Cyber Insurance Supply and Performance:

An Analysis of the U.S. Cyber Insurance Market

Abstract

This article examines the determinants of cyber insurance participation, the amount of coverage offered, and the performance of current cyber insurers. We find that insurers offer cyber insurance to capitalize on their competitive advantage in understanding and pricing cyber risks and to balance their risks between investment and underwriting. We find limited evidence that insurers participate in cyber insurance to compensate for constraints on business growth. In addition, the type of coverage offered (standalone or packaged) and the amount of coverage offered vary substantially across firm characteristics. Despite being profitable at the industry aggregate level, cyber insurance has highly volatile loss ratios, with performance varying across individual firms and types of coverage. Standalone coverage incurs higher loss ratios than packaged coverage, demonstrating its riskier nature. Growth in the cyber insurer loss ratio is not driven by premium growth, but by claim frequency and severity growth, emphasizing the significance of cyber insurance policy design.

JEL classification: G22, G32

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1. Introduction

Insurance plays a pivotal role in the modern economy. Faced with emerging risks, the insurance industry has responded to consumer demand with innovative types of coverage. The rise of cyber risks, however, presents an unprecedented challenge. The increasing occurrences of high-profile data breaches have made businesses more aware of the importance of cyber risk management, creating an exponential increase in the demand for cyber insurance coverage (Camillo, 2017). The insurance industry's reaction to this demand has received significant attention from both the industry and academia. Current research on cyber risk management focuses on the supply-side aspects of insurability, such as theoretical modeling of cyber risks (Shetty et al., 2010), pricing of cyber risks (Toregas and Zahn, 2014), and the efficacy of cyber insurance in improving network security (Kesan, Majuca, and Yurcik, 2005). A general agreement is that cyber risk is perceived to be high risk due to high information asymmetry, lack of actuarial data, and potential for catastrophic losses. Yet, cyber insurance is expected to be one of the leading growth areas in the US Property/Casualty insurance industry (A.M. Best, 2017). Despite the great growth potential, insurance carriers have diverse voices on participating in cyber lines. Warren Buffett, for instance, believes the risk is unknown and he doesn't want his company to heavily involve itself in cybersecurity insurance, while many other companies view cyber lines as a good business opportunity (Insurance Journal, 2018a). Then what truly motivates insurers to offer cyber insurance? Due to the paucity of data, few studies have empirically examined insurers' motivation to enter the cyber insurance market and the performance of cyber insurers, and this paper intends to fill the gap and enrich this strand of literature.

Based on the comprehensive cyber insurance data filing requirements of the National Association of Insurance Commissioners (NAIC), we collect cyber insurance coverage information from individual insurers to determine the motives of property-casualty (P&C)

insurers for participating in the cyber insurance market. In addition, we evaluate the determinants of the amount of cyber coverage offered by cyber insurers and the performance of these insurers. Our study offers significant insights for consumers, insurers, and regulators on developing a robust cyber insurance market. The paper also expands upon Eling and Zhu's (2018) descriptive analysis on the determinants of cyber insurance offering by using years of data to capture the dynamism of the cyber insurance market and by analyzing the volume of cyber risk assumed and performance of cyber insurers.

The dynamism nature of cyber exposures makes it difficult to define a "cyber risk." Eling and Schnell (2016) note various attempts to define and categorize cyber risks according to the activity (e.g., criminal and non-criminal), the type of attack (e.g., malware, insider attack, spam, distributed denial of service, error and malfunction), and the source of the risk (e.g., terrorists, criminals, government). Cyber risks cause not only economic losses—damages to be paid due to loss of customer data, notification costs, credit monitoring costs, regulatory expenses, extortion, business interruption, loss of intellectual property, product or service failure, and website downtime—but also intangible losses—reputation damage, customer turnover, and increased costs of customer acquisition (Willis North America, 2013; Allianz, 2015; Santos, 2017; Ponemon Institute LLC, 2018). Cybercrimes alone cost the global economy approximately $445 billion annually (McAfee, 2014; Dreyer et al., 2018). Businesses harmed by cyber risks have driven both the demand for cyber insurance coverage and the growth of the cyber insurance market. Though still in its infancy, the U.S. cyber insurance market is the largest in the world (Swiss Re, 2017). Through a thorough investigation of this market, we generate useful insights for fostering a resilient private cyber insurance market.

Cyber risks are non-traditional. Information asymmetry, high correlation of losses, insufficient number of contracts for pooling, scarcity of frequency and severity data for pricing, and dynamic changes in the risk due to the quickly changing technology innovations and legal landscape (Biener, Eling, and Wirfs, 2015) have rendered traditional insurance policies obsolete and ineffective in indemnifying cyber losses. In response, many insurers have drafted contract exclusions for cyber-related losses in traditional commercial multi-peril coverages; others have offered cyber insurance endorsements within traditional commercial general liability coverage (so-called packaged cyber coverage). Some insurers, however, have developed standalone cyber insurance products to meet the demand of policyholders with more sophisticated cyber risk exposures (Baer and Parkinson, 2007; Toregas and Zahn, 2014; Santos, 2017).

Why do some insurers offer cyber insurance? What type of insurers are more likely to offer standalone cyber insurance over packaged cyber insurance? What factors affect the supply capacity of cyber insurers and the performance of cyber insurance products? By answering these questions, this paper fills a gap in the literature on cyber risk. Our paper also directly examines the excess and surplus lines insurers' participation in the cyber insurance market, highlighting the important roles of surplus insurers in managing emerging risks.

