effects on municipal fixed-income markets.

Finally, our study contributes to the ongoing conversation about the evolution of climate risk regulation in the insurance industry. In 2008, the NAIC issued a report outlining how insurers could help mitigate and prevent losses from climate change, as well as how

[6]More broadly, Bird and Karolyi (2016) show that institutional investors place value on greater corporate transparency, suggesting that disclosure requirements can alter investors' information sets and trading behavior.

governments and the NAIC could regulate insurers with respect to climate risk (NAIC 2008). Since then, several consulting firms and public authorities have produced assessments of insurers' progress in managing climate risk. Messervy (2016) uses the NAIC Climate Risk Disclosure Survey to evaluate insurers' climate risk management practices and finds that only 16% of insurers receive a "high-quality" rating, while 64% receive "low-quality" or "minimal" ratings. Similarly, the New York Department of Financial Services (DFS) uses NAIC Climate Risk Survey responses to construct composite ratings of New York domestic insurers and concludes that most insurers are in the "making progress" category (New York DFS 2021b). The Geneva Association offers a holistic decision-making framework for P&C and life insurers and emphasizes that "the development of methodologies and tools that would produce meaningful and decision-useful information is a work in progress" (Golnaraghi 2021). In addition, the New York DFS (2021a) analyzes insurers' transition risk exposure using NAIC Schedule D data and finds that New York domestic insurers are meaningfully exposed to transition risk and that their portfolios are not aligned with the Paris Agreement. We move beyond these largely descriptive analyses of the NAIC Climate Risk Disclosure Survey by linking the survey mandate to causal changes in insurers' portfolio holdings and to spillovers in corporate bond prices.

Our paper continues with background information about the NAIC Climate Risk Disclosure Survey in the next section, followed by a discussion of our data, empirical strategy, and results.

2 Regulatory Background

The NAIC Climate Risk Disclosure Survey was first implemented by the California Department of Insurance (CDI) in 2010 to "provide regulators with a window into how insurers across all lines of insurance assess and manage risks related to climate change."[7] The

[7]Source: California Department of Insurance Website: http://www.insurance.ca.gov/0250-insurers/0300-insurers/0100-applications/ClimateSurvey/

survey is comprised of eight open-ended questions that cover a variety of topics regarding insurers' responses to climate change. Topics covered in the survey include climate risk management, mitigation of carbon emissions, and engagement with policyholders, with two questions specifically addressing the impact of climate change on the insurance company's investment portfolio and strategy (questions 5A and 5B). The full list of questions can be found in the appendix (See Table A1).

Moreover, insurance companies are mandated to file survey responses if they meet two requirements: They are licensed in a state that is participating in the survey, and they write more premiums nationally than the preset number the CDI employs. At its inception, the survey was only mandated for insurers who were licensed in California and wrote more than $500 million in premiums nationally. As the years have passed, the survey has expanded to multiple states, and the mandate requirement for national premiums has decreased. Table 1 shows the national premium and state mandate requirements for the NAIC Climate Risk Disclosure Survey throughout each reporting year.

[TABLE 1 HERE]

First, we clarify an important but potentially ambiguous naming convention of the survey. A regulator, such as the CDI, administers the climate risk survey to insurers in a specific year based on their financial numbers and licensing practices from the year prior. As a result, the CDI denotes the year of their surveys based on the year of financial information they use, and not when the survey was administered. For example, while the first survey was administered in 2010, the CDI titles the first survey as being from "Reporting Year 2009" on their online database. In our study, we remain consistent with the naming convention that the CDI uses.[8]

[8]For the rest of this paper, any mention of year when regarding the survey is referring to the reporting year, and not the year the survey was administered unless stated otherwise.

As mentioned earlier, the survey started in reporting year 2009 and was only mandated for companies licensed in California who wrote more than $500 million in premiums nationally. In reporting year 2010, the mandate requirement for national premiums dropped to $300 million, with California still being the only state to mandate the survey. In reporting year 2011, the number of states participating in the survey expanded to include New York and Washington, with the premium requirement remaining $300 million. In reporting year 2012, the number of states participating expanded again to include Connecticut and Minnesota, while the premium requirement dropped from $300 million to $100 million. In reporting year 2013, Illinois, Maryland and New Mexico participated in the survey, while the premium requirement remained at $100 million. Illinois and Maryland only participated in the survey in reporting year 2013, and left immediately after. Finally, from reporting year 2014 to reporting year 2019, California, Connecticut, Minnesota, New Mexico, New York and Washington participated in the survey, with the premium requirement remaining $100 million throughout.

[FIGURE 1 HERE]

While only six states participated in the survey in reporting year 2019, the percentage of insurers required to file a survey represents a large portion of the insurance industry. Figure 1a, left panel, presents the percentage of total premiums written by mandated U.S. life insurers relative to that of the entire U.S. life insurance market; Figure 1b, left panel, does the same for the P&C insurance market. We see in both the life and P&C markets, mandated insurers represent over 80% of the premiums written in their respective markets following 2012. However, the actual filers in 2009 and 2010 made up a very small percentage of the total written premiums in the insurance market (right panels in Figure 1). This is driven by the fact that not all mandated insurers actually responded to the survey.

[TABLE 2 HERE]

To illustrate this point more clearly, Table 2 presents the number of different types of filers throughout each reporting year. From the table, we see that from 2012 onward, more than 95% of insurers who were mandated to answer the survey did file responses to the survey.[9] In 2011, this number was around 71%, meaning that a large majority of mandated insurers did file. However, for 2009 and 2010, a very small number of mandated insurers actually responded to the survey, with the rate being lower than 3% for both years. Due to a lack of enforcement in 2009 and 2010, which led to an exceptionally low response rate in those years, we consider the survey voluntary for these years.[10] This means that, for our purposes, the survey does not become mandatory until 2011.

3 Data and Sample

3.1 Data

To perform our analysis, we utilize institutional investor data and bond characteristic data to determine the percentage of high-climate-risk bonds that an insurance company holds. First, we obtain end-of-year corporate bond holdings data, for life and P&C insurers, using NAIC Schedule D Part 1. We also use the demographic files from NAIC Schedule D to determine which state each insurer is domiciled in for each year. The state domiciled data is used in future analysis as part of an interacted fixed-effects term.

Next, we obtain corporate bond-level characteristics data from the Mergent Fixed Income Securities Database (FISD). We specifically look at the NAICS code of each corporate bond to determine whether a bond is in a sector that experiences high climate risk. We define a sector as high-climate-risk based on a report released by the U.S. Commodity Futures Trading Commission (CFTC) in 2020 (Martinez-Diaz and Keenan 2020).[11] The specific NAICS codes

[9] This percentage is equal to $Mandatory(Filed)/[Mandatory(Filed) + Mandatory(NotFiled)] * 100$ in Table 2.

[10] This initial lack of enforcement and increased participation in later years was confirmed by Rabab Charafeddine, climate risk specialist for the California Department of Insurance.

[11] Link to CFTC Report: https://www.cftc.gov/PressRoom/PressReleases/8234-20 (See Table 3.1).

that were matched with each high-climate-risk sectors defined by the CFTC can be found in the appendix of the paper (See Table A2). The high-climate-risk industries are sectors typically associated with fossil fuel production (e.g. coal, oil and gas), emissions/energy intensive (e.g. steel and transportation), or particularly susceptible to physical climate risks (e.g. agriculture, tourism, and infrastructure). We use an industry-based classification rather than firm-level scores because, unlike industry-based classifications, firm-level scores from different vendors have little correlation with each other (Berg et al. 2022).[12]

After combining the Mergent FISD data with the NAIC Schedule D data using bond identifiers (CUSIP), we use equation (1) to determine the percentage of high-climate-risk corporate bonds each insurance company is holding at the end of every year,

$$PercentageHighRisk_{i,t} = \left(\frac{\sum_{h=1}^{n} ParHighRiskBonds_{i,h,t}}{\sum_{j=1}^{n} ParAnyBond_{i,j,t}}\right) * 100. \quad (1)$$

$ParHighRiskBonds_{i,h,t}$ is the par value of a high-climate-risk bond h that insurer i holds in year t. $ParAnyBond_{i,j,t}$ is the par value of any bond j that insurer i holds in reporting year t. Equation (1) computes the ratio of the total par value of high-climate-risk corporate bonds held by insurer i in year t to the total par value of all corporate bonds held by insurer i in year t.[13] This term, multiplied by one hundred, calculates the $PercentageHighRisk_{i,t}$ variable, which we use to represent the percentage of high-climate-risk corporate bonds that insurer i holds in year t relative to their entire corporate bond portfolio.

After calculating the percentage of high-climate-risk bonds an insurer holds, we use the survey data hosted by CDI and the NAIC Schedule T data to determine whether an insurer

[12]While relatively new, the CFTC list is in line with earlier governmental reports on greenhouse gas emissions (Truitt, 2008, from EPA) and climate change disaster risk (Lavell et al, 2012, from IPCC) as well as private sector reports (PWC 2010, Climate Disclosure Project). Section 4.5 provides additional robustness analysis regarding industry classifications.

[13]We have done the same calculation using book-adjusted carrying value and fair value (instead of par value); results were similar.

was mandated to file a survey. The CDI database helps identify which insurers have filed responses to the survey, but does not specify whether they were mandated to do so. To make this distinction, we utilize NAIC Schedule T to find the annual amount of premiums written nationally for each insurer, as well as which states they are licensed in. Combining the CDI data with the NAIC Schedule T data allows us to determine which insurers were mandated to file survey responses, which insurers voluntarily filed responses, and whether an insurance company didn't file survey responses even though they were mandated to do so.

3.2 Sample

To create our regression sample, we apply some commonly used restrictions from previous literature. First, using data on net total assets and active status from the Assets Exhibit and Jurat Pages of the NAIC Insurance Regulatory Filing, we restrict our sample to mutual and stock insurance companies with positive net total assets and that are active during the reporting year.[14] We also use the data on insurers' net total assets to create a control variable, for our regressions, that serves as a proxy for firm size, which can impact the efficiency of the insurance companies' risk management operations.

Next, we drop any insurance company that holds zero high-climate-risk bonds in 2004, the first year of our sample. This allows us to minimize the censoring bias caused by the fact that insurance companies that do not hold any high-climate-risk bonds cannot reduce their holdings of these bonds any further. Finally, after applying these restrictions, we create a balanced panel from 2004 to 2019.

[14] We obtain the data for the Assets Exhibit and the Jurat Pages from the S&P Global's Insurance Statutory Financials Database.

4 Effect of Mandatory Disclosure: Empirical Results

4.1 Full Sample Regressions

We study the effect of mandatory climate disclosure on the high climate-risk bond holdings of life and P&C insurance companies. We estimate the following three fixed-effects linear regression models:

$$\begin{aligned} PercentageHighRisk_{i,t} =& \beta_0 + \beta_1 Mandatory_{i,t} + \beta_2 Mandatory_{i,t-1} + \beta_3 Mandatory_{i,t-2} \\ &+ FixedEffects + e_{i,t} \end{aligned} \tag{2}$$

$$\begin{aligned} PercentageHighRisk_{i,t} =& \beta_0 + \beta_1 Mandatory_{i,t} + \beta_2 Mandatory_{i,t-1} + \beta_3 Mandatory_{i,t-2} \\ &+ \beta_4 Voluntary_{i,t} + \beta_5 Voluntary_{i,t-1} + \beta_6 Voluntary_{i,t-2} \\ &+ FixedEffects + e_{i,t} \end{aligned} \tag{3}$$

$$\begin{aligned} PercentageHighRisk_{i,t} =& \beta_0 + \beta_1 Mandatory_{i,t} + \beta_2 Mandatory_{i,t-1} + \beta_3 Mandatory_{i,t-2} \\ &+ \beta_4 Voluntary_{i,t} + \beta_5 Voluntary_{i,t-1} + \beta_6 Voluntary_{i,t-2} \\ &+ \beta_7 FirmSize_{i,t} + FixedEffects + e_{i,t} \end{aligned} \tag{4}$$

where $PercentageHighRisk_{i,t}$ is the percentage of high-climate-risk corporate bonds that insurer i holds in year t, relative to their entire corporate bond portfolio. $Mandatory_{i,t}$ is an indicator variable that equals one if insurer i was mandated to take the survey for reporting year t, and zero otherwise. We also include the first and second lags of the $Mandatory_{i,t}$

variable because the effect may show up with a delay, not the least because the survey mandate for a given reporting year is administered in the following year.

