# The supply of cyber risk insurance*

Martin Eling Anastasia Kartasheva Dingchen Ning

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**Abstract**

Cyber risk losses are large and growing, yet the cyber insurance market is small. What constraints the insurance industry from providing larger capacity for cyber risk? We argue that cyber risk is special in that it combines heavy tails, uncertain loss distribution, and asymmetric information. We model the implications of these risk features for risk financing and then test them empirically in the context of the US cyber insurance market. Using an exogenous shock of the non-US affiliated reinsurance tax treatment in 2017, we establish the causal inference that insurers primarily rely on the internal capital market to supply cyber risk insurance. Then, we test which of the features of cyber risk contribute to the cost of external capital and confirm that all of them play a significant role.

*Keywords:* cyber risk insurance, large risks financing, internal capital market, reinsurance, information frictions.
*JEL classification:* G22, G32, L11.

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# 1 Introduction

Cyber crime economic losses are large and growing. The current estimates of global losses range between \$1-\$6 trillion in 2020 (McAfee, 2020; Cybercrime Magazine, 2020), which would translate to the estimate between \$250 billion and \$1.5 trillion for the US, weighted by the US share in global GDP. To protect against the losses, cyber risk insurance (for short, cyber insurance) market is emerging, with almost threefold premiums increase from \$1 billion to \$7.2 billion between 2015-2022. Yet, the size of the US cyber insurance market is a tiny 0.8% fraction of its property and causality (P&C) insurance market in 2022 (NAIC, 2023a). Globally, Swiss Re (2022) estimates that more than 90% of the cyber losses are not insured.

In this paper, we explore what constraints the insurance industry from providing larger capacity for cyber risk. We argue that insuring cyber risk is challenging due to the combination of three features: heavy tails, uncertain loss distribution, and asymmetric information. The possibility of sudden extreme cyber losses limits the scope for cross-sectional diversification for the insurance industry (Ibragimov, Jaffee, and Walden, 2009) and requires a significant amount of external contingent capital to pay tail losses (Jaffee and Russell, 1997; Froot, 2001; Gründl et al., 2021). However, external capital is expensive because the outside investors require high premium for asymmetric information and loss distribution uncertainty. Hence, the supply of cyber insurance relies heavily on the insurer's internal capital market. The scarcity of internal capital of insurance groups curtails the amount of cyber insurance that the insurance industry is willing to provide.

We model the relationship between the risk characteristics of insurance liabilities and the sources of financing, building on the ideas of the internal capital market (ICM) literature developed in Grossman and Hart (1986), Gertner, Scharfstein, and Stein (1994), and Stein (1997). We model financing choices between internal capital, external reinsurance and outside investors. We use hte model to explain how the pecking order of financing choices depends on the insurance liability portfolio characteristics.

To test these arguments empirically, we analyze the US cyber insurance market. We use the new cyber insurance data collected by the National Association of Insurers Commissioners (NAIC) from 2015. We first document the stylized facts about the cyber insurance market. The data reveals that large insurance groups dominate the cyber insurance market, with the top 10 largest participants taking 52% of the market share in 2022. Next, there is a pronounced use of the ICM in the form of affiliated reinsurance between the group subsidiaries. At the median level, cyber insurers reinsure at least 20% more than those underwriting other risks. Further, while there was a rapid growth of the cyber insurance market by 32.4% annually between 2015 and 2022, the cyber insurers did not compromise profitability and have also been increasing the price, indicating the growing demand for cyber insurance.

Then we establish the causal relationship between access to the ICM and the supply of cyber insurance. We exploit the regulatory change in the tax treatment of non-US affiliated reinsurance, namely, the base erosion and anti-abuse tax (BEAT) reform of 2017. The BEAT reform has significantly increased the costs of non-US affiliated reinsurance primarily located in Bermuda, and, as a consequence, it reduced its use by US insurers. We construct a measure a cyber insurer's exposure to BEAT reform. Using the difference-in-difference analysis, we explore how the BEAT reform affected the growth of cyber insurance premiums and compare the performance of the highly exposed and less exposed insurers. With binary treatment, we estimate that insurers exposed to the BEAT costs shock experienced a drop in the growth rate of cyber premiums of 14% in 2018, 30% in 2019, and 22% in 2020 compared to the control group. The results are confirmed when we use the exposure as a continuous treatment.

We also show that cyber risk is distinct in terms of utilizaiton of ICM by analyzing the effect of the BEAT reform on other insurance lines. We construct a similar measure of exposure to BEAT reform for other lines as a placebo test. Then we estimate the effect of the BEAT reform on these lines and find no significant effects in the same period.

Next, we investigate which features of the cyber risk prevent insurers from transferring risk to the external capital market. We design empirical tests to analyze the relationship between the prevalence of cyber risk features in the cyber insurer underwriting portfolio and the cost of external reinsurance. To determine the effects of heavy-tails on the external capital costs, we test whether the price of external (non-affiliated) reinsurance is positively related to the share of cyber insurance. To assess how the uncertainty of cyber risk loss distribution affects the price of reinsurance, we proxy the insurer's level of cyber knowledge and experience by the frequency of cyber product updates with the regulators and test whether the update frequency is negatively related to reinsurance prices. To test the role of information frictions, we build on the premise that reinsurers rely on the long-term relationship to limit moral hazard (Doherty and Smetters, 2005). We then develop the empirical tests to assess how the reinsurance price responds to experience rating, reinsurers' monitoring, and direct price control. We combine the factors related to features of the cyber risk in a single test and find that all features play a significant role in limiting an insurer's access to external capital to underwrite cyber risk.

This paper contributes to several strands of the literature. A few recent studies have analyzed the impact of cyber attacks on firms, indicating significant shareholder wealth loss and lower risk appetite (Kamiya et al., 2021), thus inducing strategic timing of the announcement after the attack to attenuate the negative market reaction (Foerderer and Schuetz, 2022). Florackis et al. (2023) show that cyber risk is priced in the cross-section of stock returns. Curti et al. (2023) document the financial costs of data breaches on municipalities and warn that the data breach notification laws are ineffective. Furthermore, cyberattacks have wider impacts through the network connection, such as the supply chain of the firm (Crosignani, Macchiavelli, and Silva, 2023) and the interconnected financial system (Eisenbach, Kovner, and Lee, 2022). To the best of our knowledge, our study is the first to analyze the ability of the insurance market to provide risk transfer for cyber risks.

Our analysis builds on the corporate finance literature on ICM (Gertner, Scharfstein, and Stein, 1994; Diamond, 1994; Stein, 2002). The presence of the ICM is driven by the benefits of reducing the information asymmetries, ability to redeploy assets internally, lower costs of prividing managerial incentives. We contribute to this literature by focusing on risk-financing choices of insurance companies between affiliated reinsurance, external reinsurance and outside investors, and linking these choices to the risk characteristics of insurance liabilities. By taking the ICM perspective and introducing affiliated reinsurance, we also contribute to the literature on the risk-sharing function of reinsurance (Borch, 1962) and its role in the insurer's capital structure (Garven and Lamm-Tennant, 2003; Plantin, 2006).

More broadly, our study adds to the recent literature analyzing the supply-side factors of the insurance market. Koijen and Yogo (2015), Koijen and Yogo (2022), and Ge (2022), among others, analyze how financial frictions affect the insurance market by impacting insurers' product prices and investment. We contribute to the literature by focusing on the role of internal capital in the supply of information-intensive risk coverage, that is, cyber risk.

The remainder of the paper proceeds as follows. The next section discusses the nature of the cyber risk. Section 3 describes the data and summarizes the stylized facts about the cyber insurance market. Section 4 develops a model of risk financing and proposes the hypotheses on cyber risk supply and the choice of capital. Section 5 presents empirical tests with difference-in-difference methods to show the role of the ICM in cyber insurance supply. Section 6 presents the results on the relationship between the price of reinsurance and the features of cyber risk. Section 7 concludes the paper.

# 2 The Nature of Cyber Risk

Cyber risk can be defined as an operational risk to information and technology assets that have consequences affecting the confidentiality, availability, or integrity of information or information systems, following Cebula and Young (2010). These risks include unauthorized data access resulting in breaches, malicious software attacks such as ransomware, and internal system errors that may compromise data integrity and security, among others. Cyber insurance to manage the exposure to these risks may cover direct losses to the policyholder or the liability claims of third parties that are caused by the insured cyber event (NAIC, 2023b). The *combination* of heavy tails, loss distribution uncertainty, and information asymmetries differentiates it from other large risks like natural catastrophes or product liability.

**Heavy tails.** Cyber risk exhibits heavy tails, and its loss distribution should be modeled by the family of heavy-tailed distributions, as documented using several datasets of cyber incidents: Privacy Rights Clearinghouse data (Eling and Loperfido, 2017; Farkas, Lopez, and Thomas, 2021), SAS operational risk data (Eling and Wirfs, 2019), and Advisen data (Aldasoro et al., 2022; Malavasi et al., 2022); and a combination of all three datasets (Eling, Ibragimov, and Ning, 2023). Heavy tails weakens the ability of insurers to underwrite cyber risk by reducing the scope for cross-sectional diversification, as it can induce a non-diversification trap (Ibragimov, Jaffee, and Walden, 2009).

**Uncertainty of loss distribution.** Cyber risk is still largely unknown. Falco et al. (2019) emphasize the importance of cross-disciplinary collaboration, as the scope of cyber risk encompasses computer science, economics, law, management, and political science. Loss uncertainty results in high variation in risk factor pricing in cyber insurance policies (Woods, Moore, and Simpson, 2021) and contract coverage terms and exclusions (Woods, Moore, and Simpson, 2021).

One obstacle to understanding cyber risk is data. The available data are heavily biased toward data breaches because data breaches are the only category that is compulsory to report under the US data breach notification law.[1] Other categories of cyber risk have less information, especially for non-listed firms that have no obligation to make cyber incidents public.[2]

Another factor contributing to high uncertainty is that cyber risk is rapidly evolving over time. Romanosky (2016) provides evidence of the increasing intensity of data breaches, while Edwards, Hofmeyr, and Forrest (2016) find no significant time trend. (Woods and Böhme, 2021b) explain that the analyses of the time trends of cyber risk produce divergent results depending on the methodology. Eling, Ibragimov, and Ning (2023) suggest that the differences can be driven by the report delay.

**Information asymmetry.** The underwriting results of cyber insurance heavily depend on the information advantage and monitoring efforts of the insurer. Insurers use

[1]The notification law is implemented at the state level and there are variations related to the content and the implementation time. See https://www.ncsl.org/technology-and-communication/security-breach-notification-laws.

[2]In the US, listed firms are required to disclose material cybersecurity incidents to the Securities and Exchange Commission, but the rule was introduced only in 2023. See https://www.sec.gov/news/press-release/2023-139.

various methods to screen the cyber risk of potential policyholders, including security questionnaires and minimum requirements for IT infrastructure security and operational risk management. However, Romanosky et al. (2019) cautions that the questionnaires and minimum requirements vary significantly across insurers and thus provide different levels of information depending on the insurer's expertise. After an insured cyber event occurs, containing the size of the loss requires extensive efforts by insurers (Baker and Shortland, 2023). As they are not experts in the management of information security, insurers rely on the service from third parties, such as law firms to contain litigation risk, forensics firms to investigate the cause of the loss, and IT security firms to restore the affected system. Involvement of multiple parties parties increases the challenges of the cost control for insurers (Woods and Böhme, 2021a).

# 3 Cyber Insurance Market in the US

## 3.1 Data and summary statistics

**Data.** In 2015, recognizing a lack of actuarial data as a major hurdle for quantitative assessment and tailored regulation of the cyber insurance market, the NAIC developed a new mandatory cybersecurity and identity theft insurance coverage data supplement (NAIC, 2016). All insurers writing cyber insurance are required to report annually their claims, premiums, losses, expenses, and the number of in-force policies. Cybersecurity insurance is sold to firms, and it can be either a stand-alone insurance policy or part of a package that includes other non-cyber risks. Typically, standalone policies provide wider coverage and have higher prices compared to the package policies (Romanosky et al., 2019; Woods, Moore, and Simpson, 2021). We report further details on the data supplement in Appendix A. We use these data for cybersecurity insurance coverage for the period 2015–2022.

We complement the NAIC cyber supplement data with the annual insurance regulatory filings obtained from S&P Capital IQ that contain balance sheet and income statement information, such as assets, premiums, losses, reinsurance, leverage, risk-based capital, etc.

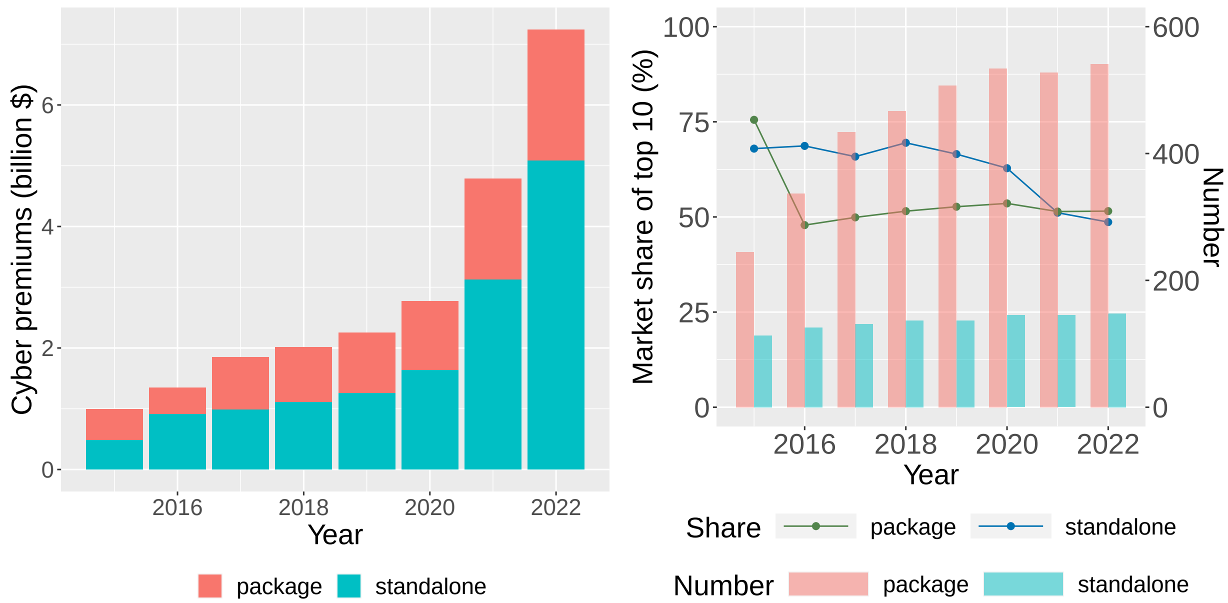


Figure 1: Cyber insurance market size

*Note*: The left figure compares the cyber premiums written for each market segment and the right figure presents the market share of the top 10 insurers and the number of participants in the cyber insurance market.