We first follow diversification literature to determine why insurers offer cyber insurance. We investigate the business growth constraint hypothesis (Berry-Stölzle et al., 2012), the coordinated risk management hypothesis (Schrand and Unal, 1998; Che and Liebenberg, 2017), and the competitive advantage hypothesis (Grant, 1991; Maksimovic and Phillips, 2002). In line with Eling and Zhu (2018), we find that current cyber insurers are larger in size, more diversified across geographical areas and business lines, and less inclined to invest in risky assets. Our analysis reveals notable differences between insurers that offer standalone and packaged cyber insurance. Mutual insurers, insurers with higher underwriting leverage, and insurers with greater business in homeowner and commercial multi-peril lines (cyber-related lines) are less likely to offer standalone coverage, while professional surplus insurers are more likely to offer standalone coverage. In contrast, mutual insurers, insurers with group affiliation, insurers with higher financial ratings, and insurers with greater business in cyber-related lines are more likely to offer packaged cyber policies. Our findings are similar when excluding professional surplus insurers. For this sample, we find that insurers affiliated with surplus insurers are more likely to offer both standalone and packaged cyber insurance. Our findings mainly suggest that insurers are more likely to offer cyber insurance when they perceive a competitive advantage in underwriting cyber risks, providing support for the competitive advantage hypothesis. The results also show that insurers offer cyber insurance to balance their risk between investments and underwriting. We fail to find consistent evidence that insurers offer cyber insurance to overcome growth constraints, as only insurers operating in smaller lines of business are found to be more likely to offer cyber insurance, but those insurers with lower overall premium growth are less likely to participate in the cyber insurance market.

In addition to cyber insurance participation, we examine factors that affect the amount of cyber insurance coverage offered. Overall, we find that larger insurers, insurers with lower underwriting leverage and investment risk, and insurers that are more geographically diversified write more cyber insurance coverage. Our findings vary between standalone and packaged coverage. Mutual insurers consistently demonstrate a preference for offering packaged coverage, while surplus insurers write more standalone coverage. Insurers that are more diversified across business lines tend to write more standalone cyber premiums, but unaffiliated insurers and insurers with greater business in cyber-related lines and with more reinsurance utilization tend to offer more packaged coverage. Similar to our cyber insurance participation results, our findings on the extent of participation provide additional support for the competitive advantage hypothesis and coordinated risk management hypothesis.

The long-term sustainability of cyber insurance supply depends on the profitability of market participants. Although cyber insurance is profitable at the industry aggregate level, there are significant variations at the level of the individual firm. From our analysis of insurer-specific loss ratios, we find that larger insurers generally incur higher loss ratios (pure and overall), while mutual insurers register lower loss ratios for standalone policies (pure and overall). Surplus insurers, pioneers of the cyber insurance market (A.M. Best, 2017), have higher loss ratios for standalone policies (pure and overall). Insurers with greater product line diversification incur lower loss ratios, particularly for packaged cyber policies, again supporting the competitive advantage hypothesis.

Following Barth and Eckles (2009), we run regressions for premium growth, claim frequency growth, and average claim severity growth against loss ratio growth to determine the drivers of cyber insurance underwriting risk. We find that for packaged policies, cyber loss ratio growth is driven by growth in both claim frequency and average claim severity. For standalone policies, cyber loss ratio growth is driven by average claim severity growth. Our findings suggest that standalone policies may have assumed greater underwriting risk than the packaged policies.[1]

The remainder of the paper is structured as follows. We begin by examining the literature relevant to cyber insurance and cyber risk management. We then formulate hypotheses pertaining to the determinants of cyber insurance participation. Next, we discuss our data and sample and the state of the U.S. cyber insurance market, followed by an analysis of our empirical results regarding the determinants of cyber insurance participation, the amount of cyber insurance coverage offered, the performance of current cyber insurers, and the drivers of cyber insurance underwriting risk. The conclusion summarizes our findings and recommends directions for further research.

2. Literature Review and Hypotheses

Cyber risk management has received considerable attention from both academia and the insurance industry. Industry reports focus on the definition and classification of cyber risk exposures, the merits of managing cyber risks, best practices in preventing cyber risks, and alternative techniques in financing cyber risks (Willis North America, 2013; Allianz, 2015; Marsh & McLennan Companies, 2017; Santos, 2017). The efficacy of insurance as a potential risk financing strategy has also been discussed (e.g., Kesan, Majuca, and Yurcik, 2005; Majuca,

[1] Our analysis is also innovative in that we identify and analyze the determinants of new cyber insurers and compare the characteristics and performance of new insurers with those of incumbent insurers in the cyber insurance market to understand the dynamics of cyber insurance participation.

Yurcik, and Kesan, 2006). Academic research encompasses many topics, such as the insurability of cyber risks, the laws and regulations that fostered the market, and the modeling and pricing of these risks (see Online-Appendix A and Eling and Schnell, 2016, for a review of the literature). There is a consensus that cyber risks have undesirable conditions for insurability, making cyber insurance a risky line of business. With this in mind, a natural question to ask is why some insurers participate in the cyber insurance market. To answer this question, we formulate three hypotheses.

In the past decade, the U.S. P&C insurance industry has been operating in a soft market with excess underwriting capacity (Insurance Journal, 2018b). At the same time, the low interest rate environment has resulted in lower investment returns, forcing insurers to generate profits through underwriting (Ernst & Young LLP, 2016). The cyclical nature of the global economy and highly competitive P&C insurance markets, with projections that substantial parts of the market might shrink (Insurance Journal, 2017) have limited insurers' growth and profitability. Berry-Stölzle et al. (2012) argue that when faced with growth constraints, insurers are more likely to diversify their product lines. Due to the fast-growing demand for cyber insurance products, insurers may consider cyber insurance a significant growth opportunity. Therefore, expanding on Berry-Stölzle et al. (2012), we hypothesize that:

H1: Insurers that face barriers to business growth are more likely to participate in cyber insurance.