Our second regression model builds upon equation (2) by adding a $Voluntary_{i,t}$ indicator variable that equals one if insurer i voluntarily filed survey responses for reporting year t, and zero otherwise. We also include the first and second lags of our $Voluntary_{i,t}$ variable in our second model.

Our final regression model is identical to equation (3), but with the addition of the $FirmSize_{i,t}$ control variable. We create the $FirmSize_{i,t}$ variable by taking the natural logarithm of the net total assets that insurer i holds in year t. We also extend this model by including a State Domiciled-Year interaction term as an additional fixed effect. Firms size may improve the ability of an insurer to manage its portfolio risk, e.g., by making it more cost effective, or hamper this ability, e.g. due to increased complexity. State Domicile may play a role by determining the insurance company's state regulator, which may play a role in their portfolio choice.

Table 3 presents our results when applying our models to the combined sample of life and P&C insurers. Columns 1-3 in the table utilize models 1-3, respectively, to perform our regression analysis. Column 4 in the table utilizes model 3, but substitutes Year fixed effects with a State Domiciled-Year interaction fixed effects term. For each fixed-effects regression, standard errors are multi-way clustered on insurance company and year.

When utilizing model 1 (column 1), we find that, on average, insurers who were mandated within the past two years lower their holdings of high-climate-risk corporate bonds by a significant amount. In particular, insurers who were mandated to file a survey for the previous year ($Mandatory_{i,t-1} = 1$) lowered their high-climate-risk corporate bond holdings by 0.63 percentage points. If an insurer was mandated to file a survey from two years ago ($Mandatory_{i,t-2} = 1$), then the percentage of holdings for high-climate-risk bonds decreased by another 1.30 percentage points in the second year. We do not find a significant

change in corporate bond holdings if an insurer was mandated to file for that reporting year ($Mandatory_{i,t} = 1$). This result is unsurprising, given the fact that the survey is administered the year following the reporting year (see Section 2 for more details on naming convention of the reporting year). These results, therefore, suggest that we see a continuing decline in high-climate risk bond holdings among mandated insurers after the survey is administered, but not leading up to its administration.[15]

[TABLE 3 HERE]

Columns 2-4 in Table 3 provide evidence that our results are robust, even when applying different models to our analysis. In model 2 (column 2), we see that after adding the $Voluntary_{i,t}$ indicator variable, along with its first and second lags, the negative relationship between mandated insurers and their holdings of high-climate-risk corporate bonds still holds. In model 3, our results still remain robust after controlling for firm size. Finally, even after adding in a State Domiciled-Year interaction fixed effects term into model 3 (column 4), we still see a significant negative relationship between insurers' mandated status in the past two reporting years and their holdings of high-climate-risk corporate bonds. Indeed, even after these controls, we find that insurers who were mandated to file a survey for the previous year lowered their high-climate-risk corporate bond holdings by 0.79 percentage points. If an insurer was mandated to file a survey for the penultimate reporting year, then the percentage of holdings for high-climate-risk bonds decreased by another 1.16 percentage points in the second year.

[TABLE 4 HERE]

To bolster our analysis, we perform the same analytical exercise on each type of insurer. Table 4 illustrates our results for the sub-sample of only life insurers and only P&C insurers

[15] Our alternative identification schemes with greater number of leads and lags confirm this argument.

respectively. Column one of the table utilizes model 3 on only life insurers. Column two utilizes model 3 again on only life insurers, but with the addition of a State Domiciled-Year interaction fixed effects term. Columns three and four in the table repeat the same analysis as the first two columns, except looking at the subset of only P&C insurers. For both types of insurers, we see that there is a significant negative relationship between insurers' high-climate-risk corporate bond holdings, and their mandated status within the last two reporting years. We also see, similar to the results in Table 3, that there is no significant change in corporate bond holdings if the insurer was mandated to file for that reporting year for both types of insurers. For life insurers (columns 1 and 2), we see that the effect of being mandated in the previous year on high-climate-risk holdings is negative and significant at the 1% level. Moreover, we see that the effect of being mandated two years ago on holdings remains negative and large in column 1. For P&C insurers (columns 3 and 4), we see that the effects of mandatory filing on P&C insurers' high-climate-risk bond holdings is more prominent for the second lag than for the first lag. We find for P&C insurers that the effect of being mandated two years ago on high-climate-risk bond holdings is negative and significant at the 1% level in column 3, and at the 10% level in column 4.

Overall these results suggest that the disclosure mandate has a significant impact on insurers' portfolios and the full impact may appear with a delay. Therefore, the rest of these sections study dynamic treatment effects using various robust frameworks.

4.2 Staggered Dynamic Difference-in-Difference

To study the dynamic effect of disclosure mandate in more detail, we start with the staggered difference-in-difference (DiD) model presented by Sun and Abraham (2021). In recent literature, there has been a pushback against DiD studies with dynamic heterogeneous treatment effects that use standard two-way fixed effects models (Callaway and Sant'Anna 2021; Sun and Abraham 2021). Therefore, we implement the estimator from Sun and Abraham (2021) to control for the potential biases that the two-way fixed effects model may induce

in a dynamic staggered DiD setting. Accordingly, we define the treatment group to be any insurer who gets mandated to file survey responses, and we define the initial treatment to be the first reporting year in which an insurer becomes mandated to file. Our control group is the "never treated" insurance companies, or in this case any insurer who is never mandated to participate in the survey. Moreover, we begin our regression sample in 2006, which is the year our regression sample in Table 3 starts because we use the second lag of the variable *Mandatory*. Using this setting, we estimate the dynamic effect of the mandated disclosure treatment.

$$PercentageHighRisk_{i,t} = \sum_{n=-5}^{n=-1} \beta_n D_{i,t}^n + \sum_{n=1}^{n=8} \beta_n D_{i,t}^n + \gamma(FirmSize_{i,t} \times Year_t) + FixedEffects + e_{i,t} \quad (5)$$

Equation (5) shows our regression specification for the Sun and Abraham estimator. The variable $D_{i,t}^n$ is an indicator variable that equals one if insurance company i is in the treatment group, and the current year t is n years since the first treatment. For example, if an insurance company was first treated in 2015, then $D_{i,t}^{-3}$ would equal one for year 2012. For never-treated insurance companies, $D_{i,t}^n = 0$ for all n and t. We also add in a Firm Size-Year fixed effects interaction term, where $FirmSize_{i,t}$ is natural logarithm of the net total assets of company i in year t. We also include insurance company and year fixed effects, and restrict our regression sample to be between RY 2006 and RY 2019 like in Tables 3 and 4. Standard errors are clustered at the insurance-company level, following Sun and Abraham (2021).

[FIGURE 2 HERE]

Figure 2 shows the results of this exercise. We find that leading up to the treatment,

there is no significant difference in high-climate-risk bond holdings compared to the control group. The period immediately following the treatment, we begin to see a difference in high-climate-risk bond holdings between the treatment group and the control group. This difference becomes statistically significant four years after the treatment, with the difference continuing to grow in magnitude and significance. Overall, Figure 2 confirms our previous results and shows that the magnitude of the cumulative effect of mandated disclosure reaches about 4 percentage points in seven years.

4.3 Non-Staggered Dynamic Difference-in-Difference

In addition to using the alternative estimator from Sun and Abraham (2021), we perform another robustness check by utilizing a standard two-way fixed effects regression on the subset of our sample without staggered treatment. More specifically, we study a sample where insurers are either never treated, or first treated in reporting year (RY) 2012. This specification allows us to simplify the control-treatment conditions to be binary: Either the insurer was never mandated to participate in the survey (control group), or the insurer was first mandated in RY 2012 (treatment group).[16] This binary treatment allows us to avoid the biased results caused by dynamic treatment effects, as discussed in Sun and Abraham (2021). Moreover, this method aids in solving potential identification issues of Sun and Abraham method because it does not require the assumption of no treatment variation across cohorts as we only have one cohort in the treatment group.[17]

We specifically use RY 2012 as our year of interest for multiple reasons. To begin with, the mandate requirements for the survey –both the premium and state participation portions–

[16]This method can also be seen as a form of a stacked DiD regression estimator, where we have a single treated stack for insurers treated in RY 2012. The methodology of stacked DiD analysis is discussed in Baker et al. (2022), and utilized in a study in 2019 discussing the effect of minimum wages on low-wag jobs (Cengiz et al. 2019).

[17]While this new approach benefits from fewer assumptions, it is disadvantaged by the fewer number of observations for the treatment group. Moreover, one can argue that its results may be considered more specific to the cohort of firms treated in RY 2012. Therefore, we think the different approaches are equally valuable, and find it encouraging that they lead to the same conclusion.

change very little following RY 2012. For the premium portion of the mandate, there is no change to the requirements following RY 2012 as the requirement drops from $300 million to $100 million in RY 2012 and does not change afterwards. Furthermore, the list of states participating in the survey has very little change post RY 2012, as the five participating states in RY 2012 continue to participate in the survey for the rest of our sample. There are 3 states that begin participating after RY 2012: New Mexico, Illinois and Maryland. While Illinois and Maryland join the survey in RY 2013, they immediately leave in the following year and represent a small portion of our sample. Similarly the number of insurers in our sample that are licensed in New Mexico but not in the 5 states participating in RY 2012 is very small. In our original sample, 261 companies became mandated for the first time in RY 2012. In comparison, only 30 companies were mandated for the first time after RY 2012 due to the addition of new participating states, with 28 of them belonging to Illinois or Maryland in RY 2013. As a result, studying first-treated insurers in RY 2012 allows us to utilize a DiD approach with standard two-way fixed effects, without worrying about the identification problem caused by staggered treatment as described in Sun and Abraham (2021).

Another advantage of using RY 2012 stems from the high response rate and large representation of the insurance industry: A large majority of the insurance market files the survey following RY 2012, especially those who were mandated to do so. As mentioned in Section 2, Table 2 shows that after RY 2012, at least 95% of insurers who are mandated to file the survey do so. In RY 2011, 71% who are mandated to file do so, and before that the response rate is below 3%. Moreover, the right panels of Figure 1A and 1B showcase that the premium-weighted portion of actual filers hits its peak at 2012, and remains near that level throughout the rest of our sample. As a result, using insurers who are first treated in RY 2012 as our treatment group enables us to analyze a large portion of the insurance market in a DiD setting without identification problems caused by staggered treatment.

Overall, this setting provides a clean, high-powered, big-adoption test with the insurers

first mandated in RY 2012 as the treatment group and the never-mandated insurers as the control group. Utilizing this new subset, we analyze the effect of the survey for periods leading up to and directly following the treatment. We perform a similar exercise to that of Figure 2, except instead of the Sun and Abraham estimator we use the canonical two-way fixed effect regression analysis.

$$PercentageHighRisk_{i,t} = \sum_{n=-6}^{n=-1} \beta_n D_{i,t}^n + \sum_{n=1}^{n=7} \beta_n D_{i,t}^n + \gamma(FirmSize_{i,t} \times Year_t) + FixedEffects + e_{i,t} \tag{6}$$

Equation (6) shows our regression specifications. Similar to equation (5), the variable $D_{i,t}^n$ is an indicator variable that equals one if insurance company i is in the treatment group, and the current year t is n years since the first treatment. For example, if we are looking at a company in the treatment group, then $D_{i,t}^3$ would equal one when $t = 2015$. We also add in a Firm Size-Year interaction term, where $FirmSize_{i,t}$ is natural logarithm of the net total assets of company i in year t. We also include insurance company and year fixed effects, and restrict our regression sample to be between RY 2006 and RY 2019 like in Tables 3 and 4.[18] Standard errors are clustered at the insurance-company level.