Where available, we obtain the data at the granularity of the business line of an insurance company. Typically, cyber package insurance is part of the commercial multiple peril line, and cyber standalone is part of the other liability line.[3] In addition, we use the insurer's financial strength ratings assigned by A.M. Best. We collect these data components for all P&C insurance companies in the US for the period of 2015–2022 and merge them by NAIC company code to the cyber supplement data. The total number of firm-year observations for the sample of the US P&C insurers is 21,160, and for the sample of P&C insurers underwriting cyber insurance is 4,082.

**Summary statistics.** The cyber insurance market has grown significantly from $1 billion in 2015 to $7.24 billion in 2022 (Figure 1, left panel). The standalone insurance segment size increased ten times, and accounted for 70% of the cyber insurance market in 2022.[4] While the number of insurers underwriting cyber insurance has been increasing, the market is highly concentrated, with the market shares of the top ten insurers in standalone

[3]The NAIC line of business matrix distinguishes 35 lines of business; see https://content.naic.org/sites/default/files/ucaa-industry-lines-of-business-matrix.pdf.

[4]There are 83 insurers that provide both standalone and package cyber policies.

and package cyber insurance segments above 50% by 2022 (Figure 1, right panel).

Table 1 reports summary statistics for the cyber insurance policies. The data indicates that standalone policies have larger size compared to package policies. For example, in 2022, 3.57 million package policies resulted in the premium volume of $2.15 billion. By comparison, only 0.34 million standalone policies accounted for the premium volume of $5.09 billion. Standalone policies are also more risky, which is reflected in their higher claim frequency of 4%-6% compared to the 0.01% claim frequency of package policies. Further, standalone policies' loss ratios are higher and more volatile than the loss ratios of package policies.[5]

To evaluate the level of cyber insurance prices and compare it to prices charged for other insured risks, we calculate the inverse loss ratio, that is, the ratio of premiums to losses.[6] Table 2 compares the prices of the two business lines, the commercial multi-peril line and the other liability line, that contain cyber package and standalone policies, respectively. The mean value of the price is 54 times higher for the cyber package policy compared to a multi-peril line and 8 times higher for the cyber standalone compared to the other liability line. Furthermore, the cyber insurance lines have striking differences across the quantiles, illustrating the volatility of losses of cyber policies, which drives insurers to charge a much higher markup compared to other insurance lines.

Insurers can also utilize non-price methods to control their exposures to cyber risk by choosing between occurrence and claims-made policies. Occurrence insurance policies cover insured events that occur within the effective dates of the policy regardless of when they are reported to the insurer. By contrast, claims-made policies cover insured events that are reported within the effective dates of the policy. Therefore, occurrence policies have a longer-term exposure than claims-made policies. Table 1, in the last column, shows that claims-made policies dominate the market for standalone policies but not for package policies. This is likely driven by the fact that standalone policies have much higher coverage

[5]Notably, the standalone segment seems to be impacted by the surge in cyber crime during the COVID-19 pandemic, as indicated by the 17% loss ratio increase from 2019 to 2020.

[6]In the insurance economics literature, the inverse loss ratio is commonly used as an indicator of insurance price (e.g., Harrington, 2004; Berry-Stölzle and Born, 2012). For one-year short-tail policies, the ratio equal to 1 corresponds to the actuarially fair price. Values of the ratio are usually above 1 signifying a positive price markup.

Table 1: Summary statistics for cyber insurance policies

| Year | Premiums (billion $) | Insurers | Insurance groups | Number of policies (million) | Claims frequency (%) | Combined loss ratio (%) | Standard deviation of loss ratio | Claims-made policy (%) |
|---|---|---|---|---|---|---|---|---|
| **Cybersecurity package policy** | | | | | | | | |
| 2015 | 0.51 | 245 | 95 | 0.86 | 0.00 | 2.33 | 8.89 | 49.37 |
| 2016 | 0.43 | 337 | 113 | 1.88 | 0.00 | 4.25 | 13.41 | 37.48 |
| 2017 | 0.86 | 434 | 141 | 2.47 | 0.01 | 23.95 | 126.19 | 42.18 |
| 2018 | 0.90 | 467 | 159 | 2.84 | 0.01 | 10.90 | 35.76 | 44.37 |
| 2019 | 0.99 | 507 | 176 | 3.15 | 0.01 | 11.47 | 38.50 | 46.91 |
| 2020 | 1.13 | 534 | 179 | 3.79 | 0.01 | 11.65 | 46.93 | 54.31 |
| 2021 | 1.66 | 528 | 193 | 3.51 | 0.01 | 13.48 | 48.25 | 48.46 |
| 2022 | 2.15 | 541 | 194 | 3.57 | 0.01 | 14.72 | 59.72 | 48.74 |
| **Cybersecurity Standalone Policy** | | | | | | | | |
| 2015 | 0.49 | 113 | 43 | 0.07 | 1.75 | 34.75 | 89.11 | 83.38 |
| 2016 | 0.92 | 126 | 49 | 0.15 | 1.82 | 27.25 | 54.85 | 98.02 |
| 2017 | 0.99 | 131 | 55 | 0.10 | 3.95 | 43.26 | 153.48 | 96.70 |
| 2018 | 1.11 | 137 | 55 | 0.12 | 4.70 | 33.13 | 107.38 | 94.55 |
| 2019 | 1.26 | 137 | 58 | 0.16 | 6.15 | 27.00 | 37.96 | 93.94 |
| 2020 | 1.64 | 145 | 60 | 0.20 | 6.28 | 43.81 | 71.42 | 93.03 |
| 2021 | 3.13 | 145 | 62 | 0.26 | 5.20 | 55.45 | 99.04 | 93.93 |
| 2022 | 5.09 | 148 | 67 | 0.34 | 4.61 | 41.75 | 83.84 | 95.55 |

*Note*: This table presents summary statistics of key variables in the cyber insurance market by year. *Premiums* are calculated as the summation of cyber premiums of all insurers in the respective segment. The number of insurance groups includes independent insurance companies without group affiliation. *Claims frequency* is calculated as the total number of claims divided by the total number of policies in the respective segment. *Combined loss ratio* is the cyber loss incurred plus direct defense and cost containment expense (also known as allocated loss adjustment expense) divided by cyber premiums earned for each insurer and the mean value is reported in this table. The columns related to loss ratios are calculated after winsorizing the top and bottom 1%, as the extreme values significantly distort the statistics. *Claims-made policy (%)* is the percentage of policies that are of claims-made type.

Table 2: Inverse loss ratio of cyber insurance compared to other lines

| | Mean | Standard deviation | Min | 1st quantile | Median | 3rd quantile | Max | Sample size |
|---|---|---|---|---|---|---|---|---|
| Multi peril | 1.02 | 0.33 | 0.05 | 0.86 | 1.00 | 1.16 | 2.22 | 3223 |
| Other liability | 1.23 | 0.67 | 0.05 | 0.85 | 1.09 | 1.45 | 3.98 | 5473 |
| Cyber package | 54.19 | 119.96 | 0.00 | 3.74 | 13.90 | 43.89 | 1095.21 | 1206 |
| Cyber standalone | 9.84 | 24.68 | 0.06 | 1.54 | 2.29 | 5.72 | 195.59 | 708 |

*Note*: This table presents the price of insurance, which is calculated as the inverse of the combined loss ratio for different insurance lines from 2015 to 2022. The data are winsorized at 95%, and all negative values are excluded. The values for *Multi peril* and *Other liability* are calculated after excluding all insurers that have cyber exposure during the sample period. The definition of lines of businesses can be found in Appendix B.

Table 3: Corporate profile of cyber insurers in 2022

| | All cyber | Cyber Standalone | Cyber Package | Non-cyber |
|---|---|---|---|---|
| Number of insurers | 606 | 148 | 541 | 2039 |
| Cyber premiums by groups (%) | 97 | 98 | 95 | 0 |
| Cyber share in top 3 insurers (%) | 3.32 | 6.29 | 1.60 | 0 |
| P&C market share (%) | 48 | 16 | 42 | 52 |
| **Median value** | | | | |
| Total assets (million $) | 311 | 523 | 296 | 51 |
| Combined loss ratio (%) | 94 | 85 | 95 | 87 |
| Leverage (%) | 58 | 63 | 57 | 48 |
| Risk-based capital (%) | 516 | 447 | 526 | 531 |
| A.M. Best rating | A | A | A | A |
| **Premium weighted average** | | | | |
| Total assets (billion $) | 5 | 3 | 12 | 37 |
| Combined loss ratio (%) | 53 | 46 | 69 | 81 |
| Leverage (%) | 60 | 61 | 58 | 56 |
| Risk-based capital (%) | 1917 | 1883 | 1998 | 1630 |
| A.M. Best rating | A+ | A+ | A+ | A |

*Note*: This table presents the key characteristics of cyber and non-cyber insurers. *Cyber premiums by groups (%)* is calculated as the percentage of cyber premiums written by insurers affiliated with insurance groups. *Cyber share in top 3 insurers (%)* is calculated as the share of cyber premiums in total group-level premiums for insurers ranked in top 3 by cyber premiums. *P&C Market share (%)* is calculated as total premiums written by insurers divided by the total premiums written in the P&C market. There are overlaps between insurers that underwrite cyber standalone policies and those insurers that underwrite cyber package policies, and thus the sum of their market shares is higher than the sum of all cyber insurers. *Total assets* is the total admitted assets in all lines reported. *Combined loss ratio (%)* is calculated as the total losses plus expenses divided by total premiums. *Leverage (%)* is calculated as total liabilities divided by total assets. *Risk-based capital (%)* is calculated as the ratio of total adjusted capital to risk-based capital requirement. *Median value* is calculated as the median level of the specified category. *Premium weighted average* is calculated as the sum of one statistic weighted by cyber premiums for cyber insurers or total premiums for non-cyber insurers.

and are riskier than package policies; therefore, cyber insurers reduce their exposure by switching to claims-made policies over time, increasing their share by 12.2% to 95.6% during the sample period. Furthermore, insurers mitigate their exposure by adjusting deductibles and coverage limits. Risk placement services (2021) reports that, due to the surge of cyber risk, insurers that offer $5 million cyber coverages in 2020 have scaled back to limits of $1-3 million, even on a renewal.

Table 3 reports corporate characteristics of insurers underwriting cyber insurance (cyber insurers) and compares them to insurers not underwriting cyber risk (non-cyber insurers). Although only 23% of P&C insurers underwrite cyber insurance, their market share in the

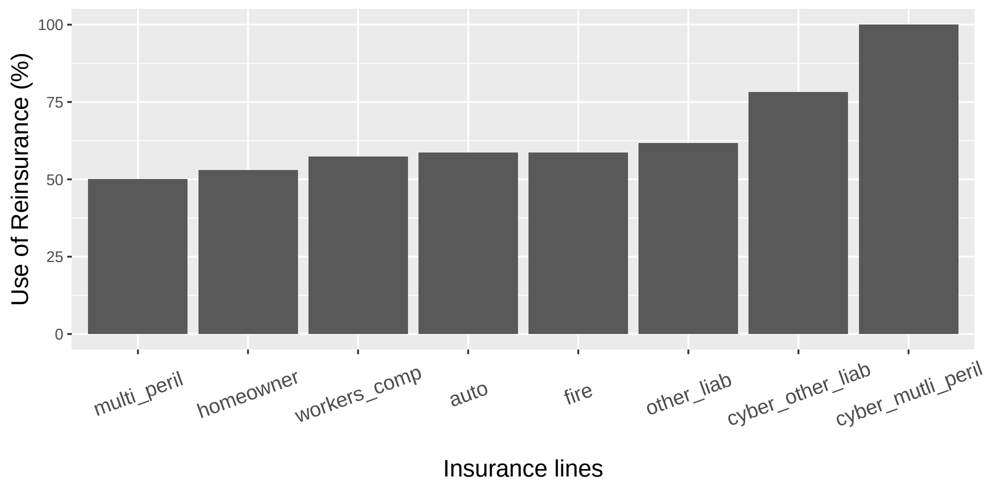


Figure 2: Use of reinsurance by insurance lines

*Note*: This figure presents the median use of reinsurance (% of total premiums) across different lines of business in 2022. *cyber_other_liab* and *cyber_mutli_peril* use the subsample of insurers with more than 50% cyber premiums in the corresponding lines.

P&C insurance market is 48%. Also, the median total assets of cyber insurers are $523 million for standalone policy writers and $296 million for package policy writers, compared to $51 million for non-cyber insurers. Further, cyber insurers have higher leverage ratios but similar A.M. Best ratings compared to non-cyber insurers.

More than 95% of cyber premiums are written by insurers that are members of insurance groups. At the group level, the exposure to cyber insurance liabilities of insurance groups underwriting cyber risk is insignificant. Even the top 3 cyber insurers by premiums have only 6.29% of their total group-level premiums in cyber standalone policies and 1.60% in cyber package policies.

## 3.2 Affiliated and non-affiliated reinsurance

Reinsurance enables optimal risk sharing among risk-averse insurers (Borch, 1962). The risk aversion of insurers is driven by the sensitivity of policyholders to insurers' default risk (Doherty and Schlesinger, 1990), cost of financial distress, agency costs of external capital, and capital market frictions to hedge insurance-specific risks (Froot, Scharfstein, and Stein, 1993; Froot and Stein, 1998; Froot, 2007). Reinsurance is used to manage these risks and agency costs and thus plays a dual role as both a risk management and financing tool (Garven and Lamm-Tennant, 2003; Plantin, 2006; Doherty, 1997). However, the empirical evidence indicates that external reinsurance, that is, the reinsurance purchased from unaffiliated reinsurers, is significantly lower than the optimal level, possibly because its price is distorted upwards by capital market frictions and reinsurers' market power (Froot, 2001; Froot and O'Connell, 2008).

The previous empirical literature has documented that insurance groups rely extensively on ICM in the form of affiliated reinsurance (Powell and Sommer, 2007; Powell, Sommer, and Eckles, 2008; Fier, McCullough, and Carson, 2013; Niehaus, 2018). The total volume of affiliated reinsurance in the US P&C insurance industry in 2022 is three times more than the volume of non-affiliated reinsurance. The dominant reliance on affiliated reinsurance is driven by the prevalence of insurance groups. More than 70% of all insurers and 90% of cyber insurers are affiliated with an insurance group in the US P&C insurance industry in 2022. Furthermore, affiliated reinsurance is the main form of ICM transaction used by insurance groups compared to other ICM transactions ( Powell, Sommer, and Eckles, 2008; Cummins and Weiss, 2016;Niehaus, 2018).