Participation in cyber insurance may also be explained by coordinated risk management theory (Schrand and Unal, 1998), which states that firms practice risk management to allocate risk internally, rather than to reduce overall risk. Consequently, firms may transfer risk from operations in which they do not have a comparative information advantage to operations in which they do. McShane, Zhang, and Cox (2012) apply the coordinated risk management framework to the insurance industry and argue that insurers have a comparative information advantage in underwriting but not in investment. They find support for the coordinated risk management hypothesis by observing that insurers hedge investment risk using derivatives while retaining higher levels of underwriting risk with limited use of reinsurance. Che and Liebenberg (2017) test the coordinated risk management hypothesis and find a negative relationship between insurer underwriting risk and asset risk.

In this paper, we test the coordinated risk management hypothesis by examining the relationship between investment risk and cyber insurance participation. In addition to the insurability aspects indicated above, Böhme and Schwartz (2010) find that conventional reinsurance risk pooling techniques may not be effective for cyber risks. Due to the high global correlation of cyber risks, reinsurers do not have adequate data to quantify cyber risks accurately and diversify them geographically. In addition, Aon (2017) argues that the difficulty in aggregating cyber risks and the loss potential of catastrophic cyber events increases underwriting volatility and further discourage insurers from offering cyber coverage. The unfavorable insurability criteria, lack of reinsurance support, and loss potential of catastrophic cyber events demonstrate that cyber insurance is a risky venture that is expected to increase underwriting risk. Consequently, we theorize that the coordinated risk management framework will loosely persist for cyber insurance. More specifically, we argue that[2]

H2: Insurers with lower investment risk are more likely to participate in cyber insurance to balance their risks between investment and underwriting.

Our last hypothesis on cyber insurance participation is based on competitive advantage theory. Grant (1991) argues that a firm's profitability is dictated by the attractiveness of the industry and the development of the firm's competitive advantages. Maksimovic and Phillips (2002) find that established comparative advantages across industries are primary determinants of diversification decisions and the extents of optimal diversification. In the case of cyber risks, interdependent losses and high global correlation are deterrents to participation in cyber insurance. However, insurers may develop competitive advantages by alleviating other insurability issues, such as lack of loss data and information asymmetry. Aon (2017) cites

[2] Since cyber insurance participation alone is not an adequate proxy for an insurer's overall underwriting risk, we do not test the relationship between an insurer's overall investment risk and its underwriting risk here.

accumulated underwriting data and underwriting expertise as potential competitive advantages for cyber insurers. Therefore, we theorize that establishing a competitive (comparative) advantage is a crucial prerequisite for prospective cyber insurers. We evaluate potential competitive advantages by an insurer's access to underwriting data and the extent of their diversification.

Surplus lines insurers have a vital function in the non-standard insurance market, providing coverage for high-capacity, distressed, and unique exposures. Emerging risks such as those in the sharing economy, drones, and cyber risks were initially underwritten by surplus insurers (A.M. Best, 2017; Baggett and Cole, 2017). As reliable loss data becomes available and consumer demand increases, coverages designed by surplus insurers for emerging risks have gradually transitioned into admitted markets. Since specialized cyber insurance coverages were initially underwritten by surplus insurers, they are more likely to have reliable loss data and superior underwriting expertise than admitted insurers. Thus, we argue that surplus insurers have a competitive advantage in underwriting cyber risks. In addition, such competitive advantages may be transferred through internal data sharing among insurers that are affiliated with surplus insurers. Accordingly, we predict that:

H3a: Professional surplus insurers and insurers that are affiliated with professional surplus insurers are more likely to participate in cyber insurance.

Maksimovic and Phillips (2002) find that conglomerates have a cost advantage when entering new industry segments. King and Tucci (2002) find that a firm's experience in previous markets provides a competitive advantage in entering a new market. Additionally, Klepper and Simons (2000) find that firms with more relevant experience are more likely to enter a related business sector and invest more in innovation, leading to greater market share and sustained profits. Rating agencies, such as S&P, acknowledge that insurers that are more diversified across geographic areas and product lines are better equipped to withstand financial challenges than their less diversified counterparts (Howard, 2016). Expanding on these findings, we argue that prospective cyber insurers that are more diversified have competitive advantages, such as experience in operating in unfamiliar product lines, underwriting expertise in combating information asymmetry, greater expense efficiency, and more product innovation. Therefore, we formulate the following hypothesis for prospective cyber insurers:

H3b: Insurers that are more diversified across geographical areas and/or product lines are more likely to participate in cyber insurance.

3. Data, Sample, and Overview of the U.S. Cyber Insurance Market

3.1. Data Source and Sample Description

The NAIC created the Cybersecurity and Identity Theft Coverage Supplement in 2015, which requires insurance companies to report financial data on cyber risk coverage. We study the state of cyber insurance supply by examining the U.S. property-casualty insurance industry from 2015 to 2017, the period for which cyber data is available. Most of our insurer-specific data, including cyber insurance premium and claim information, are obtained from S&P Global Market Intelligence (formerly SNL DataSource). Financial strength ratings are obtained from Best's Key Rating Guide. Since our study uses lagged one-year financial variables, our sample period begins in 2014.

Our original sample includes 7,815 firm-years for both affiliated and unaffiliated insurers with positive net admitted assets, as we conduct all analyses at the level of the individual firm. We then exclude firms with fewer than two consecutive years of data, as our regression utilizes lagged independent variables. The final regression sample for cyber insurance offering consists of 6,458 firm-years, a decrease that is caused by missing values of some independent variables used in the regression. The regression sample does cover more than 99% of total cyber insurance premiums written during the study period, so we conclude that this sample is representative of the industry.