[FIGURE 3 HERE]

Figure 3 shows the result of this exercise. We see that before the treatment in 2012, there is no significant difference in high risk bond holdings. However, immediately following the treatment, we see a significant negative difference in holding compared to the never-treated (control) group. This difference remains consistently significant and negative, leading to

[18]Since the treatment starts in 2012 and we use data until 2019, we can only go 7 years instead of 9 years as in the analysis with Sun and Abraham method.

around a 3% cumulative effect within 7 years.

4.4 Regression Discontinuity Design Analysis

To further extend our analysis, we perform a regression discontinuity design (RDD) analysis by conducting an exercise similar to the one in Figure 3, but looking at insurers who were near the $100 million premium mandate.

[FIGURE 4 HERE]

We first use the density test as described in Cattaneo, Jansson and Ma (2020) to see if insurers near the $100 million threshold are manipulating the amount of premiums they write. We use this density test on the period of our sample where the policy was implemented (in this case 2012 onwards), and on the period before the implementation of the policy. Figures 4a and 4b show our results. We see that both for the pre-2012 period and the post-2012 period, our empirical results show no evidence of manipulation (p-value of 0.5341 and 0.4937 respectively).

[FIGURE 5 HERE]

Next, we perform an RDD analysis where we include any company that wrote between $50 Million and $200 Million in premiums nationally in RY 2012. This choice is driven by symmetry in logarithmic scale ($200/100 = 100/50$), while still allowing us reasonably comparable number of companies in treatment and control groups (129 and 195 respectively).[19] We use the regression specification from equation (6) for our analysis, with Figure 5 showing our results. We find again that there is no significant difference in holdings before the RY 2012 treatment. Following RY 2012 treatment, however, there is a significant decrease in

[19] As an alternative, we have also used the bandwidth of $40 million to $190 million, which is less symmetric in terms of logarithmic scale while more symmetric in terms of number of companies in treatment and control groups, 191 and 187 respectively. The results remain similar.

bond holdings for insurers right above the $100 million dollar threshold compared to insurers right below the threshold. This cumulative effect again remains negative and statistically significant, leading to around a 3% cumulative effect within 7 years. This is consistent with the results in Figure 3.

As another robustness check, we perform a similar RDD analysis with additional restrictions that trade precision for accuracy. First, our results so far in this section included all firms that got first treated in 2012 in the treatment group. We now impose the additional restriction that they remain treated (i.e. their national premium remain above $100 million) from 2012 through the end of the sample period. This modification leads to a reduction in the number of firms in the analysis (we lose 46 companies in treatment group). The Cattaneo, Jansson and Ma (2020) density test, illustrated in Figure 6a and 6b, still show no evidence of manipulation around the threshold in this restricted sample before or after 2012 (p-values of 0.2461 and 0.7768 respectively) Second, instead of hand-picked bandwidths, we optimally choose bandwidths as described in Calonico et al. (2014). Based on this selection process, we set the bandwidths to be from $76.194 million to $216.303 million. As a result, we end up with 216 companies in total (instead of the 324 firms in the last exercise), which reduces the number of observations significantly but potentially leads to more suitable treatment and control groups.

[FIGURE 6 HERE]

Figure 7 shows our results analogous to those in Figure 5 but this time with this restricted sample of 216 companies. We see again, before the treatment, that there is no significant decrease in bond holdings for insurers who are right above the $100 million threshold. In the first year following the treatment, we begin to see a small decrease in high-climate-risk bond holdings. The high-climate-risk bond holdings continue to decrease, and we see a significant decrease in holdings starting 4 years post-treatment. We also see around a 4% cumulative

drop over the 7 year period. This is consistent with the results from our analysis using the Sun and Abraham (2021) estimator in Figure 2.

[FIGURE 7 HERE]

4.5 Robustness to Industry Selection

The boom-bust cycle of oil prices in 2010s may have contributed to the creditworthiness of fossil fuel (coal, oil and gas) companies. This cycle, which ended with the positive oil supply shock (and associated reduction in oil prices) in 2014, does not follow the important dates of the insurance company survey mandates. Moreover, there is no obvious reason to believe that mandated and non-mandated insurance companies' portfolios would react to this cycle differently. Nevertheless, to address any remaining concerns, we exclude bonds of issuers in coal, oil and gas industries from our sample and repeat our analysis. The results, presented in Figure 8, show that our results remain very similar to those in Figure 3.

[FIGURE 8 HERE]

As another robustness test, we use the classification from Battiston et al (2017), which is popular among European regulators, although it is not an official classification by a governmental body as our classification from CFTC.[20] Although the two classifications are not identical, there is a significant overlap between the two definitions. Therefore, not surprisingly, the results presented in Figure 9 remain similar to those in Figure 3.

[FIGURE 9 HERE]

5 Impact on Pricing of Corporate Credit: Bond Returns

Our results thus far establish that insurers subjected to mandated disclosure reduced the share of high-climate-risk bonds in their portfolios compared to their non-mandated

[20] See, for example, the recent Global Insurance Market Report by International Association of Insurance Supervisors (IAIS 2021) and Bank for the Accounts of Companies Harmonized Outlook (BACH 2021).

counterparts. A natural question arises: does this portfolio shift have broader implications for the economy? If these bonds have merely changed hands without frictions, we would not expect any significant impact on bond prices. However, recent evidence suggests that the way insurance companies allocate credit influences firms' cost of capital (Barbosa and Ozdagli 2021; Coppola 2025) and, therefore, the shift in demand by mandated insurers would likely exert downward pressure on the prices of high-climate-risk bonds they hold. We would also expect this effect to manifest faster than portfolio changes, as the market incorporates anticipated changes in future portfolio allocations into today's asset prices.

To study the effect of the mandate on bond values, we examine how the monthly bond returns in 2012 evolved depending on whether these bonds were held disproportionately by insurers that were mandated that year.[21] More specifically, for each bond, our detailed data allows us to calculate how much of the bond was held at the end of 2011 by insurers that just received their mandate in 2012. We also know the total outstanding amount of each bond at the end of 2011, whether the bond is a high-climate-risk bond, the risk characteristics of the bond (ratings and duration), the issuer of the bond, and the bond's monthly returns from Wharton Research Data Services.

This detailed information allows us to test whether high-climate-risk bonds that were more widely held by newly-mandated insurers at the end of 2011 experienced lower returns over the course of the year in 2012. For each month horizon, h, in 2012, we calculate cumulative returns from the end of 2011 until the end of horizon h and use them in the following regression framework,

[21] We choose this criterion, which corresponds to RY 2011, because this is the first year that the survey is widely adopted and corresponds to largest change in fraction held by mandated insurers. While the number of mandated insurers has more than doubled the following year, their influence on fraction held by mandated insurers is limited by their smaller size. See Table 1 and Table 2 for details.

$$
\begin{aligned}
CumulativeReturns_{j,h} =& \alpha_h + \beta_{1,h}(HighRisk_j \times FractionNewlyMandated_j) \\
&+ \beta_{2,h} HighRisk_j + \beta_{3,h} FractionNewlyMandated_j \\
&+ \gamma_h Duration_{j,h} + \delta_h Rating_{j,h} + IssuerFixedEffects_{j,h} + e_{j,h}.
\end{aligned} \tag{7}
$$

Here, the dependent variable represents the cumulative returns for bond j, h months after the beginning of 2012, from January ($h = 1$) to December ($h = 12$). $HighRisk_j$ is an indicator variable for whether bond j is a high-climate-risk bond. The variable $FractionNewlyMandated_j$ represents the fraction of the outstanding amount of bond j, at the end of 2011, that is held by insurance companies who received their mandate in 2012. *Duration* is the duration of the bond and *Rating* is the numerical value assigned to different bond ratings in Barbosa and Ozdagli (2021), which follows Drechsler, Drechsel, Marques-Ibanez, and Schnabl (2016) and Kempf and Tsoutsoura (2021). Finally, we include bond-issuer fixed effects.

[FIGURE 10 HERE]

We are interested in studying the effect of the mandate on returns of high-climate-risk bonds, that is, the coefficient $\beta_{1,h}$ in equation (7). Figure 10 shows our results. We find that when newly mandated insurers are significant investors of a high-climate-risk corporate bond, that bond experiences a large decline in cumulative returns. In particular, a high-climate-risk corporate bond that is held solely by mandated insurers would experience around 3 percent lower returns compared to a bond not held by mandated insurers. This effect is both economically and statistically significant, suggesting that the reallocation of credit due to the survey mandate affects the pricing of corporate credit.

6 Mechanism Underlying Insurers' Portfolio Reallocation

Our findings suggest that insurance companies' portfolios reacted to the survey mandate despite the fact that surveyed firms faced no legal repercussions for not being mindful of climate change risks. There are two broadly-defined potential channels which can explain our results.

The first one is the regulatory pressure/anticipation channel. Although the disclosure mandates do not have legally binding consequences for portfolio choice immediately, insurance companies may voluntarily adjust their portfolios to maintain a good relationship with the regulators. Similarly, insurance companies may anticipate that climate-risk-based capital requirements may become legally binding in the future. By voluntarily adjusting their investment practices, they can position themselves to comply with potential future regulations more easily and with less disruption.[22]

The second is the risk-assessment channel. Climate disclosure requirements can prompt companies to conduct more comprehensive assessments of their climate-related risks. This enhanced understanding can lead to better risk management strategies and informed investment decisions, even if any change in investment practices is not legally mandated.

To understand the mechanism better, we note that two main revenue sources for insurance companies are insurance premiums and investment income. Insurance premiums are directly affected by an insurance company's ability to underwrite contracts, whereas investment income depends on the freedom and flexibility in the portfolio choice of an insurance company. On the one hand, insurance companies that are more dependent on insurance premiums, as opposed to investment income, are more likely to yield to regulatory pressure

[22]This anticipation is consistent with recent supervisory initiatives that explicitly integrate climate risk into insurance oversight. For example, New York's 2021 Guidance for New York Domestic Insurers on Managing the Financial Risks from Climate Change expects insurers to incorporate climate-related financial risks into investment decisions. See https://www.dfs.ny.gov/system/files/documents/2021/11/dfs-insurance-climate-guidance-2021_1.pdf

that restricts their portfolio choice. In other words, *the regulatory pressure channel implies that high-underwriting-income insurers would adjust their portfolios more following the mandate.*[23] On the other hand, the insurance companies that depend more on investment income would be more inclined to incur the costs of climate risk assessment and re-optimize their portfolio in order to avoid investment income losses due to omitted risks. Accordingly, *risk assessment channel implies that high-investment-income insurers would adjust their portfolios more following the mandate.*

Based on this intuition, we look at whether the mandates have had more significant impact among insurance companies that depend more on underwriting income vs. investment income. For this purpose, we divide the sample into two groups: those with below the median ratio of underwriting income to the sum of underwriting and investment income as of 2012 and those with ratio above this median as of 2012.[24] If the effect we have seen in Figure 3 is stronger for the latter (high-underwriting-income) group, the evidence is consistent with the regulatory pressure channel. If the effect is instead stronger for the former (high-investment-income) group, then the evidence is consistent with the risk assessment channel. While these two channels are not mutually exclusive, the results presented in Figure 11 suggest that the effect of the mandates is both economically and statistically stronger for the high-underwriting-income group, consistent with the regulatory pressure/anticipation channel. This outcome also aligns with the argument that "disclosure is widely recognized as a soft form of regulation, incentivizing changes in corporate behavior" (Harper Ho, 2020).

[FIGURE 11 HERE]

[23] We refer the interested reader to Appendix A for a simple model that formalizes this intuition.

[24] The former subsample includes 562 insurers (112 mandated in 2012) and the latter subsample includes 563 insurers (149 mandated in 2012). The significant number of mandated insurers in both subsamples alleviates any concern that the results are driven by the possibility that there are few treated firms in either subsample.

7 Conclusion

Our paper shows that climate-change-related regulatory actions, even when they are as simple as mandated disclosure, impact portfolio allocation decisions of institutional investors as well as pricing of corporate credit. We find that insurers who were subjected to mandatory climate risk disclosure significantly decreased their holdings of high-climate-risk corporate bonds. Our cross-sectional evidence suggests that the effect of the mandates is both economically and statistically stronger for the insurers that rely more heavily on underwriting income (instead of investment income), a result that is consistent with regulatory pressure/anticipation as the mechanism underlying mandated insurers' portfolio reallocation.