A typical form of affiliated reinsurance is intercompany pooling agreements, under which all of the pooled business is ceded to the lead entity and then retroceded back to the pool participants in accordance with their stipulated shares (NAIC, 1998). For example, American Insurance Group, one of the largest insurance groups in the US, utilizes such an agreement, mandating all its P&C subsidiaries to cede 100% of its policyholder assets and liabilities to the lead insurer, National Union Fire Insurance Company. Subsequently, each member assumes its share of the pooled assets and liabilities as per the pre-specified agreement. Due to the strong interconnection among the subsidiaries under the pooling agreement, their performance and financial strength are related. Furthermore, the insurance industry rating agency A.M. Best identifies the companies that are members of the same pooling agreement as one rating unit and assigns the same rating to these insurance companies. For these reasons, we will use measures at the rating-unit level when reinsurance decisions are involved in the analysis.

Cyber insurers retain less risk and cede, that is, transfer, more risk to reinsurance

Table 4: Comparison of reinsurance activities in 2022

| | All cyber | Cyber standalone | Cyber package | Non-cyber |
|---|---|---|---|---|
| Number of firms | 606 | 148 | 541 | 2039 |
| **Median value** | | | | |
| Retention ratio (%) | 31.75 | 20.95 | 32.18 | 51.19 |
| US affiliated reinsurance (%) | 49.59 | 35.82 | 51.95 | 0.00 |
| Foreign affiliated reinsurance (%) | 0.00 | 0.00 | 0.00 | 0.00 |
| Non-affiliated reinsurance (%) | 3.58 | 11.93 | 3.05 | 2.38 |
| **Premium weighted average** | | | | |
| Retention ratio (%) | 25.42 | 23.60 | 29.75 | 40.55 |
| US affiliated reinsurance (%) | 53.43 | 54.23 | 51.52 | 47.15 |
| Foreign affiliated reinsurance (%) | 1.49 | 0.88 | 2.95 | 1.38 |
| Non-affiliated reinsurance (%) | 18.53 | 19.69 | 15.78 | 9.39 |

*Note*: This table presents the comparison of reinsurance activities of cyber insurers and non-cyber insurers in 2022. *Retention ratio (%)* is the ratio of premiums retained by the insurer to the total premiums. *US affiliated reinsurance (%)* is the ratio of premiums ceded to US affiliates to the total premiums. *Foreign affiliated reinsurance (%)* is the ratio of premiums ceded to US affiliates to the total premiums. *Non-affiliated reinsurance (%)* is the ratio of premiums ceded to external reinsurers to the total premiums. *Median value* is calculated as the median level of the specified category. *Premium weighted average* is calculated as the sum of one statistic of the specified category weighted by cyber premiums for cyber insurers or total premiums for non-cyber insurers.

compared to other insurers. Figure 2 depicts the use of reinsurance across different lines of business, including cyber. It shows that insurers focused on cyber insurance transfer a much higher share of their premiums to reinsurers. Across non-cyber lines, the use of reinsurance ranges between 50% and 60% at the median level in 2022, while the reliance on reinsurance is around 75% for the other liability line and almost 100% for the multi-peril line when these lines have over 50% cyber premiums.

Table 4 summarizes the reinsurance activity of cyber and non-cyber insurers. Although cyber insurance is only a small part of the insurers' business, the difference in utilization of reinsurance between cyber insurers and non-cyber insurers is apparent. At the median level, of all premiums written in 2022, cyber insurers retain only 32% while non-cyber insurers retain around 50%. More starkly, a median cyber insurer transfers 50% of premiums to its affiliates, while a median non-cyber insurer transfers 0%. If we consider the reinsurance activities of insurers weighted by their premiums so that insurers with higher market shares are more represented, the role of ICM for non-cyber insurers increases significantly. The reason is that the large non-cyber insurers that dominate the market transfer a substantial amount of premiums to their affiliates. However, even in comparison with large non-cyber insurers, cyber insurers still have a 15% lower retention ratio and 6% higher affiliated reinsurance, suggesting that cyber insurers rely heavily on the use of affiliated reinsurance.

To further explore the role of affiliated reinsurance activities for underwriting cyber risk, we calculate the correlation between the share of premiums ceded to affiliated reinsurance and the share of premiums written across various lines of business of an insurer. We estimate the following ordinary least squares regression,

$$\textit{Affiliated Reinsuarnce}_{it} = \beta_0 + \beta_1 cyber_{it} + \sum_j \beta_j line_{ijt} + X_{it}'\lambda + \epsilon_{it}, \tag{1}$$

where the dependent variable $\textit{Affiliated Reinsuarnce}_{it}$ is the percentage of gross premiums of the insurer ceded to its affiliates. The variable $cyber_{it}$ is defined as the percentage of cyber premiums in gross premiums written by the insurer. The variable $line_{ijt}$ is defined as the percentage of premiums of the line $j$ in gross premiums written by the insurer, and this includes all lines of businesses for P&C insurers.[7] Vector $X_{it}$ includes control variables such as the size and leverage of the insurer, and others. Our main coefficient of interest is $\beta_1$. If $\beta_1$ is positive and significant, it means that the underwriting of cyber insurance is positively correlated with the usage of affiliated reinsurance. Furthermore, if the other coefficients $\beta_j$ are insignificant or negative, it would suggest that affiliated reinsurance has a unique role in cyber insurance supply.

To exclude the potential impact of the BEAT reform (which will be explained in the following section) in 2018 on our estimation, we consider the sample period from 2015 to 2017. In addition, our sample is restricted to insurers with premiums above the first quartile ($3 million) and insurers that are affiliated with a group.

Table 5 presents the estimates of Equation 1. We find that a higher percentage of cyber premiums is positively correlated with more intensive use of affiliated reinsurance. Using the estimates in column (3), a 1% increase in the share of cyber premiums is associated

[7] Details on these lines can be found in Appendix B.

Table 5: Affiliated reinsurance and different lines of business

| Dependent variable | Use of affiliated reinsurance (%) | | |
|---|---|---|---|
| Model | (1) | (2) | (3) |
| Cyber | 1.728** | 1.346** | 1.391** |
| | (0.7161) | (0.5595) | (0.5781) |
| Homeowner | -0.1942*** | -0.1469*** | -0.1474*** |
| | (0.0648) | (0.0490) | (0.0492) |
| Accident & health | -0.7094*** | -0.4461*** | -0.4295*** |
| | (0.1170) | (0.1200) | (0.1192) |
| Fire | -0.2417*** | -0.1460** | -0.1425** |
| | (0.0804) | (0.0645) | (0.0644) |
| Auto damage | -0.0367 | 0.0184 | 0.0260 |
| | (0.0572) | (0.0414) | (0.0417) |
| Financial | -0.5869*** | -0.3127*** | -0.3132*** |
| | (0.0603) | (0.1015) | (0.0961) |
| Marine | -0.1531 | -0.0048 | 0.0136 |
| | (0.1435) | (0.1221) | (0.1230) |
| Medical | -0.0587 | 0.0630 | 0.0471 |
| | (0.0900) | (0.0775) | (0.0783) |
| Workers | -0.1013 | 0.0189 | 0.0130 |
| | (0.0645) | (0.0502) | (0.0506) |
| Other liability | -0.2331*** | -0.0753 | -0.0731 |
| | (0.0690) | (0.0547) | (0.0548) |
| Auto liability | -0.3049*** | -0.1516** | -0.1557** |
| | (0.0950) | (0.0760) | (0.0756) |
| Aircraft | -0.3851* | -0.2325 | -0.2293 |
| | (0.2270) | (0.2239) | (0.2196) |
| Fidelity | -0.4127*** | -0.3498*** | -0.3520*** |
| | (0.1012) | (0.0876) | (0.0885) |
| Other | -0.2924*** | -0.2692*** | -0.2657** |
| | (0.1091) | (0.1032) | (0.1038) |
| Year FE | N | N | Y |
| Control | N | Y | Y |
| Observations | 3,738 | 3,738 | 3,738 |
| $R^2$ | 0.06417 | 0.33659 | 0.33960 |

*Note:* This table presents estimates of the relationship between the use of affiliated reinsurance and the percentage of different lines of business. The dependent variable is the continuous value, defined as the percentage of gross premiums written ceded to affiliates. The reference line is the commercial multi-peril line, which means the coefficients of different lines are interpreted compared to this line. Clustered standard errors at the insurer level are reported in parentheses. ***, **, and * denote the statistical significance at the 1%, 5%, and 10% level, respectively.

with a 1.39% increase in gross premiums ceded to affiliates. Remarkably, the effect is not present for other insurance lines when compared to the reference group (the commercial multi-peril line). For most insurance lines, the share of premiums in the line is either insignificant or negatively correlated with the share of affiliated reinsurance.

## 3.3 Premium growth and risk

The rapid growth of the cyber insurance premiums can be driven by inadequate pricing or reserving. Conversely, the premium growth could be a consequence of the increasing price per exposure. Barth and Eckles (2009) develop a simple test to assess whether premium growth indicates more risk. The test builds on the premise that premium volume is the product of the average rate and the number of exposures. Thus, premium growth can be achieved through either selling more policies and increasing the number of exposures or increasing the average price per exposure. An increase in the number of exposures can also require cutting the average rate per exposure and thus increase the risk. If the premium growth is achieved by reducing the price of exposures or adding more risky exposures, it will be positively correlated with the growth of the loss ratios. Further, if the exposure growth is obtained due to increased risk, the growth of claims count will be positively correlated with the growth of loss ratios.

To assess the implication of the rapid cyber insurance market growth for risk and profitability of insurers, we estimate the following two regressions

$$ln(\frac{LR_{i,t}}{LR_{i,t-1}}) = \beta_i + \beta ln(\frac{P_{i,t}}{P_{i,t-1}}) + \epsilon_{i,t}, \tag{2}$$

$$ln(\frac{LR_{i,t}}{LR_{i,t-1}}) = \phi_i + \phi ln(\frac{C_{i,t}}{C_{i,t-1}}) + \epsilon_{i,t}, \tag{3}$$

where $LR$ is the loss ratio, $P$ is the premium, and $C$ is claim count, $i$ stands for insurer, and $t$ refers to the year. If the growth of the premiums derives from increasing the risk, the estimated coefficients $\beta$ and $\phi$ will be positive and significant.

Tables 6 report the results of the estimation of equations 2 and 3 for the combination of standalone and package cyber insurance market segments. In column (1)-(3), the results

Table 6: Loss growth and premiums/claims growth

| Dependent Variables: | Change in loss ratio | | | Change in loss ratio | | |
|---|---|---|---|---|---|---|
| Model: | (1) | (2) | (3) | (4) | (5) | (6) |
| Change in premiums | -0.3472** | -0.3896*** | -0.5899*** | | | |
| | (0.1393) | (0.1002) | (0.1649) | | | |
| Change in claim count | | | | 0.2566*** | 0.2535*** | 0.2559*** |
| | | | | (0.0743) | (0.0696) | (0.0890) |
| Controls | No | Yes | Yes | No | Yes | Yes |
| Firm | No | No | Yes | No | No | Yes |
| Year | No | Yes | Yes | No | Yes | Yes |
| Observations | 1,011 | 1,011 | 1,011 | 898 | 898 | 898 |
| $R^2$ | 0.01362 | 0.02994 | 0.38544 | 0.01589 | 0.03435 | 0.36665 |

*Note*: This table presents the results for the relationship between loss ratio changes and premiums changes for cyber standalone and package policies. The sample is restricted to the observations that have reasonable growth ratios between 0 and 1000%. Signif. Codes: ***: 0.01, **: 0.05, *: 0.1

show the growth of premiums leads to lower loss ratios, which suggests that insurers are increasing their prices. In column (4)-(6), the growth of claim count is positively correlated with the growth of loss ratios, indicating the the claims become more risky and lead to higher losses. In combination, the results suggest that insurers succeed in containing their exposure to cyber risk despite the rapid market growth. Although we cannot observe cyber insurance prices charged by insurers to firms, an increasing willingness to pay for cyber insurance policies by firms is a plausible explanation for interpreting the estimation results. NAIC (2021) cites several market surveys and industry reports that indicate cyber insurance price growth of 10-30% in 2020, possibly driven by increasing corporate demand for cyber insurance.

# 4 A Model of Risk Financing

We build a model that explains how the pecking order of financing sources depends on the insurance liability portfolio characteristics. We model financing choices between internal capital market, external reinsurance, outside investors. As in Gertner, Scharfstein, and Stein (1994) and Stein (1997), the distinguishing characteristics of the funding sources are information asymmetry, allocation of control rights and asset redeployment, and managerial incentives. Gertner, Scharfstein, and Stein (1994) and Stein (1997) emphasize that in an internal capital market, individual project managers do not raise funds directly from outside investors. Rather, the corporate headquarters acts as an intermediary between the project managers and outside investors. The headquaters raises funds from outside investors and possesses the control rights to distribute the funds to individual projects. Furthermore, headquaters has monitoring skills that enable it to acquire information about the projects ex ante prospects. We adopt these ideas to the insurance context. In addition, we extend the model by introducing regulatory capital requirements which is a distinctive feature of operation of the insurance companies that are subject to solvency requirements.

## 4.1 Assumptions

**Insurance company's liability portfolios.** An insurance company consists of the headquarters and two divisions, safe and risky. It operates in two dates. At date $t = 0$, each division collects insurance premiums. At date $t = 1$, it pays the indemnity to policyholders according to the insurance contract coverage. The safe division collects 2 units of premiums at $t = 0$ and realizes a loss of $2 - 2s$ at $t = 1$. Profits $2s > 0$ reflect the underwriting and investment profits of the division. A commodity-like insurance with many small and diversifiable losses such as private auto physical damage insurance is an example of a business line with such properties.

Risky division is the prototype of a division underwriting cyber risks. Risky division can choose different sizes of the liability portfolio, by collecting premiums in the amount $i \in \{0, 1, 2\}$. The division loss distribution is uncertain and depends on the portfolio size and the state of the world (Figure 3).

The risky division with an insurance portfolio of size 1 realizes either a gain of $1-y_H$ with probability $\mu$ or a loss of $1+y_L$ with probability $1-\mu$, with $0 < \mu < 1$. Then the net present value (NPV) of the risky division with liability portfolio of size 1 is the difference between the premiums and the expected returns, $y_1 = 1-\mu(1-y_H)-(1-\mu)(1+y_L) = \mu y_H-(1-\mu)y_L$. We assume that $y_1 > 0$.