We present the description and definitions of the variables used in our analyses in Table 1. Special attention is paid to the identification of professional surplus insurers. A.M. Best defines a professional surplus insurer as an insurer with at least 50% of total direct premiums written in surplus lines. Following the practice of Baggett and Cole (2017), we crossreference insurer schedule T by-state premiums written data with the licensed status of an insurer in each state. Premiums written in a state specified as "Not Licensed" or "Eligible Surplus Lines" are considered surplus lines premiums. If the sum of surplus lines premiums accounts for more than 50% of an insurer's total direct premiums written, we specify the insurer as a surplus insurer.

[Insert Table 1 Here]

3.2. Overview of the U.S. Cyber Insurance Market

In this study, the term "cyber insurance" represents an aggregation of cybersecurity and identity theft insurance. Cybersecurity insurance is primarily sold to businesses to indemnify losses resulting from cyber risks such as data breaches and business interruption. Identity theft insurance caters to individuals to indemnify losses incurred from events such as unauthorized credit card and bank account transactions. The market for identity theft coverage is only a small fraction of cyber insurance coverage, thus establishing cyber insurance as more of a commercial line of insurance.

Table 2 presents an overview of the U.S. cyber insurance market. The NAIC Cybersecurity and Identity Theft Coverage Supplement requires separate reporting on various types of cyber insurance coverage. Our study adopts these types of cyber coverage as dependent variables, such as standalone cybersecurity (*Alone_CB*, hereafter "standalone cybersecurity"), standalone identity theft (*Alone_ID*, hereafter "standalone ID theft"), packaged cybersecurity (*Packgd_CB*, hereafter "packaged cybersecurity"), and packaged identity theft (*Packgd_ID*, hereafter "packaged ID theft"). We also create two variables for aggregate standalone coverage (*Alone*, hereafter "standalone coverage") and aggregate packaged coverage (*Packgd*, hereafter "packaged coverage"), where *Alone* includes both *Alone_CB* and *Alone_ID* and *Packgd* includes both *Packgd_CB* and *Packgd_ID*. We denote an insurer's total participation in cyber insurance as *Cyber* (hereafter "cyber insurance"), which includes both *Alone* and *Packgd*.

Panel A of Table 2 summarizes the demographics of cyber insurers. From 2015 to 2017, the number of market participants increased from 453 to 615. This uptick is driven by the increasing number of insurers that offer packaged cybersecurity and packaged ID theft coverage; the number of insurers offering standalone cybersecurity coverage and standalone ID theft coverage remains constant. From 2015 to 2017, the number of professional surplus insurers participating in the cyber insurance market increased from 55 to 78. This demonstrates their growing interest in cyber insurance. Among insurers offering standalone cybersecurity coverage, roughly one-third are professional surplus insurers and roughly half are insurers affiliated with professional surplus insurers. We also observe an increase in cyber insurance participation from admitted insurers over time, especially in packaged coverage.

Panel B of Table 2 depicts the premium volume for cyber insurance. Cyber insurance accounts for a small sliver of the entire P&C industry, only about 0.34% of industry aggregate premiums in 2017. However, cyber insurance experienced tremendous growth from 2015 to 2017, as aggregate premium volume increased 31% (in 2016) and 55% (in 2017). At the same time, premiums in the entire P&C insurance industry increased by approximately 3.9% and 4.5%, respectively. In 2015, cyber insurance premium was split between standalone ($509.2m) and packaged coverage ($533.1m). Commentators believe that cyber insurance will increasingly be written as a standalone product (Romanosky et al., 2017). This trend seems to hold for 2016, when premiums for standalone coverage ($994.5m) were more than double the premiums for packaged coverage ($448.7m). However, premiums for packaged coverage ($1157.3m) saw tremendous growth in 2017, surpassing premiums for standalone coverage ($1004.6m). We attribute this change to shifting consumer demographics. Policyholders that have recently purchased cyber coverage may not have sophisticated cyber exposure and may prefer packaged cyber endorsements to more comprehensive standalone cyber coverage.

The market share data supports the notion that cyber insurance coverage is entering the realm of admitted insurance markets, as only about 20% of cyber insurance is written by professional surplus insurers. But it is noteworthy that some 60% of cyber insurance is written by firms with surplus insurer affiliations. This observation supports our information-sharing conjecture, which attributes intergroup information sharing as a competitive advantage in underwriting cyber insurance.

Panel C of Table 2 provides the market concentration for different types of cyber coverage. We observe that the industry is becoming more competitive. From 2015 to 2017, the Herfindahl–Hirschman index (HHI)[3] dropped from 562 to 352, with the market share of the top four insurers decreasing from 36% to 27%. Packaged cybersecurity insurance was initially more concentrated than standalone cybersecurity insurance in 2015. It became less concentrated in 2016, and then more concentrated in 2017. We suspect that this reversal, along with the exceptional growth of packaged cybersecurity insurance, is indicative of a “cyber insurance gold rush” driven by increased demand for cyber insurance on the part of small- to middle-sized firms (Wood, 2015). On the one hand, standalone ID theft insurance is a niche of the cyber insurance market, as the segment has very few participants, small premium volume, and constant market share among the top four insurers. On the other hand, packaged ID theft insurance has experienced steady growth both in total premium volume and in number of participants. Competition within this segment has also steadily increased. Consumer preference for packaged ID theft insurance is observed, as approximately 90% of all ID theft insurance premiums are written in this segment. The last two sections of panel C provide mean and median values for the ratio of cyber insurance premiums to total premiums for individual cyber

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[3] $HHI = \sum_{i=1}^{N} \left(100 * \frac{\text{Cyber premium}_i}{\text{Total cyber premium of the industry}}\right)^2$, where i is individual firm and N is the total number of insurers in the industry in a given year. According to the U.S. Department of Justice, a markets is considered to be moderately concentrated with the HHI being between 1,500 and 2,500 points, and to be highly concentrated if HHI is greater than 2,500 points. See https://www.justice.gov/atr/herfindahl-hirschman-index.

insurers. We find that cyber insurance comprises a small fraction of the overall business a cyber insurer underwrites.