Our findings have important implications in financial markets. There have been multiple studies which provide evidence of a decreased price for corporate bonds with higher climate risk (Allman 2022, Duan et al. 2025). Our study indicates that insurers are likely to divest from high-climate-risk corporate bonds in the face of climate-change-related regulations. This change in investment behavior may further lower the price of high-climate-risk corporate bonds in the future, as well as restricting access of high-climate-risk borrowers to funding.

Our findings also have direct implications for policymakers as well. The FIO, in their request for more information, was looking for information on how insurers manage climate risk, and to better improve climate-related regulation for insurance companies. Our results suggest that the FIO may find it useful to encourage policies that make climate risk disclosure mandatory for all insurers, as well as increasing the level of detail provided by insurance companies in their survey responses. This would in turn help the policymakers with managing the climate risk of insurers, while also obtaining more information on how the insurance industry incorporates climate change into their investment decisions. We hope that our results encourage future research in this and related topics.

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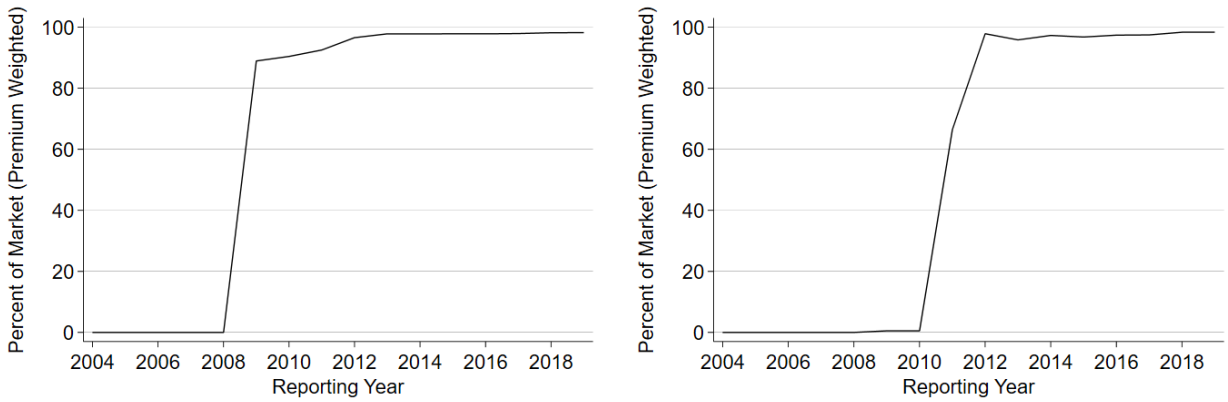
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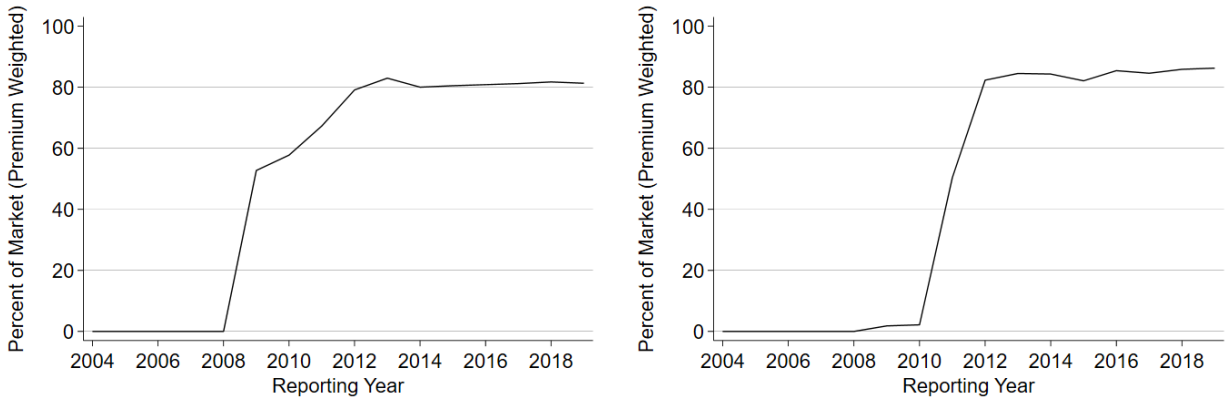
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Figure 1: Percentage of Direct Premiums Written: Mandated vs Filed

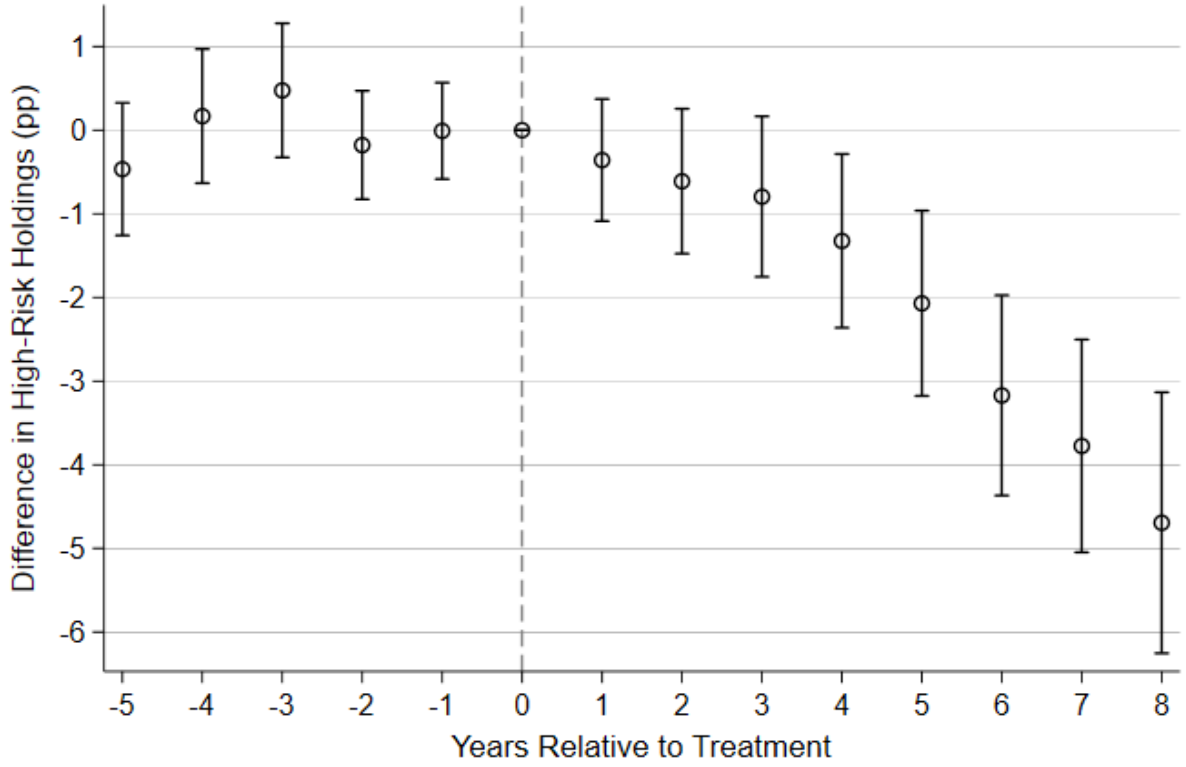


(a) Life Insurers



(b) Property & Casualty Insurers

Figure 2: Staggered Dynamic Difference-in-Difference using Sun and Abraham (2021)

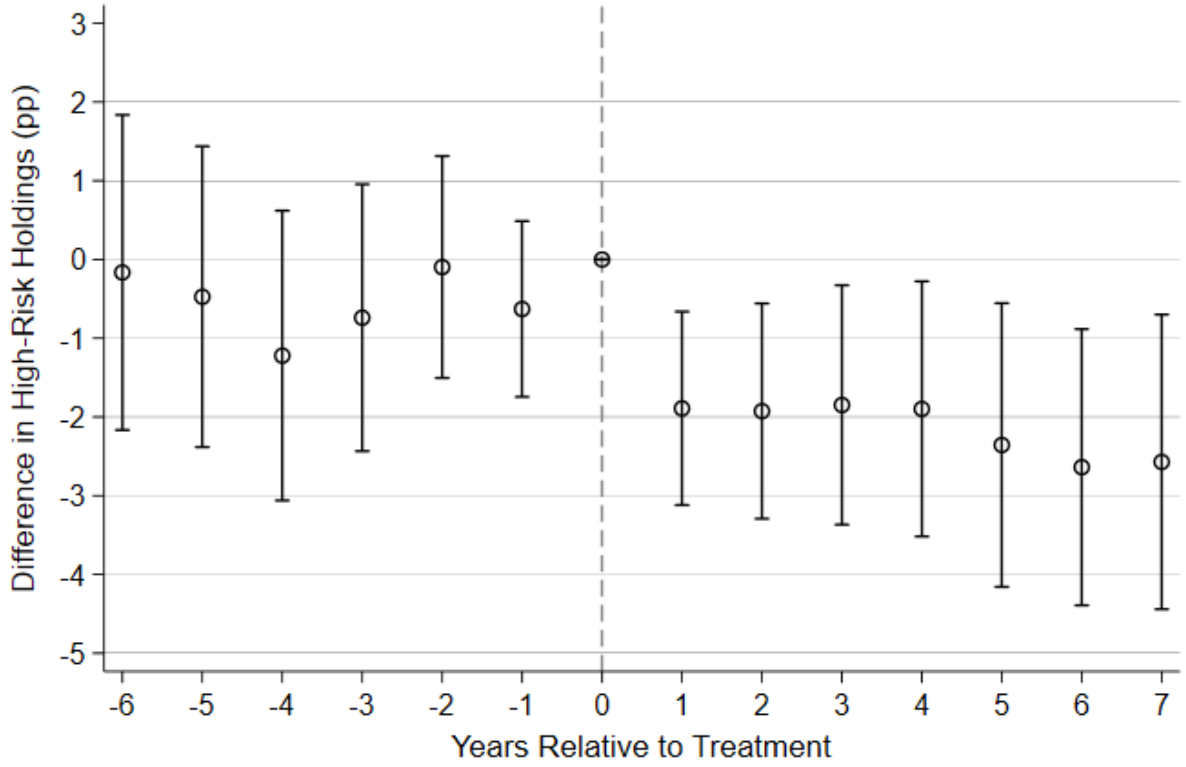


Note: The figure shows the dynamic effects using Sun and Abraham (2021) method with the following specification:

$$PercentageHighRisk_{i,t} = \sum_{n=-5}^{n=-1} \beta_n D_{i,t}^n + \sum_{n=1}^{n=8} \beta_n D_{i,t}^n + \gamma(FirmSize_{i,t} \times Year_t) + FixedEffects + e_{i,t}$$

and report the estimates of β_n, along with their 95% confidence intervals. The variable $D_{i,t}^n$ is an indicator variable that equals one if insurance company i is in the treatment group, and the current year t is n years since the first treatment. For example, if an insurance company was first treated in 2015, then $D_{i,t}^{-3}$ would equal one for year 2012. We also add in a FirmSize-Year fixed effects interaction term, where $FirmSize_{i,t}$ is natural logarithm of the net total assets of company i in year t. We also include insurance company and year fixed effects, and restrict our regression sample to be between RY 2006 and RY 2019. Standard errors are clustered at the insurance-company level, following Sun and Abraham (2021).