The distribution of returns of a larger portfolio of size 2 depends on the state of the

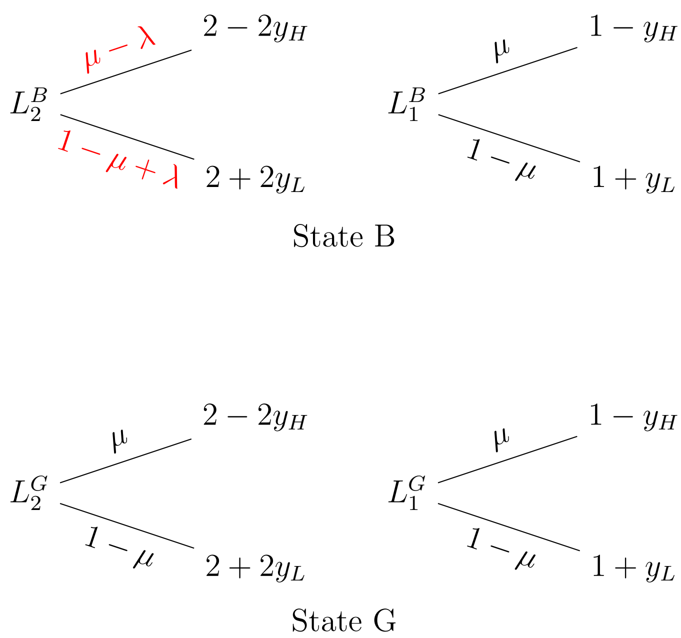


Figure 3: Loss distribution

world $\omega \in \{B, G\}$. The ex-ante probability of state $G$ and state $B$ occurring is $p$ and $1-p$, respectively, with $0 < p < 1$.

In state $B$ (”bad” state), a portfolio of size 2 of premiums realizes either a gain of $2-2y_H$ with probability $\mu - \lambda$ or a loss $2 + 2y_L$ with probability $1 - \mu + \lambda$, with $0 < \mu - \lambda < 1$. That is, in state $B$, a larger portfolio with 2 units of premiums is more likely to incur a large loss than a smaller portfolio with 1 units of premiums. The NPV of the risky division with liability portfolio of size 2 in state $B$ is $y_2^B = 2(\mu y_H - (1-\mu)y_L) - 2\lambda(y_H + y_L)$. We assume that $y_2^B > 0$.

When the state of the world is $G$ (”good” state), a portfolio of 2 units of premiums realizes either a gain of $2 - 2y_H$ with probability $\mu$ or a loss $2 + 2y_L$ with probability $1 - \mu$. In this state, the NPV of the risky division of size 2 is $y_2^G = 2y_1$.

**Assumption 1.** *The efficient size of the division depends on the state $\omega$.* The efficient size of the risky division is 2 in state $G$ and 1 in state $B$, $y_2^B < y_1$. In terms of the model parameters, we assume that $\mu < \lambda < \frac{1}{2}\mu - \frac{1}{2}\frac{y_L}{y_H + y_L}$.

**Prudential regulatory requirements and capital sources.** The regulatory requirement is that an insurance division must be solvent for all loss realizations. We normalize the equity of a risky division to zero. It implies that the insurer needs to obtain contingent capital which is paid in states where the realized losses exceed insurers' premiums/reserves. The minimum required amount of contingent capital is $R_i = iy_L$ for the portfolio of size $i = \{1, 2\}$.

There are three potential sources for raising capital. Under internal capital market financing intermediated by the headquarters, the risky division obtains affiliated reinsurance from the safe division. Under external reinsurance, the insurer signs a reinsurance treaty with an unaffiliated reinsurer. Under capital market financing, the capital is obtained from outside investors. The insurer can combine any of these sources of capital. These capital sources differ in terms of the information available to capital providers, the ability of capital providers to direct the portfolio choice of the risky insurance division, and the agency costs.

**Information structure.** The distribution of states $P(G) = p$ and $P(B) = 1 - p$ is common knowledge. The manager of the risky division and the headquarters observe the state $\omega$, but the outside investors do not. A reinsurer receives an informative signal $\sigma_\omega$ about the state of the world $\omega$, with symmetric signal precision

$$q = P(G|\sigma_G) = P(B|\sigma_B) \geq \frac{1}{2}. \tag{4}$$

When $q = 1$, the reinsurer is perfectly informed about the state $\omega$. When $q = \frac{1}{2}$, the reinsurer has no information advantage compared to the outside investors.

**Timing.** The timing of the model is depicted on Figure 4. Prior to any contracting, the state $\omega \in \{B, G\}$ is realized. An insurer observes the state $\omega$ and the reinsurer observes the signal $\sigma_\omega$. At date $t = 0$, the risky division manager chooses the portfolio size $i$ and raises contingent capital $R_i = iy_L$ from reinsurers or outside investors who compete in contract offers. Then the underwriting takes place. In the interim date, the losses are realized. At date $t = 1$, all contracts are settled.

**Payoffs.** Our focus is on the role that the internal capital market plays in providing capital for underwriting insurance portfolios with different risk characteristics. While internal capital market alleviates the information asymmetries faced by the outsize investors and

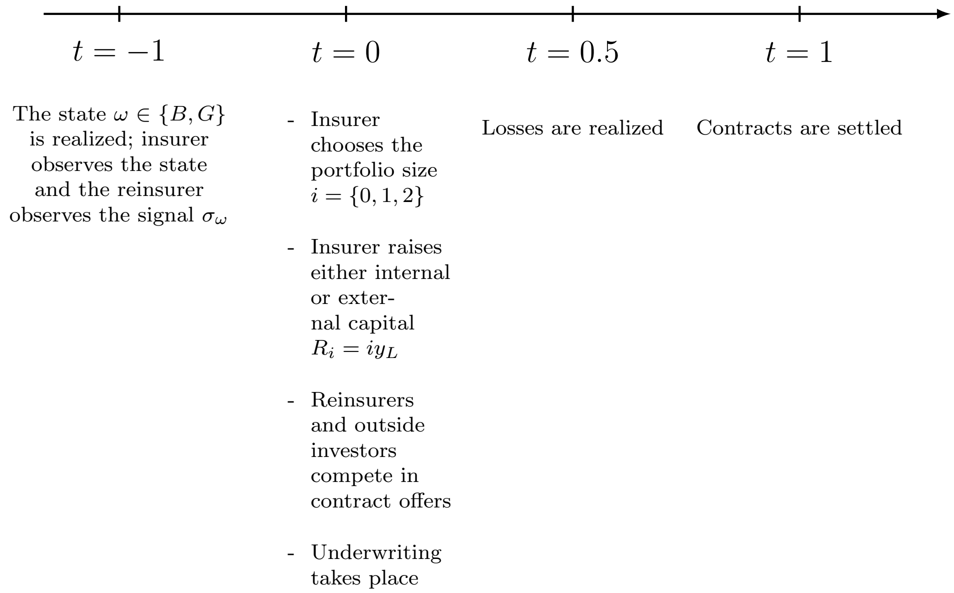


Figure 4: Timing of the model.

the headquarters are capable to direct funds to individual projects, delegation of decisions to headquarters also creates agency costs. Also, the amount of internal capital that the headquarters can provide to the risky division is constrained by the size of insurer's internal capital market. To reflect these features, we make the following assumptions on the payoffs.

**Assumption 2.** *Inclination towards over investment.* Divisions' and headquarters' managers derive private benefit from the cashflows that they control. Therefore, they tend to overstate their investment prospects.

**Assumption 3.** *Effort dilution.* Headquarters has residual control rights but reduces managers' ex-ante incentives to put forth effort.

**Assumption 4.** *Competitive financial market.* Reinsurers and investors compete in contract offers and earn zero profits.

We assume that division managers derive private benefits equal to the fraction $\beta \in (0, 1)$ of the cash flow. Further, we focus on simple contingnet debt contracts and rule out a possibility of designing revelation schemes.[8]

[8]As discussed in Stein (1997), the revelation schemes may not be feasible when the private benefit $\beta$ is too high or the probability $p$ of state $G$ is too low.

**Full information benchmark without moral hazard.** Under full information and in the absence of managerial discretion to derive private benefits, investors observe the state $\omega$ and the manager needs to raise external contingent capital to pay policyholders when the insurance portfolio incurs a loss. In state $G$, investors' competitive offer is $R_i = iy_L$ units of contingent capital for a premium $P_i = i(1-\mu)y_L$. The owner of the division is protected by limited liability and thus obtains profits

$$\Pi_i^G = i(\mu y_H + (1-\mu)max(0, -y_L + R_i)) - P_i. \tag{5}$$

Given the equilibrium premium $P_i$, the owner obtains the $NPV$, $\Pi_i^G = NPV_i^G$, and thus selects the portfolio size 2.

In state $B$, the investors' competitive offer for contingent capital $R_2 = 2y_L$ that covers the loss of portfolio size 2 is $P_2^B = 2(1-\mu+\lambda)y_L$. The terms to raise contingent capital to support portfolio size 1 are the same as in state $G$. The owner of the division obtains the profits $\Pi_i^B = NPV_i^B$. Since $y_2^B < y_1^B$, the owner chooses the insurance portfolio of size 1. Thus, the equilibrium implements the efficient allocation.

## 4.2 Division-level financing and credit rationing

Under asymmetric information, we start by analyzing the case where each division raises contingent capital directly from reinsurers or outside investors. Furthermore, we assume that the reinsurer does not have any information advantage compared to the outside investors, $q = \frac{1}{2}$. As we rule out any revelation schemes which can be used by the outside investors to make financing contingent on the state of the world, the investors can provide capital to support underwriting of either 1 or 2 units of premiums. In the case of an insurance portfolio of size 1, the NPV of the risky division is $y_1$ in either state of the world, and the outside investors provide contingent capital in the amount $R_1 = y_L$ at the premium $P_1 = (1-\mu)y_L$. In the case of the insurance portfolio of size 2, the outside investors provide contingent capital in the amount $R_2 = 2y_L$ at the premium $\overline{P}_2 = 2(p(1-\mu) + (1-p)(1-\mu+\lambda))y_L$. Asymmetric information leads to the credit rationing problem if in state $G$ the owner prefers the portfolio of size 1 rather than size 2, that is

$$2\mu y_H + (1-\mu)max(0, -2y_L + R_2) - \overline{P}_2 < y_1. \tag{6}$$

The credit rationing occurs when the probability of state $B$ is sufficiently high, which we assume to be the case.

**Assumption 5.** *Credit rationing.* We assume that model parameters satisfy

$$1 - p > \frac{\mu y_H - (1-\mu)y_L}{2\lambda y_L}. \tag{7}$$

Therefore, the owner chooses portfolio of size 1 regardless of the state and obtains $NPV_C R = y_1$. The efficiency cost of credit rationing is the surplus loss in state $G$ in the amount $p(\mu y_H - (1-\mu)y_L)$.

## 4.3 Internal capital market

We now introduce the headquarters. The headquarters observes the state of the world $\omega$. Also it is endowed with control rights to choose the size of the risky division and to source the contingent capital by means of internal reinsurance from the safe division to the risky division. Giving control right to the headquarters allows it to appropriate from the risky division project management a fraction $\phi \in (0,1)$ of the private benefit. So if the risky division manager obtains a private benefit $\beta CF_i^\omega$, the headquarters appropriates $\phi\beta CF_i^\omega$, leaving to the risky division's manager a fraction $(1-\phi)\beta CF_i^\omega$. But the ex-post opportunism by the controlling party has the ex-ante costs of reducing incentives for managers to put in effort. Thus, the control by headquarters reduces the NPV of the division by the factor $k \in (0,1)$ relative to the case of division manager's control. Thus, when the headquarters is in control, the risky division cash flow is $kCF_i^\omega$, the manager's private benefit is $k\phi\beta CF_i^\omega$, and the headquarters private benefit is $k(1-\phi)\beta CF_i^\omega$. Similarly, for the safe division, the cash flow is $2ks$, the safe division manager's private benefit is $2k\phi\beta s$, and the headquarters benefit is $2k(1-\phi)\beta s$.

The headquarters maximizes the cash flow of the two divisions. Because the headquarters observes the state, it chooses the division size efficiently. In return for providing contingent capital, the safe division should be rewarded with a share of surplus generated by the risky division. To simplify the comparison, we assume that the safe division receives a fair premium $P_i = i(1-\mu)y_L$ for providing affiliated reinsurance. But other surplus sharing rules are also admissible. Then the headquarters payoff is equal to its private benefit $(1-\phi)k(y_i^\omega + y_s)$. The internal capital market financing is feasible if

$$y_L < s, \tag{8}$$

that is, when the profits of the safe division $2s$ are sufficient to pay the loss of a risky division of size 2, $2y_L$. In this case, the ICM obtains the NPV equal to

$$NPV_I = k(py_2^G + (1-p)y_1). \tag{9}$$

It dominates the credit rationing solution if $NPV_CR < NPV_I$, as summarized in the next proposition.

**Proposition 1.** *If $k(1+p) > 1$ and $y_L < s$, the headquarters sources contingent capital from the save to the risky division in state $G$, and selects portfolio size 1 in state $B$ and portfolio size 2 in state $G$.*

The result implies that the ICM resolves the credit rationing problem when the safe division has a deep pocket, $s$ is high, the loss of the risky division is not excessive, $y_L$ is relatively low, the headquarters control has moderate incentives costs, $k$ is moderate, and the probability of state $G$ $p$ is relatively high. However, when these conditions are not met, the supply of insurance is constrained by credit rationing and thus is inefficient. In particular, the tail losses with large values $y_L$ cannot be financed by ICM alone and require external capital.

## 4.4 External financing

We now consider a situation where the condition of Proposition 1 are not satisfied. We are particularly interested in the case where $y_L > s$ and the ICM does not have sufficient resources to finance the risky division. Denote $\Delta = 2(y_L - s)$ the amount of capital that is required to enable the financing of the portfolio of size 2 in the loss state. Upon receiving an informative signal $\sigma_\omega$, the reinsurer offers continent capital at the premium

$$P_i^R(\sigma_\omega) = (Pr(G|\sigma_\omega)(1-\mu) + Pr(B|\sigma_\omega)(1-\mu+\lambda))\Delta \tag{10}$$

Suppose first that in equilibrium the headquarters raises funds from reinsurers only if the reinsurer receives a good signal $\sigma_G$. In this case, the posterior belief of the reinsurer is

$$Pr(G|\sigma_G) = \frac{pq}{pq + (1-p)(1-q)}. \tag{11}$$

and the reinsurance premium is $P_i^R(\sigma_G)$. The headquarters raises reinsurance capital $R = \Delta$ from the reinsurer in state $G$ after the reinsurer receives the signal $\sigma_G$ if doing so is better than choosing portfolio size 1 for the risky division, or

$$k[2\mu y_H + (1-\mu)max(0, -2y_L + 2s + \Delta) - (1-\mu)2s - P_i^R(\sigma_G)] > k(y_1 + 2s). \tag{12}$$

On the left hand side, the first two terms correspond to the headquarters expected payoff of portfolio size 2, the third terms is the fair price of internal reinsurance in the amount $2s$ and the last term is the price of external reinsurance. Note that the internal capital is always cheaper than the external capital, and thus the headquarters fully utilize the ICM. In terms of the model parameters, condition (12) writes

$$f = \frac{2(y_L - s)\lambda(1-p)(1-q)}{pq + (1-p)(1-q)} < \mu y_H - (1-\mu)y_L. \tag{13}$$

Differentiating function $f$ with respect to parameters $(q, s, p, y_L, \lambda)$ obtains $f_\delta < 0$ for $\delta = \{q, s, p\}$ and $f_\gamma > 0$ for $\gamma = \{y_L, \lambda\}$, leading to the following comparative statics result.