[Insert Table 2 here]

4. Analyses of Cyber Insurance Supply

4.1. Determinants of Cyber Insurance Offerings

We adopt logistic regression analyses to examine the determinants of offering cyber insurance. The regression model is as follows:

$$CYBER\_OFF_{i,t} = \alpha + \beta_1 Constraints_{i,t-1} + \beta_2 Coordinated_{i,t-1}$$
$$+\beta_3 Competitive_{i,t-1} + \gamma X_{i,t-1} + \theta Year\_dummy + \varepsilon_{i,t} \qquad (1),$$

where the dependent variable $CYBER\_OFF$ is a dummy variable that indicates participation in a specific segment of the cyber insurance market. We perform separate regressions for seven dependent variables corresponding to different types of cyber coverage. In addition, we run separate regressions on a sample including all insurers (hereafter "all-insurer sample") and a sample excluding professional surplus insurers (hereafter "admitted insurer sample").

$Constraints$ is a vector of variables that measures constraints on insurer growth. We first follow Berry-Stölzle et al. (2012) in constructing two variables that capture potential growth constraints. *LB_size* measures the size of a specific insurance line an insurer operates relative to the overall insurance market. For single-line insurers, the variable is calculated as that specific line's fraction of the total industry premium. For multi-line insurers, the variable is calculated as the weighted average of the relative sizes of all lines the insurers underwrite. Insurers operating in smaller product lines have limited opportunities to grow within such segments; thus, a lower value of *LB_size* indicates that an insurer is subject to greater growth constraints. *LB_conc* is calculated as the weighted average of line-specific Herfindahl indexes, with an insurer's fractions of direct premiums written in each line used as weights, and measures the degree of competition within the business lines an insurer operates in. As argued by Berry-Stölzle et al. (2012), less growth opportunity will be present in more concentrated business lines. Consequently, a higher value of *LB_conc* indicates that an insurer operates in more concentrated business lines and is therefore subject to greater growth constraints. If the growth constraint hypothesis (H1) holds, we can expect a negative relationship between *LB_size* and cyber insurance participation and a positive relationship between *LB_conc* and cyber insurance participation.

We include a third variable, year-to-year premium growth (*d_dpw)*, to capture potential growth constraints.[4] Choi and Weiss (2005) consider market growth to be a causal indicator of insurer profitability. Insurers that are not able to sustain adequate premium growth are more susceptible to lower profits. Therefore, a lower value of *d_dpw* indicates that an insurer is subject to more growth constraints. If the growth constraint hypothesis (H1) holds, we can expect a negative relationship between *d_dpw* and cyber insurance participation.

Coordinated includes the variable *Asset_risk*, which captures the relationship between insurer investment risk and cyber insurance participation. *Asset_risk* is calculated as the fraction of investments in common stocks and high-yield bonds (bonds rated 3-6 by NAIC) over total invested assets (Che and Liebenberg, 2017). *Asset_risk* represents an insurer's investment risk, with higher values indicating greater investment risk. Since cyber insurance is perceived to have high underwriting risk, a negative relationship between *Asset_risk* and cyber insurance participation lends support to the coordinated risk management hypothesis (H2).

Competitive is a vector of variables that measures the competitive advantages of prospective cyber insurers. As discussed in the hypothesis section, the first two variables we construct specify the surplus status of an insurer. *Surplus insurer* is a dummy variable that

[4] Ideally, it is more accurate to measure the premium growth using total premiums net of cyber insurance premiums. Unfortunately, cyber insurance premium data is available only from 2015 to 2017, while the data we need to calculate *d_dpw* ranges from 2013 to 2016. We argue that because cyber insurance premium accounts for a very small fraction of total premiums of cyber insurers, its impact on the estimations can be negligible.

indicates whether an insurer is a professional surplus insurer, and *Surplus_aff* is a dummy variable that indicates whether an insurer has a group affiliation to a professional surplus insurer. *Surplus_aff* is utilized only in the admitted insurer sample. Since cyber insurance was predominantly written in non-admitted markets by professional surplus insurers, we argue that such insurers are more likely to have reliable cyber loss data and robust underwriting experience. A positive relationship between these two variables and cyber insurance participation supports the competitive advantage hypothesis (H3a).

The final two variables measure potential competitive advantages that are developed by the diversification of insurers. *Lbherf_dpw* represents the extent of diversification across different insurance product lines, and *Pwherf* represents the extent of diversification across geographical areas. Both variables are calculated as the complement of the Herfindahl indices based on direct premiums written, with higher values representing greater diversification. Insurers that are more diversified across both product lines and geographical areas are expected to have more experience in underwriting emerging risks. Therefore, a positive relationship between these two variables and cyber insurance participation supports the competitive advantage hypothesis (H3b).

$X_{i,t-1}$ in equation (1) consists of a vector of control variables that is common in the insurance literature.[5,6] As larger firms have greater resources and financial capacity, they are better equipped to insure complicated risks and are more resilient to unexpected larger losses. Consequently, we expect a positive relationship between *Size* and cyber insurance participation. Older insurers potentially have an advantage when it comes to experience, as insurers with a longer operational history arguably have more experience in insuring emerging risks. Therefore,

[5] All the control variables take the year *t-1* value except for firm age (*age*), public trading status (*list*), organization form (*mutual*), and group affiliation (*unaffiliated*) for which the year *t* value is used.