Figure 3: Non-Staggered Dynamic Difference-in-Difference

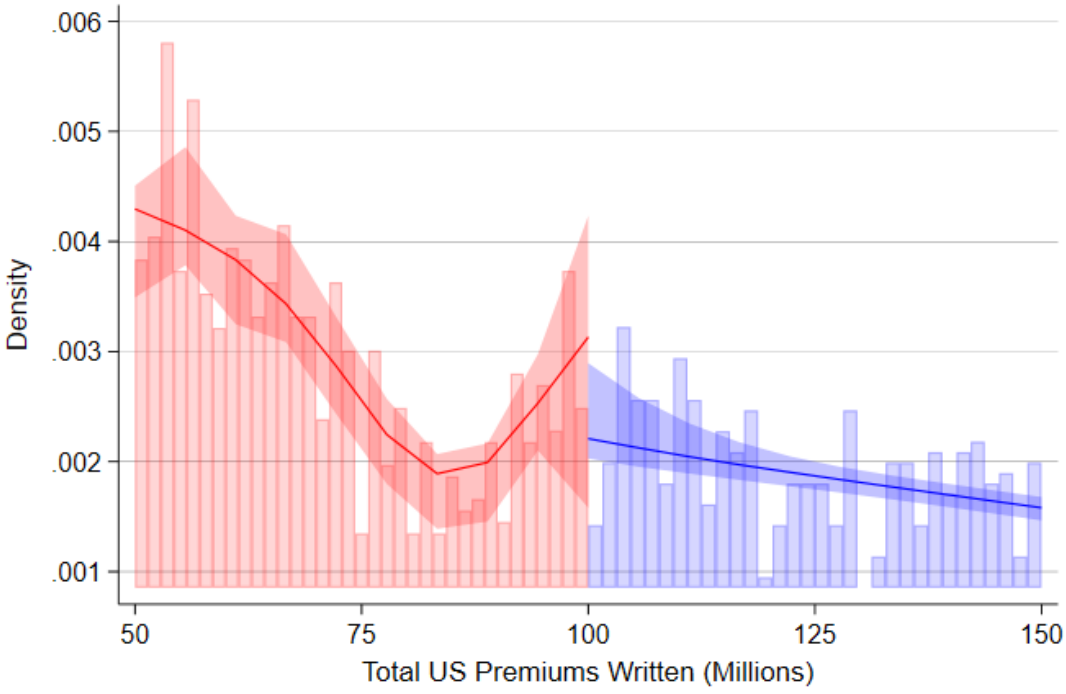


Note: The figure shows the dynamic effects using the standard DiD (two-way fixed effects) regression method with the treatment group of companies that are first-treated in 2012 and with the control group of companies that are never treated. We use the following specification:

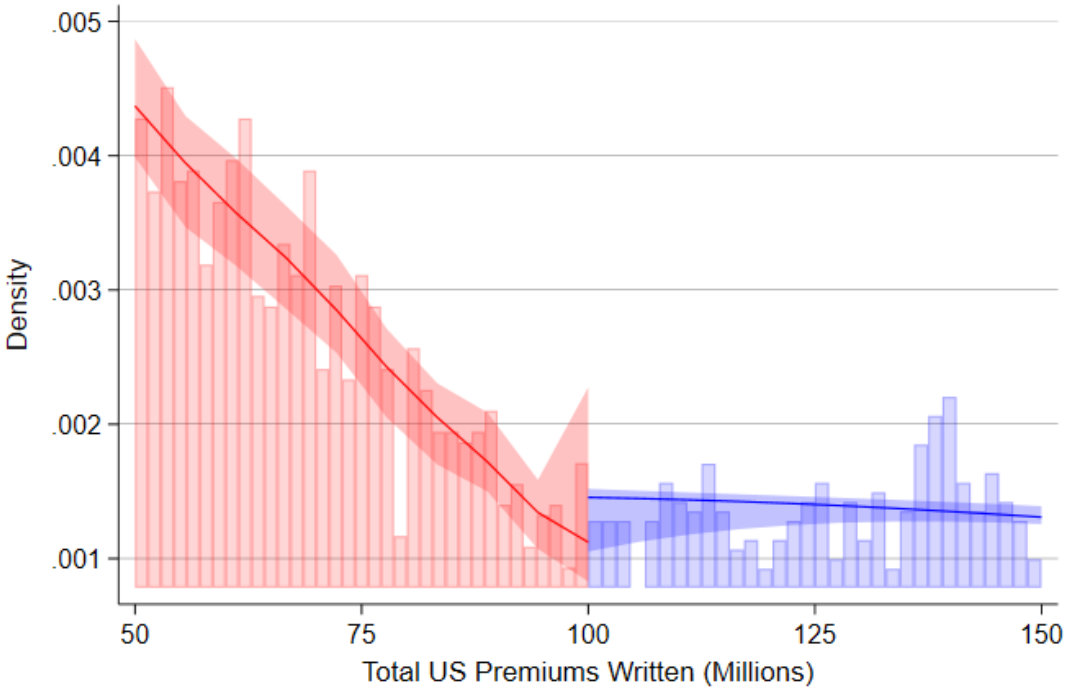
$$PercentageHighRisk_{i,t} = \sum_{n=-6}^{n=-1} \beta_n D^n_{i,t} + \sum_{n=1}^{n=7} \beta_n D^n_{i,t} + \gamma(FirmSize_{i,t} \times Year_t) + FixedEffects + e_{i,t}$$

and report the estimates of β_n, along with their 95% confidence intervals. The variable $D^n_{i,t}$ is an indicator variable that equals one if insurance company i is in the treatment group, and the current year t is n years since the first treatment. For example, if we are looking at a company in the treatment group, then $D^3_{i,t}$ would equal one when $t = 2015$. We also add in a FirmSize-Year FE interaction term, where $FirmSize_{i,t}$ is natural logarithm of the net total assets of company i in year t. We also include insurance company and year fixed effects, and restrict our regression sample to be between RY 2006 and RY 2019. Standard errors are clustered at the insurance company level.

Figure 4: Density Test: Pre/Post 2012 for Figure 3 Sample

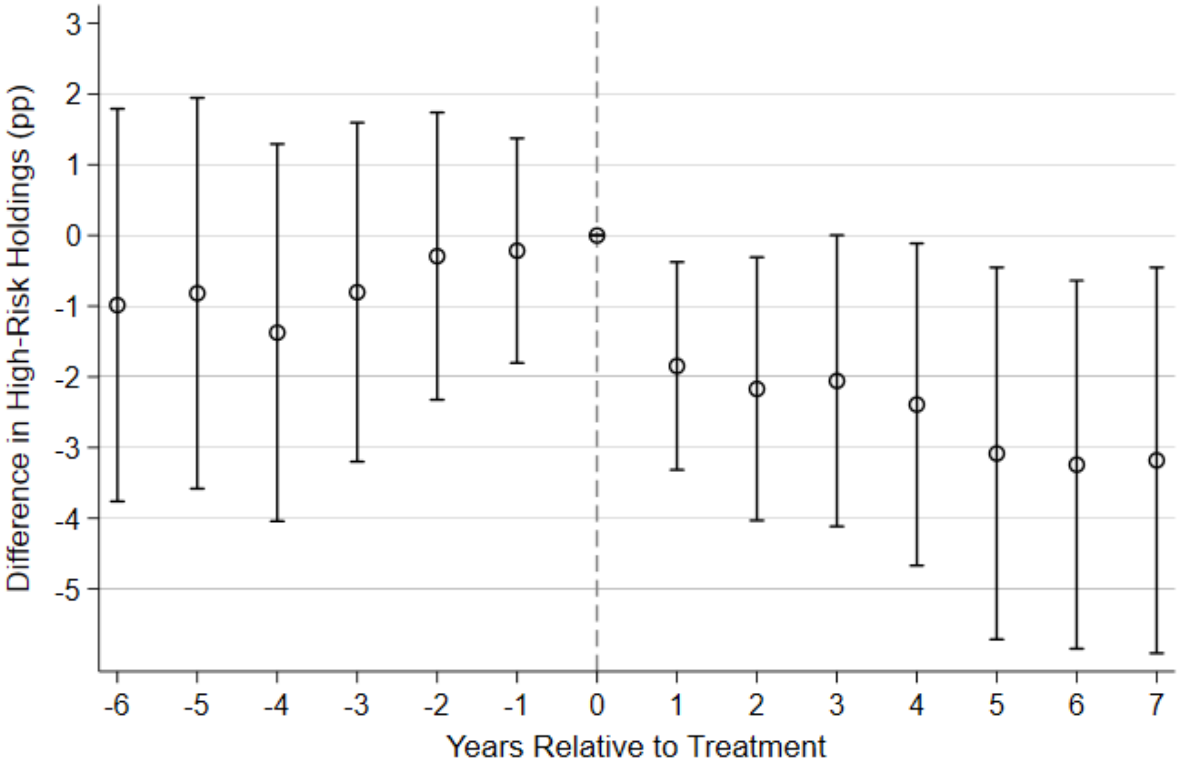


(a) Pre-2012 Density Test: US Premiums



(b) Post-2012 Density Test: US Premiums

Figure 5: Standard Difference-In-Difference: Symmetric Bandwidth

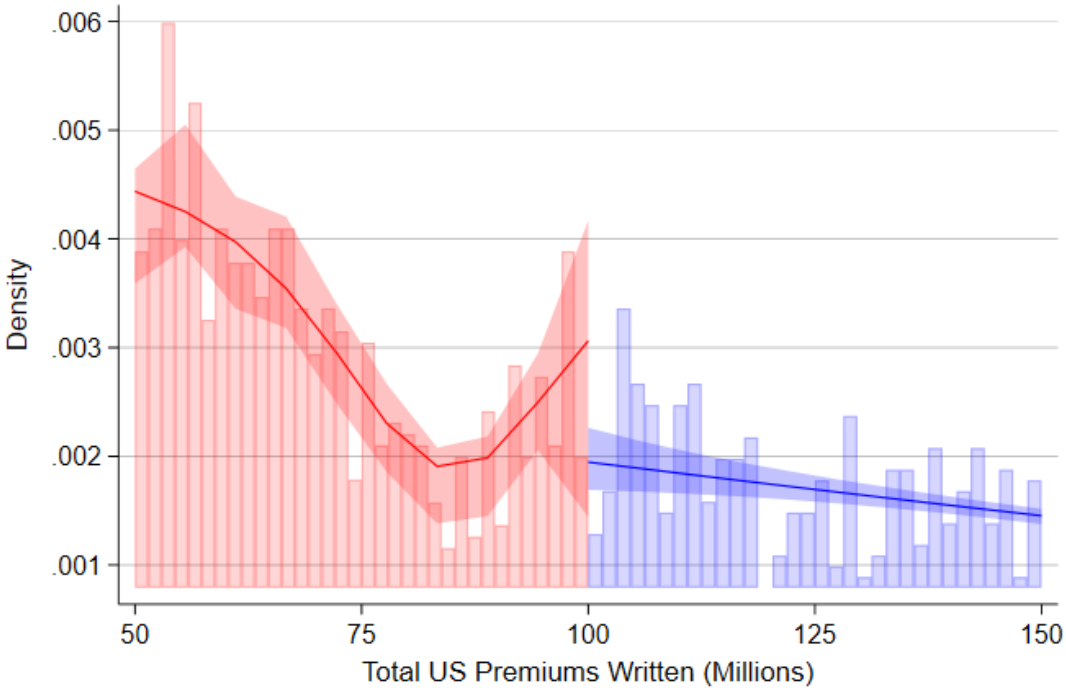


Note: The figure shows the dynamic effects using the standard DiD (two-way fixed effects) regression method with the treatment group of companies that are first-treated in 2012 and with the control group of companies that are never treated. The sample is restricted to those firms with $50 to $200 million national-level premium. We use the following specification:

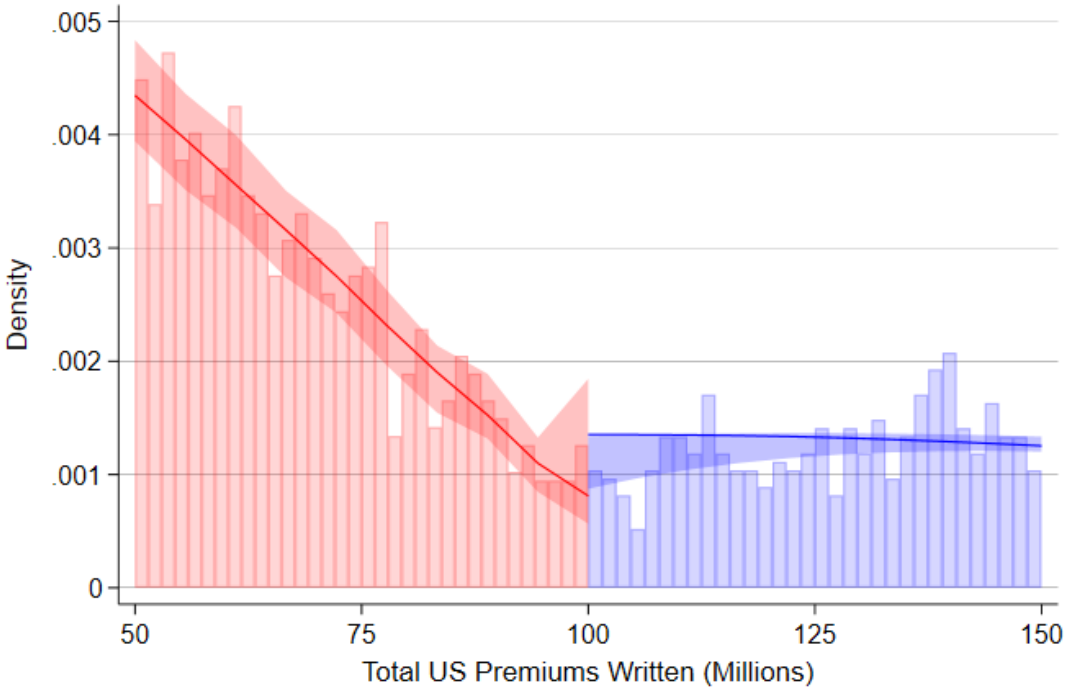
$$PercentageHighRisk_{i,t} = \sum_{n=-6}^{n=-1} \beta_n D_{i,t}^n + \sum_{n=1}^{n=7} \beta_n D_{i,t}^n + \gamma(FirmSize_{i,t} \times Year_t) + FixedEffects + e_{i,t}$$

and report the estimates of β_n, along with their 95% confidence intervals. The variable $D_{i,t}^n$ is an indicator variable that equals one if insurance company i is in the treatment group, and the current year t is n years since the first treatment. For example, if we are looking at a company in the treatment group, then $D_{i,t}^3$ would equal one when $t = 2015$. We also add in a FirmSize-Year FE interaction term, where $FirmSize_{i,t}$ is natural logarithm of the net total assets of company i in year t. We also include insurance company and year fixed effects, and restrict our regression sample to be between RY 2006 and RY 2019. Standard errors are clustered at the insurance-company level.

Figure 6: Density Test: Pre/Post 2012 for All Treated Sample

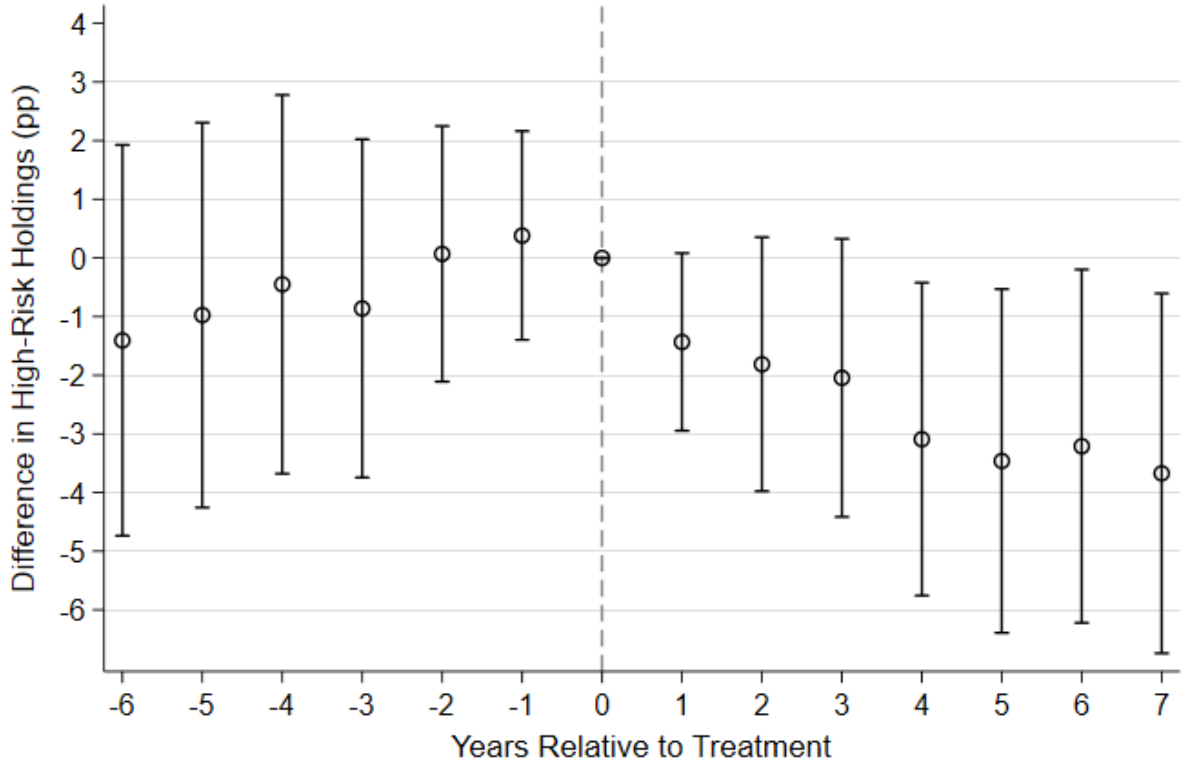


(a) Pre-2012 Density Test: US Premiums



(b) Post-2012 Density Test: US Premiums

Figure 7: Standard Difference-In-Difference: Optimal Bandwidth

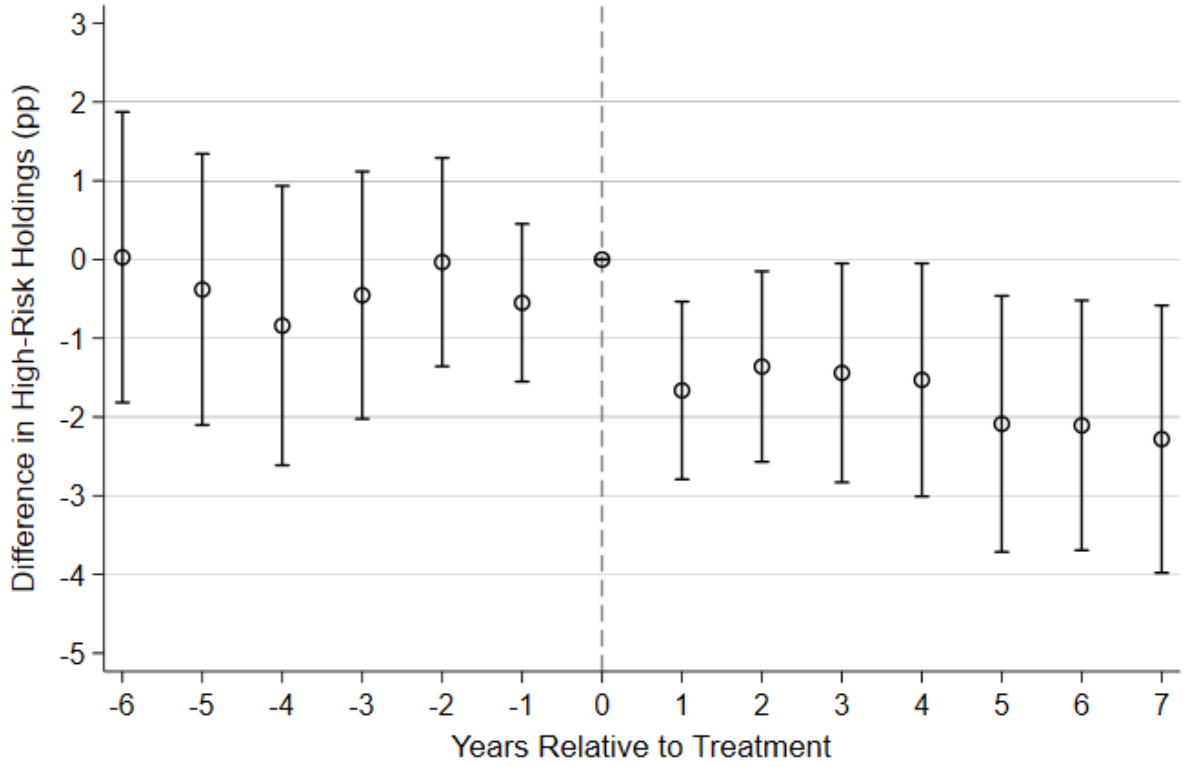


Note: The figure shows the dynamic effects using the standard DiD (two-way fixed effects) regression method with the treatment group of companies that are first-treated in 2012 and remained treated through the end of the sample period and with the control group of companies that are never treated. The sample is restricted to those firms within the optimal bandwidth, determined using Calonico et al. (2014) procedure. For the regression model, we use the following specification:

$$PercentageHighRisk_{i,t} = \sum_{n=-6}^{n=-1} \beta_n D_{i,t}^n + \sum_{n=1}^{n=7} \beta_n D_{i,t}^n + \gamma(FirmSize_{i,t} \times Year_t) + FixedEffects + e_{i,t}$$

and report the estimates of β_n, along with their 95% confidence intervals. The variable $D_{i,t}^n$ is an indicator variable that equals one if insurance company i is in the treatment group, and the current year t is n years since the first treatment. For example, if we are looking at a company in the treatment group, then $D_{i,t}^3$ would equal one when $t = 2015$. We also add in a FirmSize-Year FE interaction term, where $FirmSize_{i,t}$ is natural logarithm of the net total assets of company i in year t. We also include insurance company and year fixed effects, and restrict our regression sample to be between RY 2006 and RY 2019. Standard errors are clustered at the insurance-company level.

Figure 8: Non-Staggered Dynamic Difference-in-Difference: Excluding Fossil Fuel Industries

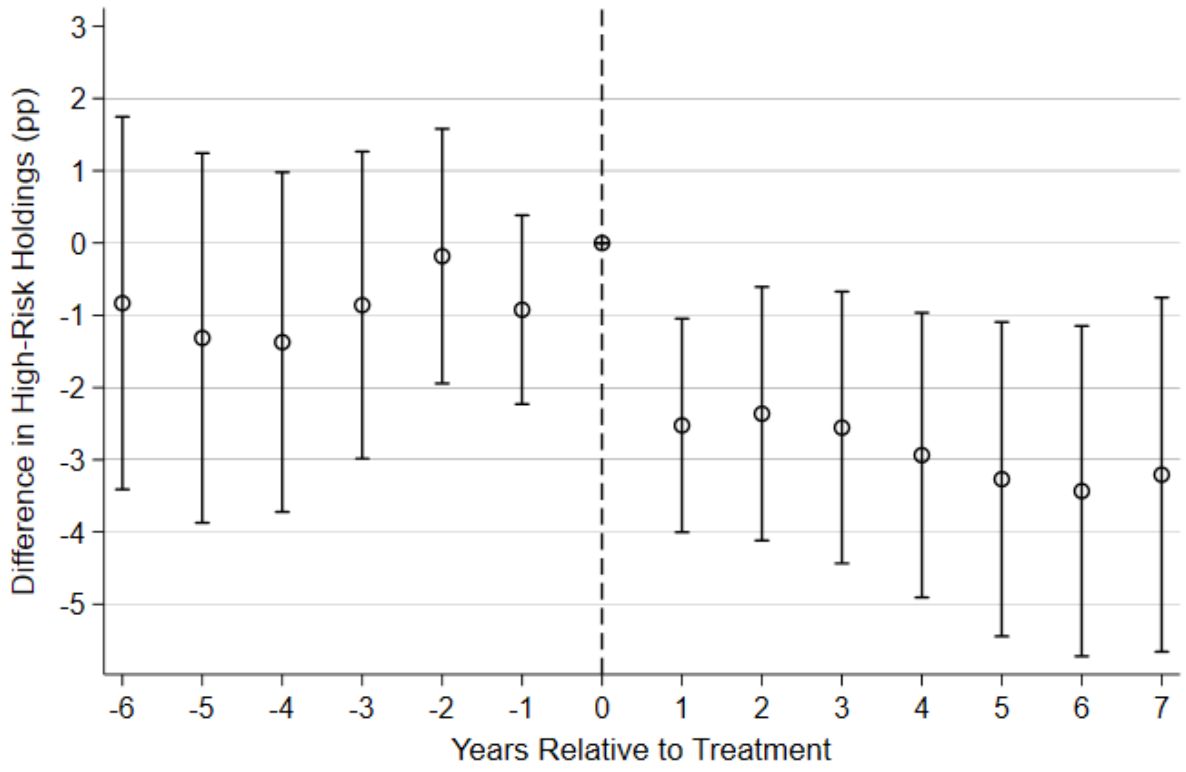


Note: The figure shows the dynamic effects using the standard DiD (two-way fixed effects) regression method with the treatment group of companies that are first-treated in 2012 and with the control group of companies that are never treated. We use the following specification:

$$PercentageHighRisk_{i,t} = \sum_{n=-6}^{n=-1} \beta_n D^n_{i,t} + \sum_{n=1}^{n=7} \beta_n D^n_{i,t} + \gamma(FirmSize_{i,t} \times Year_t) + FixedEffects + e_{i,t}$$

and report the estimates of β_n, along with their 95% confidence intervals. The variable $D^n_{i,t}$ is an indicator variable that equals one if insurance company i is in the treatment group, and the current year t is n years since the first treatment. For example, if we are looking at a company in the treatment group, then $D^3_{i,t}$ would equal one when $t = 2015$. We also add in a FirmSize-Year FE interaction term, where $FirmSize_{i,t}$ is natural logarithm of the net total assets of company i in year t. We also include insurance company and year fixed effects, and restrict our regression sample to be between RY 2006 and RY 2019. Standard errors are clustered at the insurance-company level. Coal, oil and gas companies from Table A2 are excluded both from the numerator and denominator when calculating the dependent variable.

Figure 9: Non-Staggered Dynamic Difference-in-Difference: Using the Classification of Battiston et al. (2017) for Climate Policy Relevant Sectors

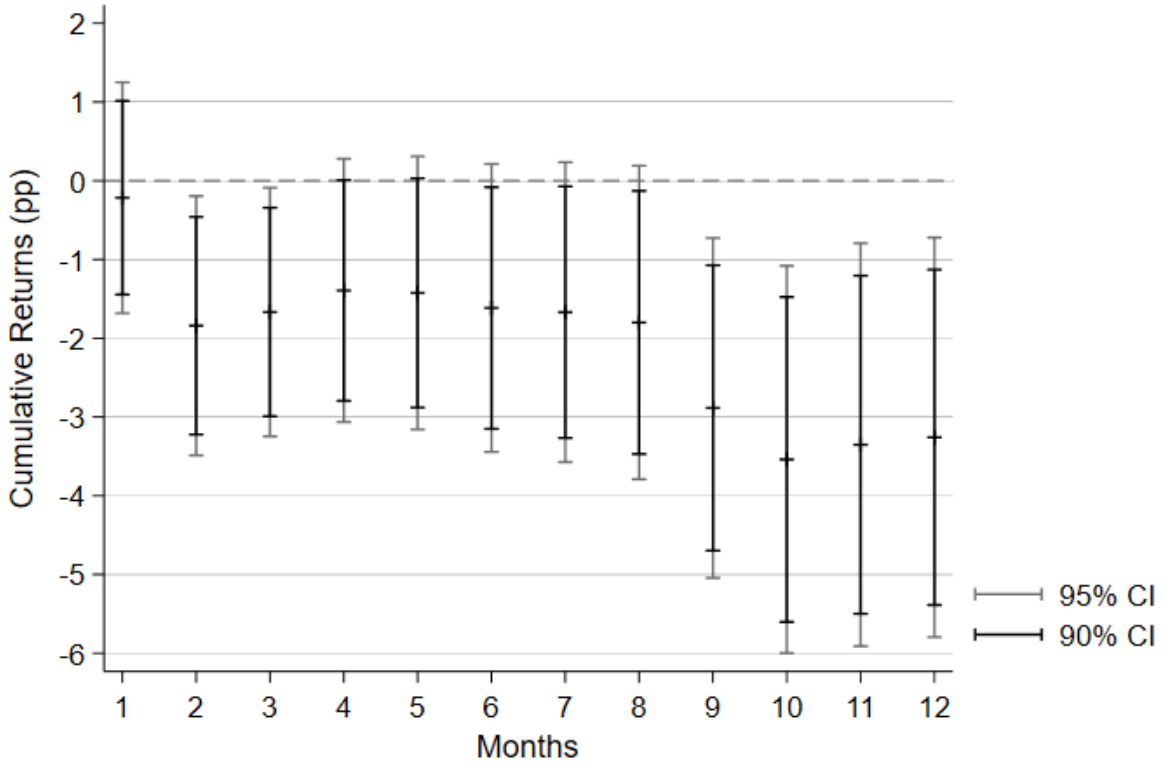


Note: The figure shows the dynamic effects using the standard DiD (two-way fixed effects) regression method with the treatment group of companies that are first-treated in 2012 and with the control group of companies that are never treated. We use the following specification:

$$PercentageHighRisk_{i,t} = \sum_{n=-6}^{n=-1} \beta_n D^n_{i,t} + \sum_{n=1}^{n=7} \beta_n D^n_{i,t} + \gamma(FirmSize_{i,t} \times Year_t) + FixedEffects + e_{i,t}$$

and report the estimates of β_n, along with their 95% confidence intervals. The variable $D^n_{i,t}$ is an indicator variable that equals one if insurance company i is in the treatment group, and the current year t is n years since the first treatment. For example, if we are looking at a company in the treatment group, then $D^3_{i,t}$ would equal one when $t = 2015$. We also add in a FirmSize-Year FE interaction term, where $FirmSize_{i,t}$ is natural logarithm of the net total assets of company i in year t. We also include insurance company and year fixed effects, and restrict our regression sample to be between RY 2006 and RY 2019. Standard errors are clustered at the insurance-company level. We use the Battiston et al. (2017) classification of Climate Policy Relevant Sectors to determine high-climate-risk sectors.

Figure 10: Impact of Survey Mandate on Bond Returns

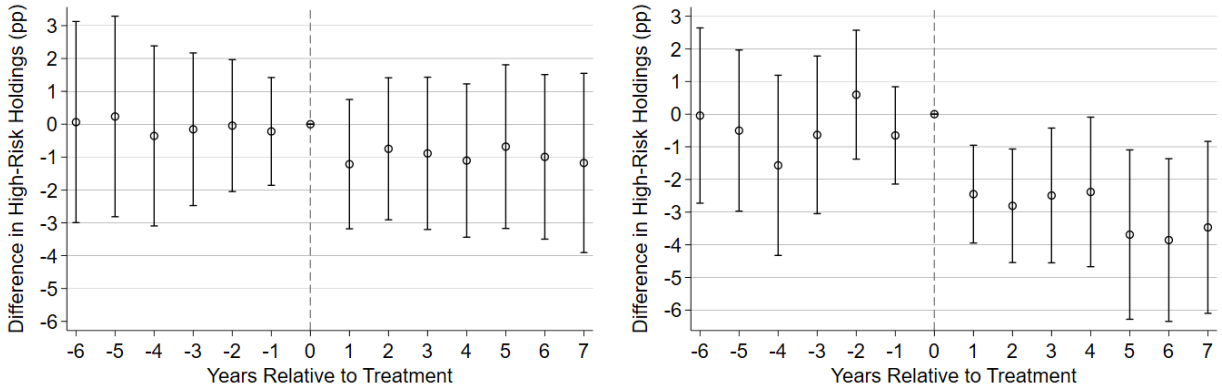


Note: The figure shows the dynamic effect of the mandate on cumulative monthly bond returns in 2012. We use the following regression specification:

$$\begin{aligned} CumulativeReturns_{j,h} =& \alpha_h + \beta_{1,h}(HighRisk_j \times FractionNewlyMandated_j) \\ &+ \beta_{2,h} HighRisk_j + \beta_{3,h} FractionNewlyMandated_j \\ &+ \gamma_h Duration_{j,h} + \delta_h Rating_{j,h} + IssuerFixedEffects_{j,h} + e_{j,h} \end{aligned}$$

and report the estimates of $\beta_{1,h}$, along with their 90% and 95% confidence intervals. The dependent variable represents the cumulative returns for bond j, h months after the beginning of 2012, from January ($h = 1$) to December ($h = 12$). $HighRisk_j$ is an indicator variable for whether bond j is a high-climate-risk bond. The variable $FractionNewlyMandated_j$ represents the fraction of the outstanding amount of bond j, at the end of 2011, that is held by insurance companies who received their mandate in 2012. *Duration* is the duration of the bond and *Rating* is the numerical value assigned to different bond ratings in Barbosa and Ozdagli (2021), which follows Drechsler, Drechsel, Marques-Ibanez, and Schnabl (2016) and Kempf and Tsoutsoura (2021). Finally, we include bond-issuer fixed effects.

Figure 11: Non-Staggered Dynamic Difference-in-Difference: The role of the importance of underwriting income



(a) Low Share of Underwriting Income (b) High Share of Underwriting Income

Note: The figure shows the dynamic effects using the standard DiD (two-way fixed effects) regression method with the treatment group of companies that are first-treated in 2012 and with the control group of companies that are never treated. We use the following specification:

$$PercentageHighRisk_{i,t} = \sum_{n=-6}^{n=-1} \beta_n D^n_{i,t} + \sum_{n=1}^{n=7} \beta_n D^n_{i,t} + \gamma(FirmSize_{i,t} \times Year_t) + FixedEffects + e_{i,t}$$

and report the estimates of β_n, along with their 95% confidence intervals. The variable $D^n_{i,t}$ is an indicator variable that equals one if insurance company i is in the treatment group, and the current year t is n years since the first treatment. For example, if we are looking at a company in the treatment group, then $D^3_{i,t}$ would equal one when $t = 2015$. We also add in a FirmSize-Year FE interaction term, where $FirmSize_{i,t}$ is natural logarithm of the net total assets of company i in year t. We also include insurance company and year fixed effects, and restrict our regression sample to be between RY 2006 and RY 2019. Standard errors are clustered at the insurance-company level. The sample in the left (right) panel includes those insurance companies with the ratio of underwriting income to the sum of underwriting and investment income below (above) its cross-sectional median in 2012.

Table 1: NAIC Climate Risk Survey: Mandate Requirements

Reporting Year	***States Participating***	***National Premium Requirement ($)***
2009	CA	500 Million
2010	CA	300 Million
2011	CA, NY, WA	300 Million
2012	CA, CT, MN, NY, WA	100 Million
2013	CA, CT, IL, MD, MN, NM, NY, WA	100 Million
2014	CA, CT, MN, NM NY, WA	100 Million
2015	CA, CT, MN, NM NY, WA	100 Million
2016	CA, CT, MN, NM NY, WA	100 Million
2017	CA, CT, MN, NM NY, WA	100 Million
2018	CA, CT, MN, NM NY, WA	100 Million
2019	CA, CT, MN, NM NY, WA	100 Million

Table 2: Summary Statistic of Filers

Reporting Year	***Firms***	***Filers***	***Mandatory (Filed)***	***Voluntary***	***Mandatory (Not Filed)***
2009	3053	12	7	5	239
2010	3024	22	10	12	330
2011	2994	303	293	10	122
2012	2953	942	740	202	28
2013	2915	1005	799	206	33
2014	2886	1023	788	235	17
2015	2845	977	777	200	37
2016	2833	999	818	181	12
2017	2815	985	803	182	42
2018	2769	1057	852	205	1
2019	2755	1095	869	226	6

Table 3: Effect of Mandatory Disclosure on High Climate Risk Bonds for All Insurers

VARIABLES	(1) PercentageHighRisk	(2) PercentageHighRisk	(3) PercentageHighRisk	(4) PercentageHighRisk
Mandatory	0.533	0.592	-0.175	-0.0384
	(0.362)	(0.374)	(0.395)	(0.414)
MandatoryLag	-0.630***	-0.701**	-0.884***	-0.794**
	(0.200)	(0.240)	(0.291)	(0.310)
MandatorySecondLag	-1.303**	-1.399**	-1.492**	-1.163**
	(0.488)	(0.498)	(0.525)	(0.479)
Voluntary		0.268	0.111	0.152
		(0.708)	(0.678)	(0.662)
VoluntaryLag		-0.627	-0.658	-0.601
		(0.433)	(0.459)	(0.503)
VoluntarySecondLag		-0.789	-0.660	-0.327
		(0.506)	(0.488)	(0.486)
FirmSize			3.854***	3.591***
			(0.369)	(0.356)
Observations	22,932	22,932	22,932	22,901
R-squared	0.700	0.700	0.712	0.730
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	No
State Domiciled-Year Interaction FE	No	No	No	Yes

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Note: Each observation corresponds to an Insurance Company-Year pair. PercentageHighRisk represents the par-value weighted portion of high climate risk bonds in an insurer's total corporate bond portfolio. FirmSize is equal to the natural log a firm's net total asset. Columns 1-3 of the table utilize Models 1-3, respectively, to perform our analysis. Column 4 utilizes model 3, but substitutes Year Fixed Effects with a State Domiciled-Year interaction fixed effects term. All standard errors are multi-way clustered on Insurance Company and Year.