**Proposition 2.** *There are threshold values $(\overline{q}, \overline{s}, \overline{p}, \overline{y}_L, \overline{\lambda})$ for parameters $(q, s, p, y_L, \lambda)$ such that, other things equal, the headquarters raises external reinsurance to finance portfolio size 2 if parameter values are such that $q > \overline{q}$, $s > \overline{s}$, $p > \overline{p}$, $y_L < \overline{y}_L$, and $\lambda < \overline{\lambda}$.*

Proposition 2 establishes that the external reinsurance financing is feasible when, keeping the otehr parameters fixed, the information expertise of the reinsurer is sufficiently high, $q > \overline{q}$, the size of the internal capital market is suffciently large, $s > \overline{s}$, the probability of state$G$ is sufficiently high, $p > \overline{p}$, the tail loss is restricted, $y_L < \overline{y}_L$, and the loss distribution uncertainty is sufficiently low, $\lambda < \overline{\lambda}$. In the next result, we show how the combination of these risk characteristics interact and map into risk financing choices.

**Proposition 3.** *Model parameters $(q, s, p)$ are strategic substitute in that increasing one parameter lowers the threshold value that needs to be satisfied by the other parameters to ensure reinsurance financing. Model parameters $(y_L, \lambda)$ are strategic complements in that increasing one parameter increases the threshold that need to be satisfied by the other parameters to ensure reinsurance financing.*

Note that it is also plausible that the reinsurance market has limited capacity $\overline{\Delta}$, which implies that for tail risks such that $\Delta > \overline{\Delta}$ the reinsurance financing is not feasible even through reinsurers posses strong information expertise (high $q$) and the probability of the good state is high (high $p$).

Given Assumption 5, it can be verified that in equilibrium the headquarters obtain reinsurance financing only after the reinsurer receives signal $\sigma_G$ and not after signal $\sigma_B$. It implies that the equilibrium is constraint efficient and there is surplus loss in state $G$ in the amount $p(1-q)(\mu y_H - (1-\mu)y_L)$. However, this surplus loss is lower than under credit rationing, precisely because the reinsurer possesses information advantage compared to outside investors.

## 4.5 Matching risk characteristics and financing choices

The features of cyber risk discussed in Section 2 suggest that in terms of the model parameters it it the risk with high $y_L$, high $\lambda$ and low $q$. Thus the model analysis suggests the supply of cyber insurance is more pronounced for insurers with deep ICM, high $s$, and higher ability to select "good" risks, high $p$. Also the model suggests that the difference in the cost of external and internal capital can be pronounced. Yet, the cyber risk loss distribution features may require more capital per unit of exposure for underwriting cyber risk compared to other insured risks. The stylized facts about the US insurance market summarized in Section 3 also indicate that insurers underwriting cyber risk rely more heavily on affiliated reinsurance. We further hypothesize that when the cost of affiliated reinsurance is reduced or its cost is increased, the supply of cyber insurance will be reduced. We also hypothesize that the effect of a shock will be less pronounced for other types of insurance. Finally, we hypothesize that the cost of external reinsurance will be increasing in the intensity of heavy tails, loss uncertainty and asymetric information.

# 5 The Internal Capital Cost and the Supply of Cyber Insurance

We aim to establish a causal relationship between the cost of affiliated reinsurance and the supply of cyber insurance. We first describe the BEAT reform that was an external shock to the cost of affiliated reinsurance which enable us to establish a causal relationship. Then, we formulate our empirical tests and report the estimation results.

## 5.1 The BEAT reform

To establish a causal inference, we assess the impact of the external shock that increased the costs of affiliated reinsurance transferred by the US insurance groups to their subsidiaries outside the US, located primarily in Bermuda. In 2017, the Tax Cuts and Jobs Act introduced the Base Erosion and Anti-Abuse Tax (BEAT) which aimed to more effectively reduce multinational companies profit shifting to tax heavens and thus curb base erosion (IRS, 2023). BEAT designates a minimum tax of 10% that applies to certain multinational companies that make "base erosion payments" to foreign-related parties. To be subject to the BEAT, a corporate taxpayer must satisfy the following criteria. First, must have average annual gross receipts of at least $500 million for the prior three tax years. Second, it must have a base erosion percentage for the taxable year of 3% or more. The threshold is generally calculated by dividing the aggregate amount of the taxpayer's "base erosion tax benefits," or deductions attributable to "base erosion payments," by the total amount of the taxpayer's deductions for the year. Third, it must not be a regulated investment company, real estate investment trust, or S corporation.[9]

We rely on the first criterion to define the treatment group. We classify insurers into two groups according to their gross premiums written in the past three years. According to tax regulation, a taxpayer who is a member of an aggregate group determines their status as an applicable taxpayer by reference to the gross receipts and the base erosion percentage of the aggregate group. Thus even small subsidiaries of a large insurance group are subject to BEAT criteria. We do not have sufficient information to calculate the base erosion percentage specified in the second criterion. The third criterion is not relevant for insurance companies (Joint Committe on Taxation, 2019; Kelley et al., 2023).

There are two unique types of cross-country affiliated transactions for insurance companies: reinsurance transferred to and claims payments made to a foreign affiliated insurer. The claims payments are exempted from the BEAT tax liability but the foreign affiliated reinsurance is not. Therefore, BEAT tax reform impacts primarily the cost of foreign affiliated reinsurance. Figure 5 shows the effect of BEAT on the treatment group. Both the number of insurers using foreign affiliated reinsurance ($R_F$) (extensive margin) and the average volume of non-US affiliated reinsurance (intensive margin) decreased after 2017.

## 5.2 Empirical specification and results

We estimate the effect of the exogenous shock to the costs of foreign affiliated reinsurance resulting from the BEAT reform on the supply of cyber insurance. We specify the following difference-in-difference (DiD) model

$$Y_{it} = \alpha + \beta_1 D_i + \beta_2 Post_t + \delta(D \times Post)_{it} + X_{it}'\lambda + \tau_t + \sigma_i + \epsilon_{it} \tag{14}$$

where the subscripts $i$ and $t$ represent the firm and the year. The dependent variable, $Y_{it}$, is the outcome variable that measures the supply of cyber insurance. We consider two outcome variables, the growth rate of cyber premiums and the growth rate in cyber

[9]The S corporation is a business structure that is permitted under the tax code to pass its taxable income, credits, deductions, and losses directly to its shareholders.

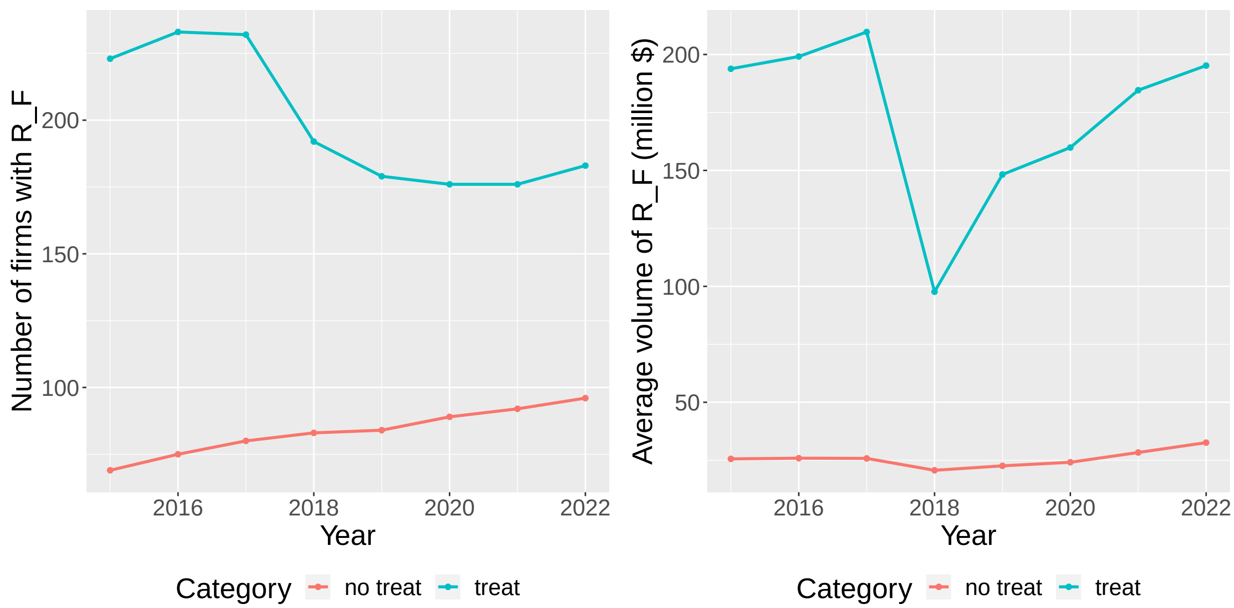


Figure 5: The impact of the BEAT on the use of foreign affiliated reinsurance

*Note*: This figure presents the foreign affiliated reinsurance ($R_F$) usage of all insurers in the market. The treatment group is the insurers with gross premiums higher than $500 million, and the non-treatment group is the insurers with gross premiums lower than this threshold. The percentage is calculated as the number of firms using foreign affiliated reinsurance divided by the number of firms in the group. The average volume is calculated as the mean value of foreign affiliated reinsurance premiums in the respective group.

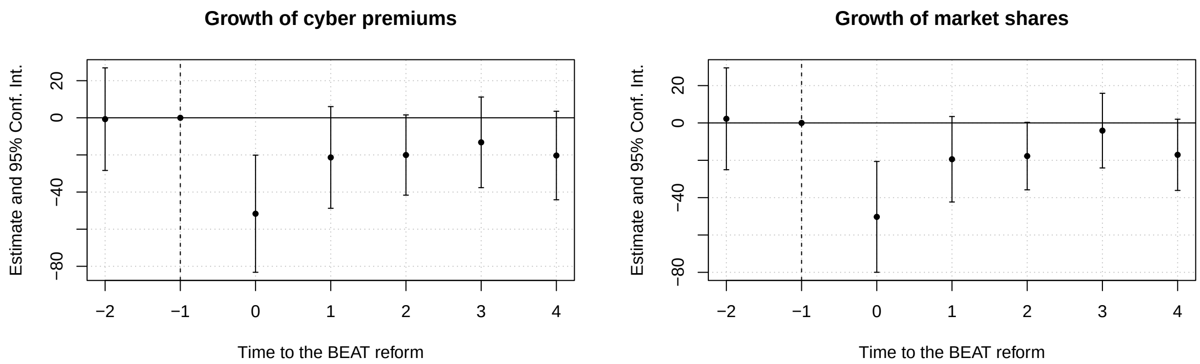


Figure 6: Event study: 2016-2022

*Note*: The figures report the event study results for the insurers that are affected by BEAT. The control group is the insurers below the threshold of \$500M premiums, and the treatment group includes the ones with premiums higher than \$500M. The dependent variable is the growth rate of cyber premiums for the left figure and the growth rate of market shares for the right figure.

insurance market share, of an insurer $i$ in year $t$. The reason why we consider growth rates rather than levels is that we estimate the impact of the cost of affiliated reinsurance during the times of the rapid cyber insurance market growth. In Appendix C, we also report the results for the outcome variables defined in terms of levels.

To verify the parallel trend assumption for DiD analysis, we adjust the standard DiD model by including periods before the BEAT reform. We consider a binary treatment measure, $D_i = 1$ if the firm $i$ is above the threshold of \$500 million gross premiums and $D_i = 0$ otherwise. Figure 6 shows the results of event study. Using 2017 as the baseline year ($t = -1$), the graph shows the difference in changes of cyber insurance supply over time between control and treatment groups. The result at $t = -2$ indicates that there is no significant difference before the BEAT reform between the treatment and control firms, providing evidence that parallel assumptions hold. The effects on the growth of cyber premiums and market shares are significantly negative after the reform ($t = 0$).

However, as the insurers affected by the BEAT reform are those with more than \$500 million in gross premiums, insurers that fall below this threshold may not be the suitable control group, since there are various factors linked to the firm size that affect the validity of comparison. To address this concern, we consider the continuous measure of $D_i$ that exploits the variation of insurers' exposure to the BEAT reform within the treatment group.

The exposure is related to two factors, the size of cyber premiums and the share of foreign affiliated reinsurance in gross premiums. As reinsurance is reported on the level of an insurer, which can underwrite different lines of insurance, we allocate the reinsurance share by line according to the share of premiums of the line in the total premiums of the insurer. Thus, the continuous treatment is defined as

$$D = \frac{DPW_C}{GPW - R_D} \cdot \frac{R_F}{GPW - R_D}, \tag{15}$$

where $DPW_C$ is the direct cyber premiums written by the insurer, $GPW$ is the gross premiums written of all lines by the insurer, $R_F$ is the premiums ceded to non-US affiliates, and $R_D$ is the premiums ceded to US affiliates. As explained in Section 3.2, the impact on the affiliated reinsurance affects all subsidiaries in the same rating unit. Thus we calculate the measure $D$ using rating-unit level data rather than individual company level. We use the difference between $GPW$ and $R_D$ in the denominator because it eliminates the double counting of affiliated reinsurance premiums at the rating unit level. We refer to Appendix D for further details on intercompany pooling and reinsurance arrangements of rating units. The measure of exposure to the shock, $D$ is calculated using the data in 2017 for each insurer.

The variable *Post* in Equation 14 is a post-reform dummy. To study the possible long-term effect, we use the dummy variable for the years 2018, 2019, and 2020 and the interaction terms of these dummies and the treatment variable in the regression. The interaction $\delta$ is the coefficient of interest, measuring the effect of BEAT on the supply of cyber insurance. Vector $X_{it}$ is a set of lagged financial variables of the insurers, such as direct premiums written, leverage, and growth of operating incomes of the insurer. $\tau_t$ is the time fixed effect, $\sigma_i$ is a time-invariant firm fixed effect, and $\epsilon_{it}$ controls for unobserved factors.

As our dependent variables are the first-order differences (change in premiums, change in market share), we ensure the data are consistent over time to avoid jumps in values. We use the insurers that are affected by BEAT (over \$500 million total premiums), have stable cyber premiums over \$1 million, and have positive premiums ceded to affiliates from 2015 to 2017. Table 7 presents the summary statistics of the variables in Equation (14).