[6] As a robustness check, we also include either standard deviation of loss ratio or standard deviation of combined ratio as a control variable to measure the overall underwriting risk of an insurer. Neither of the two variables is significant and including them reduces our sample size significantly due to missing values, so we have dropped them from our regressions.

we also expect a positive relationship between *Age* and cyber insurance participation. *List* is a dummy variable that indicates whether an insurer is publicly traded. Publicly traded insurers have easier access to capital than private insurers, creating a potential advantage in underwriting cyber risks, which are perceived to have more volatile underwriting results and greater need for capital. We thus expect a positive relationship between *List* and cyber insurance participation.

Mutual is a dummy variable that indicates whether an insurer has a mutual organizational form. We made a twofold prediction. On the one hand, Mayers and Smith (1988) argue that mutual insurers have higher owner-manager agency costs than stock insurers, so mutual insurers should engage in lines of business that require less managerial discretion in pricing and underwriting to reduce the cost of controlling potentially opportunistic management. Their conjecture dictates that mutual insurers should be less likely to participate in cyber insurance. On the other hand, the roles of owner and policyholder are combined in mutual insurance companies. Since mutual insurers primarily serve their policyholders, an increase in demand for cyber insurance may prompt mutual insurers to offer cyber insurance products. *Unaffiliated* is a dummy variable that indicates whether an insurer is a member of an insurance group. We expect a negative relationship between this variable and cyber insurance participation, as unaffiliated single insurers lack internal capital market support that affiliated insurers can utilize to provide surplus relief.

Liab_phs measures an insurer's financial leverage, and *Npw_phs* measures an insurer's underwriting leverage. Adequate capital is vital in offering cyber insurance, as cyber losses are volatile and difficult to predict (Friedman and Thomas, 2017). The literature (Carson and Hoyt, 1995; Cummins and Sommer, 1996) argues that higher leverage signals greater financial constraints and a greater probability of bankruptcy, both of which are associated with higher costs of providing insurance services, a lower capacity for unexpected losses, and less flexibility in recovery. Therefore, we expect negative relationships between both *Liab_phs* and *Npw_phs* and cyber insurance participation. In contrast, insurers with better financial strength ratings are less likely to face financial difficulties. Therefore, we expect a positive relationship between *Rating* and cyber insurance participation. *ROI* measures an insurer's investment performance. During the time frame of our study, insurers have been operating in a low interest rate environment. Insurers with poor investment performance are likely to resort to underwriting activities to retain profitability. Therefore, we expect a negative relationship between *ROI* and cyber insurance participation.

As cybersecurity insurance is primarily a commercial line, it is convenient for insurers specializing in commercial multiple-peril lines to provide cybersecurity coverage in a packaged policy as a supplementary coverage. Additionally, many homeowners' insurance policies offer identity theft endorsements. We thus expect insurers with greater business in commercial multi-peril or homeowners insurance (*Related_cyber*) to be more likely to offer cyber insurance, especially packaged cyber coverage. Aon (2017) mentions that cyber insurers rely on reinsurance to transfer underwriting risks that stem from increased amounts of cyber coverage. Therefore, we include overall reinsurance usage (*Rein_ceded*) in the regression. Greater reinsurance usage may indicate that an insurer has an advantage in accessing reinsurance markets, thus increasing the likelihood that the insurer will offer cyber insurance or write more cyber coverage. However, higher reinsurance utilization may also suggest that the insurer is subject to surplus drain or that the insurer requires reinsurance support to manage the underwriting risk in its insurance portfolio, thus decreasing the likelihood that the insurer will expand into new businesses.[7] Lastly, we control for the risk-based capital ratio (*RBC_ratio*) in

[7] As a robustness check, we also run regressions with unaffiliated reinsurance usage. The results of our key independent variables and other control variables are not affected by the change. The unaffiliated reinsurance usage is only positively significant at the 10% level for the *Alone_ID* regression with the all-insurer sample. It is also positively significant for the *Alone_ID* regression but negatively significant for the *Packgd_CB* regression when using the admitted insurers sample only. We also find that unaffiliated reinsurance usage has no significant impact on the cyber premium volume provided by cyber insurers.

the regression. Insurers with higher risk-based capital ratio hold more capital to buffer underwriting and investment risks, and thus we argue are more likely to assume additional underwriting risks brought forth by participating in the cyber insurance market. Table 1 presents detailed definitions of these variables, and Table 3 presents the summary statistics.

[Insert Table 3 here]

Panel A of Table 4 presents regression results for the all-insurer sample. The coefficients of *d_dpw* are significantly positive (in six of the seven regressions), while the coefficients of *LB_conc* are significantly negative (in four of the seven regressions), contradicting the predictions of the business growth constraint hypothesis (H1) and suggesting that insurers with lower premium growth and insurers operating in more concentrated environments are less likely to offer cyber insurance. However, the coefficients of *LB_size* are significantly negative (in five of seven regressions), suggesting that insurers operating in smaller lines of business (and thus subject to less growth potential) are more likely to participate in cyber insurance. Due to our mixed findings for the business growth constraint hypothesis (H1), we conclude that overcoming growth constraints is not a predominant motive for most cyber insurers, but it may incentivize some insurers that operate in specialized niche markets. The coefficients of *Asset_risk* are significantly negative in nearly all of the regressions, suggesting insurers that have more risky asset holdings are less likely to participate in the cyber insurance market, lending support to the coordinated risk management hypothesis (H2). The coefficients of *Surplus_insurer* are significantly positive (in three of the seven regressions). Professional surplus insurers are more likely to offer cyber insurance, especially standalone cybersecurity coverage, supporting the competitive advantage hypothesis (H3a).[8] The coefficients of *Lbherf_dpw* and *Pwherf* are significantly positive in nearly all the regressions,

[8] The regressions show that professional surplus insurers are less likely to offer packaged ID theft coverage which is not surprising because ID theft coverage is typically offered as endorsements to homeowners' and commercial multi-peril insurance policies. Professional surplus insurers usually are not actively involved in such lines of business.

suggesting that diversified insurers are more likely to offer cyber insurance. Our findings support the competitive advantage hypothesis (H3b).