Table 4: Effect of Mandatory Disclosure on High Climate Risk Bonds for Life and P&C Insurers

VARIABLES	(1) PercentageHighRisk	(2) PercentageHighRisk	(3) PercentageHighRisk	(4) PercentageHighRisk
Mandatory	-0.665	-0.750	0.0351	0.127
	(0.628)	(0.632)	(0.398)	(0.435)
MandatoryLag	-1.292***	-1.193***	-0.739	-0.729
	(0.274)	(0.264)	(0.431)	(0.472)
MandatorySecondLag	-1.300**	-0.698	-1.637**	-1.309*
	(0.575)	(0.545)	(0.634)	(0.633)
Voluntary	1.606	1.392*	-0.204	-0.178
	(0.989)	(0.732)	(0.750)	(0.762)
VoluntaryLag	0.0648	0.0831	-0.784	-0.782
	(0.799)	(0.685)	(0.614)	(0.649)
VoluntarySecondLag	0.173	1.037	-0.810	-0.548
	(1.175)	(1.140)	(0.501)	(0.511)
FirmSize	3.282***	3.199***	4.053***	3.835***
	(0.646)	(0.627)	(0.439)	(0.416)
Observations	6,818	6,750	16,114	16,076
R-squared	0.755	0.785	0.621	0.652
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
State Domiciled-Year Interaction FE	No	Yes	No	Yes

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Note: Each observation corresponds to an Insurance Company-Year pair. PercentageHighRisk represents the par-value weighted portion of high climate risk bonds in an insurer's total corporate bond portfolio. FirmSize is equal to the natural log of a firm's net total asset. Columns 1 & 3 utilize Model 3 for Life and P&C insurers respectively. Column 2 & 4 utilizes model 3 for Life and P&C insurers respectively but substitutes Year Fixed Effects with a State Domiciled-Year interaction fixed effects term. All standard errors are multi-way clustered on Insurance Company and Year.

Appendix

A A Simple Model of Portfolio Allocation under Climate Regulation

The framework is based on a short set of intuitive assumptions:

Assumption 1: *Returns, R, on the insurance company's investment portfolio depends on the share (c) of assets (A) invested in high-climate-risk portfolio (C), $c \equiv C/A$. There is an optimal level of portfolio climate-risk-exposure c^* such that $c^* = \arg\max_c R(c)$.*

This assumption tells us that there is an optimal weight of high-climate-risk assets in an insurance company's portfolio that achieves the goals of the insurance company in the absence of any climate regulation. The generality of this assumption allows for various goals, such as risk-return tradeoffs or other regulatory considerations.

Assumption 2: *Non-investment income, derived from underwriting activities, is proportional to the policy amount underwritten, and hence liabilities towards the policyholders, L.*

This assumption recognizes that fees and other income generated from underwriting activities are greater the larger the amount underwritten and allows for the possibility that some insurance companies are better than other in generating fees.

Assumption 3: *Climate risk regulation is imposed in the form of risk-based-capital (RBC) requirement that requires the insurance company to hold higher amount of equity, E, the greater the climate risk in its portfolio. That is, $E/A \geq \phi(C/A)$ where $\phi' > 0$ and $\phi'' > 0$.*

This assumption is a common way of introducing regulatory requirements in the previous literature (Koijen and Yogo, 2015; Sen 2023) where our contribution is tying the capital constraint explicitly to high-climate-risk asset's weight in the insurer's portfolio.

Under these assumptions, and noting $E = A - L$, we can write the optimization problem of the insurer as

$$\max_{C,L} R(C/A)\, A + fL \text{ subject to } A - L \geq \phi(C/A)\, A$$

where fL captures non-investment income.[25]

This objective function can be simplified using the fact that both the objective function

[25] This framework allows leverage to be constrained for reasons other than climate-related regulation, with $1 - \phi(C/A) \equiv 1 - \bar{l} + \psi(C/A)$. In the absence any climate regulation, $\psi(C/A) = 0$, $\phi(C/A) = 1 - \bar{l}$, $\phi'(C/A) = 0$, and hence $c = c^*$

and the RBC constraint are homogeneous in L and A. Letting $l \equiv L/A$ be the leverage and remembering $c \equiv C/A$, we get

$$\max_{c,l} R(c) + fl \text{ s.t. } l \leq 1 - \phi(c)$$

and the Lagrangian is given by

$$\mathcal{L} = R(c) + fl - \lambda [l - (1 - \phi(c))]$$

which leads to the following solution

$$\begin{aligned} \partial\mathcal{L}/\partial l &= 0 \Longrightarrow \lambda = f \\ \partial\mathcal{L}/\partial c &= 0 \Longrightarrow R'(c) = \lambda\phi'(c) \end{aligned}$$

The first of these equations is pretty intuitive: the marginal benefit of increasing leverage, f, should be equal to the shadow cost of leverage due to regulatory constraint, λ. Embedding this to the second equation we get

$$R'(c) = f\phi'(c). \tag{A-1}$$

In the absence of any climate-related regulatory constraint, $\phi'(\cdot) = 0$, the firm chooses $c = c^*$. When there is a regulatory constraint the firm chooses $c = c_0 < c^*$. Moreover, equation (A-1) implies $dc_0/df < 0$, that is, the higher the importance of non-investment income the greater the decline in climate risk exposure following the regulation.

B Additional Tables and Figures

Table A1: List of NAIC Survey Questions

Question Number	***Survey Question***
Question 1	Does the company have a plan to assess, reduce or mitigate its emissions in its operations or organizations?
Question 2	Does the company have a climate change policy with respect to risk management and investment management? If yes, please summarize. If no, how do you account for climate change in your risk management?
Question 3	Describe your company's process for identifying climate change-related risks and assessing the degree that they could affect your business, including financial implications.
Question 4	Summarize the current or anticipated risks that climate change poses to your company. Explain the ways that these risks could affect your business. Include identification of the geographical areas affected by these risks.
Question 5A	Has the company considered the impact of climate change on its investment portfolio?
Question 5B	Has it altered its investment strategy in response to these considerations? If so, please summarize steps you have taken.
Question 6	Summarize steps the company has taken to encourage policyholders to reduce the losses caused by climate change-influenced events
Question 7	Discuss steps, if any, the company has taken to engage key constituencies on the topic of climate change
Question 8	Describe actions the company is taking to manage the risk of climate change poses to your business including, in general terms, the use of computer modeling

Table A2: NAICS Codes for CFTC High-Climate-Risk Sectors

CFTC Sector	***NAICS Code Used***
Automotive	3361, 33611, 336111, 336112, 33612, 336120, 3362, 33621, 336211, 336212, 336213, 336214, 3363, 33631, 336310, 33632, 336320, 33633, 336330, 33634, 336340, 33635, 336350, 33636, 336360, 33637, 336370, 33639, 336390, 4231, 42311, 423110, 42312, 423120, 42313, 423130, 42314, 423140, 4413, 44131, 441310, 44132, 441320, 484, 4841, 48411, 484110, 48412, 484121, 484122, 4842, 48422, 484220, 48423, 484230, 485113, 4411, 44111, 441110, 44112, 441120, 4413, 44131, 441310
Aviation	3364, 336411, 336412, 336413, 481, 4811, 48111, 481111, 481112, 4812, 48121, 481211, 481212, 481219
Cement	3273, 32731, 327310, 32732, 327320, 32733, 327331, 327332, 32739, 327390
Coal	2121, 21211, 212111, 212112, 212113, 324, 42352, 423520, 32419, 324199
Oil & Gas	211, 2111, 21112, 211120, 21113, 211130, 231111, 32512, 325120, 33313, 333132, 23712, 237120, 324191, 32512, 325120, 3241, 32411, 324110, 324191
Power	2211, 221112, 221118, 23713, 237130, 44421, 444210, 22112, 221121, 221122 , 23713, 237130
Steel	3311, 33111, 331110, 3312, 33121, 331210, 33122, 331221, 331222, 331512, 331513, 332111, 23812, 238120
Shipping	484, 4841, 48411, 484110, 48412, 484121, 484122, 4842, 48421, 484210, 48422, 484220, 48423, 484230, 481112, 481212, 483111, 483113, 486, 4861, 48611, 486110, 4862, 48621, 486210, 48691, 486910, 48699, 486990, 491, 4911, 49111, 491110, 4922, 49221, 492210 , 4869 , 4921 , 49211 , 492110
Agriculture	111, 1111, 11111, 111110, 11112, 111120, 11113, 111130, 11114, 111140, 11115, 111150, 11116, 111160, 11119, 111191, 111199, 1112, 11121, 111211, 111219, 1113, 11131, 111310, 11132, 111320, 11133, 111331, 111332, 111333, 111334, 111335, 111336, 111339, 1114, 11141, 111411, 111419, 11142, 111421, 111422, 1119, 11191, 111910, 11192, 111920, 33311, 333111, 333112, 42382, 423820, 1151, 11511, 115111, 115112, 115113, 115114, 115115, 115116, 11193, 111930, 11194, 111940, 11199, 111991, 111992, 111998
Communications Infrastr.	3342, 33421, 334210, 33422, 334220, 33429, 334290

Chemicals	325, 3251, 32511, 325110, 32512, 325120, 32513, 325130, 32518, 325180, 32519, 325193, 325194, 325199, 3253, 32531, 325311, 325312, 325314, 32532, 325320, 3254, 32541, 325411, 325412, 325413, 325414, 3255, 32551, 325510, 32552, 325520, 3256, 32561, 325611, 325612, 325613, 32562, 325620, 3259, 32591, 325910, 32592, 325920, 32599, 325991, 325992, 325998 , 3252, 32521, 325211, 325212, 32522, 325220
Plastics	3261, 32611, 326111, 326112, 326113, 32612, 326121, 326122, 32613, 326130, 32614, 326140, 32615, 326150, 32616, 326160, 32619, 326191, 326199, 4246, 42461, 424610, 42469, 424690
Tourism/Real Estate	7211, 7211, 72111, 721110, 72112, 721120, 72119, 721191, 721199, 5615, 56151, 561510, 56152, 561520, 56159, 561591, 561599, 531, 5311, 53111, 531110, 53112, 531120, 53113, 531130, 53119, 531190
Metals/Mining	33313, 333131, 2122, 21221, 212210, 21222, 212221, 212222, 21223, 212230, 21229, 212291, 212299, 2123, 21231, 212311, 212312, 212313, 212319, 21232, 212321, 212322, 212324, 212325, 21239, 212391, 212392, 212393, 212399, 213, 2131, 21311, 213111, 213112, 213113, 213114, 213115, 331, 3311, 33111, 331110, 3312, 33121, 331210, 33122, 331221, 331222, 3313, 33131, 331313, 331314, 331315, 331318, 3314, 33141, 331410, 33142, 331420, 33149, 331491, 331492, 4235, 42351, 423510, 42352, 423520, 42381, 423810, 2121, 21211, 212111, 212112, 212113
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