Table 7: Summary statistics for DiD analysis

| | N | Mean | St. Dev. | Min | Max |
|---|---|---|---|---|---|
| Growth of cyber premiums (%) | 288 | 16.371 | 41.472 | −100.000 | 104.174 |
| Growth of market share (%) | 288 | −0.859 | 43.259 | −100.000 | 104.174 |
| D, Exposure to BEAT | 288 | 20.477 | 41.408 | 0.000 | 147.900 |
| Lag asset (log) | 288 | 13.946 | 2.019 | 9.671 | 17.589 |
| Lag direct premiums (log) | 288 | 13.489 | 1.258 | 9.525 | 15.750 |
| Lag combined ratio (%) | 288 | 75.048 | 44.124 | −5.032 | 131.391 |
| Lag leverage (%) | 288 | 79.705 | 65.346 | 0.000 | 231.988 |
| Growth of direct premiums (%) | 288 | 7.365 | 19.838 | −94.423 | 175.110 |

*Note:* This table presents the summary statistics of key variables for our DiD estimation. $D$ is the cyber exposure of insurers to the BEAT reform. We winsorize the data at the top 10% to control for the impact of outliers.

Table 8 displays the estimates of the exposure to the tax reform on the growth rates of cyber premiums and market shares. The results show that exposure to BEAT reform has a real economic effect on cyber insurers by reducing the growth of cyber insurance premiums and reducing the growth of market shares. In Panel A, the coefficients on the interaction term in 2019 are significantly negative, suggesting that the exogenous shock affects the supply of cyber insurance after one year. In terms of economic magnitude, all else equal, one standard deviation increase of cyber exposure to BEAT leads to a 14.88% decrease in the growth rate of cyber premiums (column 3) and a 16.22% decrease in the growth rate of the market share (column 6) in 2019. The insignificant results in 2020 indicate that the impact is only temporary. Two years after the BEAT reform insurers substitute foreign affiliated reinsurance with the US affiliated reinsurance or other sources[10].

Panel B provides additional support by estimating Equation 14 for the binary treatment group which is defined as cyber insurers that rely heavily on foreign affiliated reinsurance, that is, above the median exposure $D$. We find that the effect of the shock becomes even more pronounced. The insurers with high reliance of foreign affiliated reinsurance experienced a drop of 30% in the growth rate of cyber premiums (column 3) and 31% in

[10]The results are significant in 2019 rather than 2018 as in the case of event study results. The possible reason is that Table 8 focuses only on treated firms and these firms all reduce the supply immediately, which leads to no different reaction in 2018. But due to the difference in exposures, their reactions differ over time, i.e., in 2019.

the growth rate of the market share in 2019.

To further highlight the unique link between the supply of cyber insurance and the availability of affiliated reinsurance, we examine the impact of the BEAT reform on the supply of other types of insurance for the same set of insurers (Hypothesis 2). We follow the specification defined by Equation (15) and calculate the exposure of each insurance line to the BEAT reform for each insurer. Table 9 and 10 present the regression results for 14 different insurance lines. All the $\delta$ coefficients for these insurance lines are not significant, suggesting that the cyber line is the only business line significantly affected by the shock to the availability of affiliated reinsurance.[11]

# 6 Which Characteristics of Cyber Risk Curtail Risk Transfer Outside the Insurance Group?

The significant reliance on the internal market suggests limited access to the external capital market. Otherwise, insurers could easily replace internal capital with external funding. In this section, we analyze the relationship between the features of the cyber risk and the cost of external reinsurance market.

## 6.1 Heavy tails

Heavy-tailedness is an important property of cyber risk and this may affect the risk transfer to reinsurers as cyber insurance is exposed to more extreme risks than other insurance lines. Empirically, this indicates that the price of cyber reinsurance is higher than other types of reinsurance to compensate for the additional risk. However, as there is no data available for cyber reinsurance, one possibility is to estimate its use by considering the share of cyber premiums.

As standalone cyber policies are categorized into the other liability line and package policies into the commercial multi-peril line, we use the share of cyber premiums in each line

[11]The financial guarantee line is dropped due to the fact that there are too few insurers underwriting this type of insurance, and thus, very little cross-sectional variation.

Table 8: The BEAT reform and the supply of cyber insurance

| Panel A: Continuous treatment variable | | | | | | |
|---|---|---|---|---|---|---|
| Dependent variable | Growth of cyber premiums (%) | | | Growth of market share (%) | | |
| Model | (1) | (2) | (3) | (4) | (5) | (6) |
| Treat*Y2018 | -0.1201 | -0.1645 | -0.1441 | -0.1537 | -0.1957 | -0.1801 |
| | (0.1359) | (0.1492) | (0.1369) | (0.1541) | (0.1606) | (0.1558) |
| Treat*Y2019 | -0.2680* | -0.3110** | -0.3542* | -0.2774* | -0.3227** | -0.3861** |
| | (0.1595) | (0.1499) | (0.1863) | (0.1624) | (0.1614) | (0.1873) |
| Treat*Y2020 | 0.1378 | 0.0589 | -0.0417 | 0.1017 | 0.0228 | -0.0944 |
| | (0.1391) | (0.1599) | (0.1902) | (0.1816) | (0.1721) | (0.2337) |
| Insurer FE | N | N | Y | N | N | Y |
| Year FE | N | N | Y | N | N | Y |
| Control | N | Y | Y | N | Y | Y |
| Observations | 288 | 288 | 288 | 288 | 288 | 288 |
| $R^2$ | 0.06381 | 0.16234 | 0.41877 | 0.02058 | 0.10820 | 0.35407 |

| Panel B: Binary treatment variable | | | | | | |
|---|---|---|---|---|---|---|
| Dependent Variable | Growth of cyber premiums (%) | | | Growth of market share (%) | | |
| Model | (1) | (2) | (3) | (4) | (5) | (6) |
| Treat*Y2018 | -16.08 | -13.82 | -14.00 | -14.00 | -11.74 | -11.79 |
| | (9.820) | (12.52) | (9.481) | (11.60) | (13.50) | (11.27) |
| Treat*Y2019 | -28.20** | -26.84** | -30.36** | -27.65** | -26.37* | -30.74** |
| | (12.15) | (12.53) | (11.80) | (12.75) | (13.50) | (12.53) |
| Treat*Y2020 | -15.34 | -16.46 | -22.05* | -12.82 | -13.84 | -19.43 |
| | (13.41) | (12.71) | (12.86) | (13.82) | (13.70) | (13.56) |
| Insurer FE | N | N | Y | N | N | Y |
| Year FE | N | N | Y | N | N | Y |
| Control | N | Y | Y | N | Y | Y |
| Observations | 288 | 288 | 288 | 288 | 288 | 288 |
| $R^2$ | 0.06363 | 0.16072 | 0.42139 | 0.01807 | 0.10358 | 0.35378 |

*Note:* This table presents estimates of the impact of the BEAT on the growth rate of cyber premiums and the market share for the insurers. The continuous treatment (exposure to the BEAT reform) in Panel A is calculated as the share of cyber premiums multiplied by the share of non-US affiliated reinsurance in gross premiums written by the insurer. The treatment group in Panel B is defined as the insurers that have exposure to the BEAT reform above the median. Clustered standard errors at the insurer level are reported in parentheses. ***, **, and * denote the statistical significance at the 1%, 5%, and 10% level, respectively.

Table 9: The impact of the BEAT on different lines of businesses; dependent variable: growth rate of direct premiums written (%)

| Model | Accident & health (1) | Homeowner (2) | Auto damage (3) | Fire (4) | Multi-peril (5) | Marine (6) | Medical liability (7) |
|---|---|---|---|---|---|---|---|
| Treat*2018 | -0.0084 | -0.6200 | 0.0540 | -0.0074 | -0.0206 | -0.1245 | -0.1012 |
| | (0.0408) | (0.7090) | (0.0637) | (0.0382) | (0.0495) | (0.1220) | (0.2431) |
| Treat*2019 | -0.0638 | -1.027 | 0.0819 | 0.0038 | -0.0456 | -0.0982 | 0.2539 |
| | (0.0570) | (0.8845) | (0.0556) | (0.0350) | (0.0506) | (0.0874) | (0.2587) |
| Treat*2020 | -0.1360 | -0.8985 | 0.1509 | 0.0372 | -0.0446 | -0.1152 | -0.0369 |
| | (0.1315) | (0.6860) | (0.2290) | (0.0416) | (0.0415) | (0.1222) | (0.3945) |
| Insurer FE | Y | Y | Y | Y | Y | Y | Y |
| Year FE | Y | Y | Y | Y | Y | Y | Y |
| Control | Y | Y | Y | Y | Y | Y | Y |
| Observations | 256 | 285 | 269 | 266 | 229 | 266 | 240 |
| $R^2$ | 0.21451 | 0.40283 | 0.28009 | 0.21883 | 0.17574 | 0.19021 | 0.31038 |

| Model | Workers' comp (8) | Other liability (9) | Auto liability (10) | Aircraft (11) | Fidelity (12) | Other (13) |
|---|---|---|---|---|---|---|
| Treat*2018 | 0.0809 | 0.0049 | -0.1370 | -0.2529 | -0.1939 | 0.7242 |
| | (0.0670) | (0.0064) | (0.1063) | (0.3373) | (0.1981) | (0.7379) |
| Treat*2019 | 0.0112 | 0.0079 | -0.0562 | -0.2131 | -0.0607 | 0.5628 |
| | (0.0719) | (0.0071) | (0.0611) | (0.3364) | (0.1271) | (0.6405) |
| Treat*2020 | -0.1448 | 0.0009 | 0.1101 | -0.2606 | -0.6843 | 0.5513 |
| | (0.1686) | (0.0042) | (0.2263) | (0.2561) | (0.6868) | (0.6891) |
| Insurer FE | Y | Y | Y | Y | Y | Y |
| Year FE | Y | Y | Y | Y | Y | Y |
| Control | Y | Y | Y | Y | Y | Y |
| Observations | 255 | 268 | 252 | 276 | 189 | 236 |
| $R^2$ | 0.28164 | 0.42233 | 0.22224 | 0.35976 | 0.21970 | 0.21779 |

*Note:* This table presents estimates of the impact of the BEAT on the growth rate of direct premiums written by different lines of businesses. The treatment is the continuous variable as in Equation 15, replacing the cyber premiums with the premium of each line. Insurer and year-fixed effects are controlled for all regressions. Clustered standard errors at the insurer level are reported in parentheses. A detailed definition of each line of business is provided in Appendix B. ***, **, and * denote the statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 10: The impact of the BEAT on different lines of businesses; dependent variable: growth rate of market share (%)

| Model | Accident & health (1) | Homeowner (2) | Auto damage (3) | Fire (4) | Multi-peril (5) | Marine (6) | Medical liability (7) |
|---|---|---|---|---|---|---|---|
| Treat*2018 | 0.0027 | -0.5896 | 0.0539 | -0.0067 | -909.9 | -0.1238 | -0.0997 |
| | (0.0388) | (0.7042) | (0.0606) | (0.0376) | (867.6) | (0.1179) | (0.2421) |
| Treat*2019 | -0.0607 | -1.036 | 0.0821 | 0.0043 | -1,491.3 | -0.0974 | 0.2320 |
| | (0.0573) | (0.8820) | (0.0523) | (0.0340) | (1,093.9) | (0.0867) | (0.2520) |
| Treat*2020 | -0.1030 | -0.8919 | 0.1542 | 0.0339 | -1,525.5 | -0.1142 | -0.0442 |
| Insurer FE | Y | Y | Y | Y | Y | Y | Y |
| Year FE | Y | Y | Y | Y | Y | Y | Y |
| Control | Y | Y | Y | Y | Y | Y | Y |
| Observations | 256 | 285 | 269 | 266 | 229 | 266 | 240 |
| $R^2$ | 0.22001 | 0.39832 | 0.27194 | 0.22653 | 0.25687 | 0.19054 | 0.31110 |

| Model | Workers' comp (8) | Other liability (9) | Auto liability (10) | Aircraft (11) | Fidelity (12) | Other (13) |
|---|---|---|---|---|---|---|
| Treat*2018 | 0.0756 | -1.258 | -0.1344 | -0.2597 | -0.1845 | 0.7222 |
| | (0.0675) | (3.169) | (0.1039) | (0.3426) | (0.1902) | (0.7366) |
| Treat*2019 | 0.0149 | -4.027 | -0.0557 | -0.2468 | -0.0558 | 0.5623 |
| | (0.0731) | (7.475) | (0.0589) | (0.3406) | (0.1230) | (0.6387) |
| Treat*2020 | -0.1311 | -5.721 | 0.1148 | -0.3078 | -0.6861 | 0.5492 |
| | (0.1698) | (9.098) | (0.2289) | (0.2632) | (0.6901) | (0.6871) |
| Insurer FE | Y | Y | Y | Y | Y | Y |
| Year FE | Y | Y | Y | Y | Y | Y |
| Control | Y | Y | Y | Y | Y | Y |
| Observations | 255 | 268 | 252 | 276 | 189 | 236 |
| $R^2$ | 0.28620 | 0.24746 | 0.22041 | 0.34865 | 0.22131 | 0.21770 |

*Note:* This table presents estimates of the impact of the BEAT on the growth rate of market share by different lines of businesses. The treatment is the continuous variable as in Equation 15, replacing the cyber premiums with the premium of each line. Insurer and year-fixed effects are controlled for all regressions. Clustered standard errors at the insurer level are reported in parentheses. A detailed definition of each line of business is provided in Appendix B. ***, **, and * denote the statistical significance at the 1%, 5%, and 10% levels, respectively.

as a proxy for the share of reinsurance, assuming that the reinsurance usage is proportional to premiums written.[12] Therefore, the share of cyber premiums is positively related to the price of reinsurance for the whole line of business, because a higher share indicates more cyber exposure being reinsured, which results in a higher reinsurance price.

### 6.2 Risk uncertainty

As cyber risk is constantly evolving, it is difficult to accurately measure the cyber exposure in the portfolio. Thus, insurers with more expertise in the underwriting of cyber risk may have a competitive advantage in estimating cyber exposure and negotiating reinsurance prices. To measure the level of expertise in cyber risk of different insurers, we use the data from the System for Electronic Rates and Forms Filing, which collects all the insurance product filings in the US. As explained in Section 3.1, the standalone cyber products are categorized into the other liability line, and package products are categorized into the commercial multi–peril line. In rare cases, cyber products are classified under other lines. Therefore, we use text mining together with GPT API to identify the cyber products in all lines of businesses. We check the filing description of each record, which typically summarizes the purpose and content of the filing. This description provides sufficient information to identify whether the submission is related to cyber products. GPT API is an efficient tool for this purpose, and it achieves more than 90% accuracy in our manually generated training sample. We filtered the initial sample of more than 100,000 filings from 2013 to 2022, achieving 1,372 filings that are relevant to our analysis.