For the control variables, most of the results are in line with our expectations. We find that larger insurers are more likely to offer cyber coverage (both standalone and packaged). Mutual insurers, however, are less likely to offer standalone coverage but are more likely to offer packaged coverage. This result supports both predictions on the relationship between organizational form and cyber insurance offering, as standalone coverage requires greater managerial discretion, and packaged coverage serves the demand of policyholders. Unaffiliated insurers are less likely to offer cyber insurance, especially packaged cyber coverage, than are insurers with a group affiliation. Insurers with higher underwriting leverage are less likely to offer cyber insurance, especially standalone cybersecurity insurance, suggesting that standalone cybersecurity insurance[9] may require greater capital support. In contrast, insurers with higher financial strength ratings are more likely to offer packaged cybersecurity coverage. We find that insurers with higher proportions of business in homeowners' insurance and commercial multi-peril insurance are less likely to offer standalone cyber coverage, but more likely to offer packaged cyber coverage. However, reinsurance usage and RBC ratio have only a negligible impact on an insurer's participation in cyber insurance. The year dummies show that more insurers offered cyber insurance (especially packaged coverage) in 2016 and 2017 than in 2015.

Panel B of Table 4 (shown in the Online Appendix B) presents regression results for the admitted insurer sample. Similar results are observed for the independent variables previously discussed. The coefficients of *Surplus_aff* are significantly positive (in five of the seven regressions). This result suggests that insurers affiliated with professional surplus

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[9] According to Friedman and Thomas (2017), larger organizations tend to seek standalone cyber coverage, while packaged cyber policies are generally written for smaller businesses. Aon (2017) also mentions that standalone cyber products were developed for firms with more sophisticated and more specific cyber risk exposures that are not adequately covered by endorsements or add-ons of traditional packaged policies. Therefore, perceivably, standalone cyber coverage handles more complicated cyber risks than does packaged cyber coverage.

insurers are more likely to provide cyber insurance (both standalone and packaged coverage), confirming an information-sharing phenomenon and supporting the competitive advantage hypothesis (H3a).

[Insert Panel A of Table 4 here]

4.2. Determinants of Cyber Insurance Premium Size

In the next step of analysis, we identify firm characteristics that affect the amount of coverage offered by cyber insurers. We run the following regression model[10]:

$$Ln\_DPW_{i,t} = \alpha + \beta X_{i,t-1} + \theta Year\_dummy + \varepsilon_{i,t} \quad (2),$$

where the dependent variable $Ln\_DPW_{i,t}$ is the logarithm of one plus the direct premiums written in each of the seven cyber coverages as indicated in Table 5. $X_{i,t-1}$ is a vector of firm characteristic variables, including a subset of variables from the first-stage regression on cyber insurance participation (see Table 5).

Panel A of Table 5 presents the regression results for the all-insurer sample. We find that insurers with higher premium growth rate tend to write more cyber insurance premiums, contradicting the prediction of the growth constraint hypothesis (H1).[11] Insurers with greater investment risk write less cyber coverage. The negative relationship between cyber premiums written and investment risk supports the coordinated risk management hypothesis (H2). Professional surplus insurers write more standalone coverage and less packaged coverage, supporting the notion that surplus insurers pioneer nonstandard risks and operate less in traditional insurance markets in which cyber coverage is offered as packaged endorsements. Insurers that are more geographically diversified write more cyber insurance coverage (both

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[10] To control for potential selection bias within our sample, we conduct a robustness analysis by employing a Heckman two-step estimation procedure. The first step implements a probit regression for equation (1), and an inverse Mills ratio is calculated from the first equation to be included in the second stage regression as specified by equation (2). The results of the Heckman two-step regressions are materially the same as those of OLS regressions. As the Mills ratio is insignificant in five of the seven regressions, we choose to report OLS results. The Heckman two-step regressions results are provided in the Online-Appendix C.

[11] We have omitted by-line size (*LB_size*) and by-line concentration (*LB_conc*) in the premium volume regressions by arguing that these two variables may affect a firm's decision to expand into a new line, but should not impact how much premium an insurer can generate from the new line. They are also omitted out of identification concern when implementing the Heckman two-step procedure as a robustness check.

standalone and packaged cybersecurity coverage), and insurers that are more diversified across product lines write more standalone coverage. Both findings are consistent with the notion that diversified firms are more cost-efficient and more proficient in operating in new product lines (Maksimovic and Phillips, 2002). These results support the competitive advantage hypothesis (H3a and H3b).

For other variables, we find that larger insurers write more in both standalone and packaged coverages. Our results are consistent with the argument that larger insurers have greater financial capacity and lower insolvency risk, so they are more comfortable taking risks (Liebenberg and Sommer, 2008). Mutual insurers write less standalone coverage but more packaged coverage than stock insurers, echoing their cyber participation decisions. Unaffiliated single insurers write more packaged coverage than affiliated insurers. Insurers with higher underwriting leverage write less cyber coverage, consistent with the predicted negative relationship between underwriting leverage and the capacity to underwrite additional business. Insurers with higher financial strength ratings write less standalone coverage, and insurers with greater return on investment also tend to write less cyber insurance premiums.