We consider the number of pages and filing frequency of cyber products as a proxy for the level of cyber knowledge/experience of one insurer. Intuitively, the insurer with more knowledge could provide more detailed risk classification and price differentiation for different customers, this would require a higher number of pages to describe the product and a higher frequency of updating their products. However, after the manual check, we find that the number of pages as a proxy has is noisy. For example, the types of forms that are filed for approval within each cyber product are not standardized across

[12] This might be a lower bound of the cyber reinsurance as insurers tend to transfer more risky businesses to reinsurers.

insurers. Therefore, some insurers have a higher number of pages because they include more administrative forms (with little relevant information) that are not filed by other insurers. In addition, for package policies, it is common that the cyber coverages are filed together with other coverages in the package, thus blurring the relevance of such filings for our purpose. Therefore, we concluded that the filing frequency of cyber products is a more informative proxy to measure the experience of cyber underwriting of the insurer.

## 6.3 Information asymmetry

Directly measuring information asymmetry in the reinsurance market is challenging. Doherty and Smetters (2005) propose an indirect measure, as reinsurers use price incentives and monitoring in the long-term insurance contract to limit moral hazard in the presence of information asymmetry. Therefore, we can empirically test the use of experience rating, monitoring, and direct price control to provide evidence on the severity of information asymmetry issues in the market.

*Experience rating* is measured by the ratio of direct premiums to direct losses. If reinsurers "experience rate" the past losses to control for moral hazard, high past losses (low premium-to-loss ratio) would lead to high current prices. Thus, the relationship between this measure and the reinsurance price is predicted to be negative. However, cross-sectionally, this ratio can be positively related to the dependent variable as the firms with high past losses tend to have high reinsured losses (the inverse of the reinsurance price). *Monitoring* is proxied by the share of reinsured losses in total losses, as there is no direct measure. The reason we use such a proxy for monitoring is that investment in monitoring is reflected in prices and it increases in the share of reinsured losses. Therefore, the relationship between this variable and the reinsurance price should be positive if monitoring is in place. Lastly, *direct price control* is measured by experience rating multiplied by the share of reinsured losses as the sensitivity of prices to past losses increases as more losses are reinsured. The relationship between the dependent variable and the price control is predicted to be negative when reinsurers use direct price control.

## 6.4 Empirical specification and results

We aim to estimate how the reinsurance price depends on various factors discussed above. We measure the price of reinsurance as the ratio of reinsurance premiums over the reinsured losses for insurer $i$ at time $t$, similarly to the inverse loss ratio calculated for primary insurance in Table 2. We estimate the correlation between the price of reinsurance and the empirical measures of heavy tails, risk uncertainty, and information asymmetry.

To calculate the price for external reinsurance, we need to distinguish between affiliated and non-affiliated reinsurance. However, insurers do not report data at this level of granularity. Therefore, we use the share of non-affiliated reinsurance in total reinsurance as a proxy, which estimates the difference in prices between these two types of reinsurance. To understand how the issue of information asymmetry is related to cyber insurance, we use the interaction terms of information asymmetry measures with the share of cyber premiums. Furthermore, we also include the interaction terms with the share of non-affiliated reinsurance to estimate the severity of information asymmetry issues for different levels of non-affiliated reinsurance usage. Therefore, there are interaction terms with at most three variables. The empirical specification is as follows:

$$\begin{aligned}
Reinsurance\,price_t = \alpha + & \underbrace{\beta \cdot cybershare_{t-1}}_{\text{Heavy tail}} + \underbrace{\gamma \cdot non\ aff_{t-1}}_{\text{Non-affiliated reinsurance}} + \underbrace{\lambda \cdot update\,freq_{t-1}}_{\text{Risk uncertainty}} \\
& \underbrace{\epsilon \cdot control_{t-1} + \delta \cdot exp_rate_{t-1} + \omega \cdot monitor_{t-1}}_{\text{Info asymmetry}} + \\
& \underbrace{cybershare_{t-1} \cdot non\ aff_{t-1} \cdot (\epsilon 1 \cdot control_{t-1} + \delta 1 \cdot exp_rate_{t-1} + \omega 1 \cdot monitor_{t-1})}_{\text{Info asymmetry for lines with cyber insurance and non-aff reinsurance}} + \\
& \underbrace{\lambda 1 \cdot cybershare_{t-1} \cdot non\ aff_{t-1} \cdot update\,freq_{t-1}}_{\text{Risk uncertainty for lines with cyber insurance and non-aff reinsurance}} + other\ interaction\ terms,
\end{aligned} \tag{16}$$

where $cybershare$ is the share of cyber insurance in the corresponding line of business, $non\ aff$ is the share of non-affiliated reinsurance, and $update\,freq$ is the number of updates for cyber products since 2013. Direct price control *control*, experience rating *exp_rate*, and monitoring *monitor* are the measures of information asymmetry. The interaction terms with three variables such as $cybershare_{t-1} \cdot non\ aff_{t-1} \cdot control_{t-1}$ estimate the effects of information asymmetry and risk uncertainty for lines with cyber insurance and non-affiliated reinsurance. *other interaction terms* include all interaction terms among *cybershare*, *non aff*, and the measures of information asymmetry and risk uncertainty. We refer to Table 11 for the summary of the factors affecting the reinsurance prices and their economic interpretations.

We use the data at the rating unit level and focus on insurance groups with more than $500 million in gross premiums written. As we argue in Section 3.2, the reinsurance decisions are likely coordinated inside the rating unit and thus it is more reasonable to aggregate reinsurance data to rating unit level for the analysis of the reinsurance usage and prices. We do not restrict the sample based on cyber premiums, as we consider the insurers with or without cyber exposures. Table 12 presents the summary statistics of key variables used in our analysis for the other liability line and multi-peril line.

Table 13 reports the regression results. For standalone policies (columns 1-3), the coefficients for the share of cyber insurance and non-affiliated reinsurance are significantly positive, which provides evidence that higher exposure to cyber insurance and the use of non-affiliated reinsurance lead to higher reinsurance prices. More specifically, a 1% increase in the use of non-affiliated reinsurance relates to a 0.4% increase in reinsurance price cross-sectionally (column 2), assuming the insurers have average characteristics in other dimensions. The effect of cyber insurance on reinsurance price is much stronger, given an insurer with average characteristics, a 1% increase in the share of cyber insurance is associated with a 41.5% increase in reinsurance price (column 3).

Furthermore, the interaction term *non-aff* × *cybershare* × *monitor* is positive, and *non-aff* × *cybershare* × *control* is negative, indicating that information asymmetry issues are more significant for insurers with more cyber exposure and use of external reinsurance. The results for package policies (columns 4–6) are mostly not significant, indicating information asymmetry and heavy tails are not decisive factors for this market. But the interaction

Table 11: Interpretation: Factor decomposition of cyber reinsurance price

| | |
|---|---|
| non_aff | reinsurance price reaction to the share of external reinsurance (+, **external reinsurance is more expensive**) |
| cybershare | reinsurance price reaction to the share of cyber insurance (+, **cyber reinsurance is more expensive** ) |
| exp_rate | reinsurance price reaction to experience rating or past losses (–, **experience rating is used by reinsurers** ) |
| monitor | reinsurance price reaction to the monitoring efforts (+, **monitoring is used by reinsurers** ) |
| control | reinsurance price reaction to the direct control (–, **direct price control is effective as it increases the sensitivity of reinsurance price to experience rating**) |
| update_freq | reinsurance price reaction to update frequency (–, **higher frequency reduces reinsurance prices**) |
| cybershare × update_freq | reinsurance price reaction to update frequency given the level of cyber share (–, **higher update frequency leads to a lower price when the cyber share is higher**) |
| non_aff × update_freq | reinsurance price reaction to update frequency given the level of non-affiliated reinsurance (–, **higher update frequency leads to a lower price when non-affiliated reinsurance is higher**) |
| non_aff × cybershare × exp_rate | reinsurance price reaction to experience rating given the level of non-affiliated reinsurance and cyber insurance shares (–, **experience rating is used more intensively with more non-affiliated reinsurance and cyber insurance** ) |
| non_aff × cybershare × monitor | reinsurance price reaction to monitoring efforts given the level of non-affiliated reinsurance and cyber insurance shares (+, **with more non-affiliated reinsurance and cyber insurance, the effect of monitoring on reinsurance price is higher** ) |
| non_aff × cybershare × control | reinsurance price reaction to direct price control given the level of non-affiliated reinsurance and cyber insurance shares (–, **with more non-affiliated reinsurance and cyber insurance, the sensitivity of price to direct price control is higher** ) |
| non_aff × cybershare × update_freq | reinsurance price reaction to update frequency given the level of non-affiliated reinsurance and cyber insurance shares (–, **with more non-affiliated reinsurance and cyber insurance, the update frequency of cyber insurer reduces more significantly the reinsurance prices** ) |

*Note*: This table presents the interpretation of key terms in Equation 16 and the predicted signs of the coefficients.

term *non-aff* $\times$ *update_freq* is negative, which is consistent with the argument that high update frequency of cyber products reduce the reinsurance price when the insurer uses more non-affiliated reinsurance.

In general, the results show that all three factors play a role in affecting the reinsurance price and thus limiting the access to the external capital for cyber insurers. In particular, the effects are stronger for the standalone segment than the package segment.

Table 12: Summary statistics

| Statistic | N | Mean | St. Dev. | Min | Max |
|---|---|---|---|---|---|
| **Other liability line** | | | | | |
| cybershare | 720 | 0.383 | 1.483 | 0.000 | 14.344 |
| non-aff | 720 | 46.288 | 37.327 | 0.000 | 100.000 |
| price | 720 | 1.672 | 2.042 | 0.016 | 18.436 |
| exp_rate | 720 | 1.550 | 1.213 | 0.016 | 9.110 |
| monitor | 720 | 0.549 | 0.292 | 0.0002 | 1.000 |
| control | 720 | 0.841 | 0.841 | 0.0003 | 7.208 |
| update_freq | 720 | 1.732 | 2.954 | 0 | 22 |
| **Commericial multi-peril line** | | | | | |
| cybershare | 597 | 1.998 | 7.989 | 0.000 | 97.842 |
| non-aff | 597 | 42.063 | 36.275 | 0.000 | 100.000 |
| price | 597 | 1.600 | 1.944 | 0.001 | 18.683 |
| exp_rate | 597 | 1.346 | 0.855 | 0.007 | 9.517 |
| monitor | 597 | 0.492 | 0.325 | 0.001 | 1.000 |
| control | 597 | 0.656 | 0.737 | 0.001 | 7.830 |
| update_freq | 597 | 1.851 | 2.724 | 0 | 16 |

*Note*: This table presents the summary statistics for the variables in our sample. *cybershare (%)* is the percentage of cyber premiums in the total premiums written in the other liability line or the multi-peril line. *non-aff (%)* is the percentage of reinsurance premiums that are ceded to non-affiliated reinsurance. *price* is the reinsurance price, exp_rate is the experience rating, *monitor* is the variable for monitoring, and *control* is the variable for direct price control. *update_freq* is the cumulative number of updates of cyber products for the insurer from the year 2013 (the start of our sample period).

# 7 Conclusion

In this paper, we investigate the supply of cyber insurance and argue that it is characterized by a combination of unique features — heavy tails, uncertain loss distribution, and

Table 13: Factor decomposition of cyber reinsurance price

| Dependent Variable | Reinsurance price | | | | | |
|---|---|---|---|---|---|---|
| | Other liability line | | | Commericial multi-peril line | | |
| Model | (1) | (2) | (3) | (4) | (5) | (6) |
| non-aff | 0.0249** | 0.0234*** | 0.0132 | -0.0002 | 0.0003 | 0.0108 |
| | (0.0102) | (0.0056) | (0.0204) | (0.0132) | (0.0087) | (0.0168) |
| cybershare | 1.332 | 1.309 | 2.824*** | -0.1275 | -0.1387 | 0.0931 |
| | (0.9208) | (0.9261) | (0.8556) | (0.1647) | (0.2535) | (0.1423) |
| exp_rate | 1.676*** | 1.629*** | 0.3296 | 0.3903 | 0.3942 | 1.596 |
| | (0.2185) | (0.1415) | (0.5106) | (0.8103) | (0.3714) | (1.177) |
| monitor | 0.9114 | 0.7559 | -0.1353 | -1.094 | -1.158 | -0.7165 |
| | (0.5984) | (0.5578) | (1.300) | (1.261) | (0.7838) | (1.960) |
| control | -1.368*** | -1.306*** | -0.1371 | -0.2718 | -0.2830 | -1.242 |
| | (0.3256) | (0.2410) | (0.6625) | (0.9290) | (0.4853) | (1.327) |
| update_freq | 0.0103 | 0.0114 | -0.0053 | 0.0215 | 0.0331 | 0.0676 |
| | (0.0408) | (0.0353) | (0.0585) | (0.0294) | (0.0453) | (0.0622) |
| non-aff × cybershare | -0.0308 | -0.0294 | -0.0738** | $-8 \times 10^{-5}$ | 0.0003 | -0.0013 |
| | (0.0230) | (0.0182) | (0.0327) | (0.0020) | (0.0032) | (0.0015) |
| cybershare × exp_rate | -1.234* | -1.165** | -2.042*** | 0.0147 | 0.0406 | -0.0783 |
| | (0.6545) | (0.4961) | (0.6971) | (0.1116) | (0.1334) | (0.0791) |
| cybershare × monitor | -1.824 | -1.908 | -5.020*** | 0.1092 | 0.1452 | -0.0235 |
| | (1.548) | (1.973) | (1.319) | (0.1843) | (0.2931) | (0.1495) |
| cybershare × control | 1.653* | 1.635* | 3.356*** | 0.0088 | -0.0335 | 0.0671 |
| | (0.9612) | (0.9852) | (0.8540) | (0.1318) | (0.1735) | (0.0893) |
| non-aff × exp_rate | -0.0119** | -0.0115*** | -0.0055 | 0.0034 | 0.0027 | -0.0122 |
| | (0.0059) | (0.0026) | (0.0104) | (0.0105) | (0.0053) | (0.0121) |
| non-aff × monitor | -0.0272* | -0.0254*** | -0.0141 | -0.0014 | -0.0036 | 0.0026 |
| | (0.0138) | (0.0086) | (0.0242) | (0.0153) | (0.0129) | (0.0197) |
| non-aff × control | 0.0136* | 0.0129*** | 0.0049 | -0.0029 | -0.0017 | 0.0096 |
| | (0.0079) | (0.0040) | (0.0126) | (0.0118) | (0.0069) | (0.0135) |
| cybershare × update_freq | 0.0049 | 0.0052 | 0.0212 | 0.0063 | 0.0034 | -0.0057 |
| | (0.0196) | (0.0501) | (0.0178) | (0.0045) | (0.0115) | (0.0060) |
| non-aff × update_freq | -0.0003 | -0.0003 | 0.0001 | -0.0041*** | -0.0042*** | -0.0011 |
| | (0.0018) | (0.0009) | (0.0018) | (0.0015) | (0.0013) | (0.0013) |
| non-aff × cybershare × exp_rate | 0.0265 | 0.0249* | 0.0629* | 0.0003 | $-2.22 \times 10^{-5}$ | 0.0011 |
| | (0.0198) | (0.0138) | (0.0320) | (0.0015) | (0.0018) | (0.0009) |
| non-aff × cybershare × monitor | 0.0421 | 0.0408 | 0.1172*** | 0.0014 | 0.0008 | 0.0012 |
| | (0.0330) | (0.0350) | (0.0448) | (0.0024) | (0.0043) | (0.0017) |
| non-aff × cybershare × control | -0.0351 | -0.0335 | -0.0955** | -0.0016 | -0.0009 | -0.0016 |
| | (0.0259) | (0.0220) | (0.0433) | (0.0021) | (0.0032) | (0.0013) |
| non-aff × cybershare × update_freq | -0.0003 | -0.0002 | -0.0004 | $7.11 \times 10^{-5}$ | $6.77 \times 10^{-5}$ | $5.26 \times 10^{-5}$ |
| | (0.0004) | (0.0010) | (0.0003) | ($7.08 \times 10^{-5}$) | (0.0002) | ($7.85 \times 10^{-5}$) |
| Controls | No | Yes | Yes | No | Yes | Yes |
| Firm | No | No | Yes | No | No | Yes |
| Year | No | Yes | Yes | No | Yes | Yes |
| Observations | 720 | 720 | 720 | 597 | 597 | 597 |
| $R^2$ | 0.32849 | 0.34051 | 0.62496 | 0.14714 | 0.16715 | 0.56073 |

*Note*: This table presents the results for the factor decomposition of reinsurance price in the other liability line. Column (1) to (3) are the results for affiliated reinsurance, and Column (4) to (6) are the results for non-affiliated reinsurance. Column (1) and (4) do not include controls and fixed effects, Column (2) and (5) include controls and year fixed effects, Column (3) and (6) include controls and firm-year fixed effects. Clustered standard errors at the insurance group level are reported in parentheses. ***, **, and * denote the statistical significance at the 1%, 5%, and 10% level, respectively.

information asymmetries. These features create the need to finance tail exposures by holding more capital while also increasing the wedge between the cost of internal and external capital. This results in a situation in which insurers heavily rely on ICM in the form of affiliated reinsurance. Further, we establish a causal link using the regulatory change in the taxation of the non-US affiliated reinsurance as identification. We find that insurers reduce their supply of cyber insurance in response to the shock. We then analyze factors that drive the cost of external capital and show that all of the features of cyber risk play a role.

Our findings imply that the growth of the cyber insurance market is constrained by supply-side factors, and it is challenging for the insurance market alone to provide sufficient coverage for cyber risk. These observations suggest that both public and private sectors are to play a role in protecting the economies from cyber risk. The design of such partnerships is a policy-relevant topic that we leave for future research.

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# Appendices

## A NAIC Cyber security reporting

According to NAIC (2023b), cybersecurity insurance (cyber insurance) coverage is commercial insurance either through a single policy or multi-peril coverage part solely intended to help manage risks associated with exposures arising out of network intrusions and improper handling of electronic data. The covered risks may include direct losses to the policyholder (first party) or the liability claims of third parties that are caused by the insured cyber event (third party). Examples of the direct costs to the policyholder include business interruptions and extra expenses resulting from an unauthorized person preventing access to the Internet, the policyholder's website, or other parts of the policyholder's network; costs related to a data breach such as restoring data, forensic investigations, legal expenses, public relations, breach notification, and regulatory expenses; cyber extortion against the policyholder; and ransom payments. The third-party liability protection consists of coverage for the exposure arising out of theft or loss of client's or customer's digital assets, the introduction of malware and other malicious computer code to third parties, and liability and damages resulting from network failures, among others.

The supplement distinguishes between two features of insurance policies to define the market segments. The first feature is whether the policy applies to commercial or personal lines, that is, cybersecurity or identity theft insurance. Cybersecurity insurance is designed for businesses and offers protection against losses stemming from risks such as data breaches and business interruptions. Identity theft insurance is intended for individuals and provides compensation for losses resulting from theft of credit cards, social security numbers, or bank account numbers. The second feature is whether the policy is standalone or a part of package policies that include coverage for other non-cyber risks. Thus, the supplement identifies four market segments: cybersecurity package, cybersecurity standalone, identity theft package, and identity theft standalone.

According to NAIC (2024), the data reported in the supplement provide a partial view of the identity theft insurance market. The reason is that many entities in the identity

Table 14: Summary statistics for Identity theft insurance market

| Year | Premiums (billion $) | Insurers | Insurance groups | Number of policies (million) | Claims frequency (%) | Combined loss ratio (%) | Standard deviation of loss ratio |
|---|---|---|---|---|---|---|---|
| **Identity theft package policy** | | | | | | | |
| 2015 | 0.21 | 282 | 90 | 11.21 | 0.00 | 0.00 | 1.66 |
| 2016 | 0.19 | 292 | 99 | 13.50 | 0.00 | 0.00 | 17.23 |
| 2017 | 0.20 | 353 | 118 | 12.93 | 0.00 | 0.00 | 1.66 |
| 2018 | 0.21 | 374 | 124 | 14.15 | 0.00 | 0.00 | 1.10 |
| 2019 | 0.21 | 388 | 128 | 12.61 | 0.01 | 0.00 | 0.32 |
| 2020 | 0.22 | 405 | 136 | 13.53 | 0.06 | 0.00 | 1.26 |
| 2021 | 0.23 | 388 | 132 | 13.47 | 0.00 | 0.00 | 3.92 |
| 2022 | 0.24 | 388 | 134 | 13.61 | 0.00 | 0.00 | 1.33 |
| **Identity theft Standalone Policy** | | | | | | | |
| 2015 | 0.02 | 14 | 9 | 0.50 | 0.01 | 1.45 | 32.76 |
| 2016 | 0.02 | 14 | 8 | 0.28 | 0.02 | 0.00 | 33.65 |
| 2017 | 0.02 | 15 | 9 | 0.23 | 0.02 | 0.00 | 92.72 |
| 2018 | 0.01 | 18 | 10 | 0.24 | 0.01 | 0.00 | 113.54 |
| 2019 | 0.01 | 18 | 9 | 0.31 | 0.00 | 0.00 | 8.58 |
| 2020 | 0.01 | 15 | 7 | 0.30 | 0.00 | 0.00 | 34.62 |
| 2021 | 0.01 | 14 | 8 | 0.28 | 0.01 | 15.37 | 39.14 |
| 2022 | 0.01 | 17 | 7 | 0.10 | 0.00 | 0.83 | 29.28 |

*Note*: This table presents summary statistics of key variables in the cyber insurance market by year. *Premiums* are calculated as the summation of cyber premiums of all insurers in the respective segment. The number of insurance groups includes independent insurance companies without group affiliation. *Claims frequency* is calculated as the total number of claims divided by the total number of policies in the respective segment. *Combined loss ratio* is the cyber loss incurred plus direct defense and cost containment expense (also known as allocated loss adjustment expense) divided by cyber premiums earned for each insurer and the mean value is reported in this table. The last two columns are calculated after winsorizing the top and bottom 1%, as the extreme values significantly distort the statistics.

theft market are not insurers but rather credit card companies and specialized identity theft protection service companies.[13] Recognizing the issue, NAIC (2024) indicates that the supplement does not provide meaningful data on the identity theft segment and recommends eliminating this reporting requirement from the cyber supplement. For these reasons, we focus on the cybersecurity insurance data in our analysis.

This appendix provides the basic descriptive statistics for the identity theft segment of the market. Table 14 shows that the identity theft market is negligible measured by market size and has been stagnant over time.

[13] The reported identity theft segment has been relatively stagnant in 2015–2022 and had a significantly smaller size of $0.25 billion than the cybersecurity segment.

## B The definition of lines of business

The abbreviations for lines of businesses in this paper are defined as (from S&P Global Market Intelligence, S&P MI):

- Accident & health: accident insurance and health insurance lines
- Homeowner: homeowners and farmowners' multiple peril insurance
- Auto damage: private passenger auto insurance
- Fire: fire and allied lines combined
- Multi–peril: commercial multiple peril insurance
- Financial: financial and mortgage guaranty insurance
- Marine: marine lines combined
- Medical liability: medical professional liability insurance
- Workers' comp: workers' compensation
- Other liability: other liability and product liability insurance combined
- Auto liability: commercial auto liability insurance
- Aircraft: aircraft insurance (all perils)
- Fidelity: fidelity and surety insurance
- Other: other commercial insurance

# C Additional DiD results

This section presents the DiD results for the impact of the BEAT reform on the supply of cyber insurance using level measures rather than first-order differences. We consider the changes in absolute measures for cyber premiums and market shares rather than the growth measures in the main results. Table 15 reports the results. There is no strong evidence of a significant negative impact on cyber insurance supply. The reason is that the whole market is increasing during the sample period, and the insurers affected by the BEAT reform are also the leading insurers in the market with a rapid growth rate. Therefore, the real effect is reflected more significantly in the first-order differences of premiums and market shares.

Table 15: The BEAT reform and the supply of cyber insurance (level measures)

| Panel A: Continuous treatment variable | | | | | | |
|---|---|---|---|---|---|---|
| Dependent Variable: | Cyber premiums (log) | | | Market share (%) | | |
| Model: | (1) | (2) | (3) | (4) | (5) | (6) |
| Treat*2018 | -0.0002 | -0.0015 | -0.0021 | 0.0017 | 0.0018 | 0.0022 |
| | (0.0020) | (0.0055) | (0.0026) | (0.0024) | (0.0058) | (0.0025) |
| Treat*2019 | -0.0083 | -0.0097* | -0.0097 | 0.0006 | -0.0009 | -0.0002 |
| | (0.0097) | (0.0056) | (0.0108) | (0.0026) | (0.0058) | (0.0029) |
| Treat*2020 | 0.0034 | -0.0004 | -0.0039 | 0.0047 | 0.0020 | 0.0012 |
| | (0.0042) | (0.0059) | (0.0053) | (0.0042) | (0.0062) | (0.0035) |
| Insurer FE | N | N | Y | N | N | Y |
| Year FE | N | N | Y | N | N | Y |
| Control | N | Y | Y | N | Y | Y |
| Observations | 288 | 288 | 288 | 288 | 288 | 288 |
| $R^2$ | 0.05588 | 0.30502 | 0.77925 | 0.05553 | 0.20179 | 0.87421 |

| Panel B: Binary treatment variable | | | | | | |
|---|---|---|---|---|---|---|
| Dependent Variable: | Cyber premiums (log) | | | Market share (%) | | |
| Model: | (1) | (2) | (3) | (4) | (5) | (6) |
| Treat*2018 | 0.0298 | 0.0666 | -0.0160 | 0.2468 | 0.2313 | 0.2467 |
| | (0.1588) | (0.4733) | (0.1615) | (0.2053) | (0.4949) | (0.1970) |
| Treat*2019 | -0.4108 | -0.3172 | -0.2755 | 0.1536 | 0.1818 | 0.0895 |
| | (0.5251) | (0.4734) | (0.4530) | (0.1913) | (0.4950) | (0.1862) |
| Treat*2020 | -0.0890 | -0.2371 | -0.3552 | 0.2492 | 0.1226 | 0.0916 |
| | (0.4382) | (0.4804) | (0.4282) | (0.2130) | (0.5023) | (0.1804) |
| Insurer FE | N | N | Y | N | N | Y |
| Year FE | N | N | Y | N | N | Y |
| Control | N | Y | Y | N | Y | Y |
| Observations | 288 | 288 | 288 | 288 | 288 | 288 |
| $R^2$ | 0.04909 | 0.27663 | 0.77468 | 0.04003 | 0.16042 | 0.87443 |

*Note:* This table presents estimates of the impact of the BEAT on the cyber premiums and the market share for the insurers. The continuous treatment (exposure to the BEAT reform) in Panel A is calculated as the share of cyber premiums multiplied by the share of non-US affiliated reinsurance in gross premiums written by the insurer. The treatment group in Panel B is defined as the insurers that have exposure to the BEAT reform above the median. Clustered standard errors at the insurer level are reported in parentheses. ***, **, and * denote the statistical significance at the 1%, 5%, and 10% level, respectively.

# D Affiliated reinsurance and intercompany pooling agreement

This appendix provides detailed information about the reinsurance relationships of insurers, including the intercompany pooling agreement mentioned in Section 3.2. As defined above, the intercompany pooling agreement allows the participants to cede all pooled business to the lead entity and then assume back their stipulated shares from the pool. This provides diversification benefits to the participants by sharing their risks but increases the systematic risk of the group.

This agreement is *de facto* a conventional quota share reinsurance contract, except that the participants are affiliated entities. Therefore, as in normal reinsurance contracts, only the policy-issuing entity has direct liability to its policyholders or claimants, other participants are liable as reinsurers for their share of the issuing entity's obligations. In the accounting process, the direct premiums, losses, and other expenses are recorded as direct businesses, and the proportion ceded to or assumed from the pool is recorded as ceded/assumed reinsurance as typical reinsurance contracts (NAIC, 1998).

Furthermore, the participants of the pooling agreement are not limited to this pooled reinsurance contract. They still have the option of using external reinsurance or other types of reinsurance within the insurance group. The order of pooled reinsurance and other types of reinsurance is not fixed. For example, external reinsurance can be transacted prior to pooling, which means the participants first cede their premiums to third parties and then transfer the rest of their premiums to the pool. Alternatively, the participants could cede premiums to third parties after they assume their shares from the pool. The latter approach is common for the lead insurers in the agreement.

In our data, we can identify the participants of the intercompany pooling agreement by the rating group categorization in AM Best. To estimate the reliance of the rating unit on foreign-affiliated reinsurance, we use the following calculation in Section 5.2:

$$\frac{R_F}{GPW - R_D},$$

where $GPW$ is the gross premiums written of all lines by the rating unit, $R_F$ is the premiums ceded to non-US affiliates, and $R_D$ is the premiums ceded to US affiliates. The reason we use the difference between $GPW$ and $R_D$ in the denominator is that the premiums ceded to the pool are counted twice in the measure of gross premiums. More specifically, the direct underwriting premiums of the participants are first counted as the direct business in their gross premiums and then counted as the assumed business in their lead insurer's gross premiums. Although we do not have information about the order of different types of reinsurance, this does not affect our estimation as we focus on the aggregate premium allocations. However, this measure might underestimate the reliance on foreign-affiliated reinsurance because theoretically, the participants of the pooling agreement may transfer part of their premiums to third parties outside their rating unit (insurers in Bermuda, for example) and then to foreign affiliates.