Additionally, consistent with our prediction, insurers with greater business in homeowners insurance and commercial multi-peril insurance write more packaged cyber premiums, especially packaged ID theft premiums. We also find that insurers with greater reinsurance usage write more cyber coverage, especially packaged coverage. The lack of a developed reinsurance market has been noted as a challenge for cyber insurers, since the data and methodology required to adequately model catastrophic cyber risks have not yet been made available for reinsurers (Allianz, 2015; Aon, 2017). Our findings suggest that a more developed cyber reinsurance market will encourage primary insurers to offer more coverage. The time dummies demonstrate that cyber insurance (both standalone and packaged) premium size in the U.S. P&C industry has been growing over time.

Panel B of Table 5 (shown in the Online Appendix D) presents regression results for the admitted insurer sample. Similar results are observed for all independent variables previously discussed. Insurers affiliated with surplus insurers write, on average, less coverage than other admitted insurers, especially standalone coverage. This result is counter-intuitive to the competitive advantage hypothesis (H3a), as the benefits of information sharing should arguably enable insurers to better understand cyber risks and offer more coverage. One possible explanation is that these insurers may direct more sophisticated cyber risks from businesses, which require larger amounts of standalone coverage, to surplus insurers within the same group, keeping the more standard risks for themselves.

[Insert Panel A of Table 5 here]

5. Cyber Insurance Performance

5.1. Loss Ratio Analysis

As cyber insurance pricing is still "more art than science" (AIR, 2017, p. 5),[12] assessing cyber loss ratios provides insurers with information pertaining to performance and potential direction in improving underwriting standards and coverage design. Panel A of Table 6 provides industry aggregate loss ratios for cyber insurance. Both the pure loss ratio (cyber losses incurred over cyber premiums earned) and the overall loss ratio (loss ratio with defense and cost containment included) are calculated for the seven types of cyber coverage. Our report focuses on the overall loss ratio.

At the industry level, the cyber insurance market is immensely profitable, as the highest loss ratio observed was 44.7% in 2016. At the level of the individual firm, cyber insurer loss ratios vary significantly on loss experience and expenses. Panel B of Table 6 displays firm-level loss ratio distributions. The cyber insurance market incurred a median overall loss ratio of 0% for all years from 2015 to 2017, revealing that most insurers offering both standalone and packaged coverage have yet to incur cyber claims. However, at the 75_ptcl and above, standalone coverage consistently demonstrates higher loss ratios than the packaged coverage,

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[12] In 2018, both RMS and AIR Worldwide released new cyber risk modeling systems that support accurate pricing of cyber risks and facilitate the growth of the cyber insurance market. See https://www.rms.com/newsroom/press-releases/press-detail/2018-03-07/rms-releases-industrys-first-probabilistic-cyber-risk-model and https://www.insurancejournal.com/news/national/2018/10/22/505209.htm .

reinforcing the inherently riskier nature of standalone policies.

In addition, our results illustrate potential hazards for selective marketing strategies of insurers. We observe an increasing trend in packaged cybersecurity loss ratios (at the 75_ptcl, 90_ptcl, and 95_ptcl), while standalone cybersecurity loss ratios steadily decrease. Coupled with the observation that most cyber insurers do not incur losses, we emphasize the potential for mispricing packaged cybersecurity amidst the "cyber insurance gold rush." Although we concede that the emergence of losses corrects pricing within new product lines, insurers that are motivated solely by the profitability of packaged cyber endorsements may not adequately consider the loss potential of cyber risks.

[Insert Table 6 here]

We conduct further regressions to examine the relationship between firm characteristics and cyber insurance loss ratios. The regression model is specified as follows:

$$Ln\_LossRatio_{i,t} = \alpha + \beta X_{i,t-1} + \theta Year\_dummy + \varepsilon_{i,t} \quad (3),$$

where the dependent variable $Ln\_LossRatio_{i,t}$ is the logarithm of one plus the loss ratio in each of the seven types of cyber coverage as indicated in Table 7. $X_{i,t-1}$ is a vector of firm-specific variables that specify insurer's general characteristics such as firm size, age, public trading status, organizational form, group affiliation and variables proxying an insurer's competitive advantages on underwriting cyber risks (see Table 7). Separate regressions are performed on both pure loss ratio and overall loss ratio, while our discussion is based on overall loss ratio.

Panel B.1 of Table 7 presents regression results for the all-insurer sample. We find that surplus insurers have higher overall loss ratios for cyber coverage and standalone coverage, but they have lower loss ratios for packaged ID coverage. The finding that surplus insurers experience higher loss ratios in standalone coverage suggests that standalone segment policyholders are more susceptible to cyber losses, presumably due to their more sophisticated cyber exposures. Insurers that are more diversified across product lines have lower loss ratios for cyber coverage and packaged coverage, providing further support for the competitive advantage hypothesis (H3b), which argues that diversified insurers have superior underwriting expertise. In contrast, insurers that are more diversified across geographic areas tend to have higher loss ratios for cyber coverage. The mixed results emphasize the difficulty in dispersing cyber risks across geographic areas (Baer and Parkinson, 2007).

For other variables, we find that larger insurers have higher loss ratios for cyber coverage. In previous regressions, we found that larger insurers are more likely to offer cyber insurance and write more coverage. Based on these results, we theorize that consumer preference causes larger insurers to be less profitable. Consumers with complicated cyber risk exposures may prefer to be insured by larger insurers with lower insolvency risk, causing larger insurers to underwrite a larger proportion of “high risk” exposures with greater loss potential. Mutual insurers are found to have lower loss ratios for standalone cybersecurity coverage. We therefore conclude that the reluctance of mutual insurers to offer standalone coverage results in stricter underwriting guidelines and higher profitability in standalone coverage.

Panel B.2 of Table 7 presents regression results for the admitted insurer sample. Similar results are observed for all independent variables previously discussed. Affiliation with surplus insurers does not have a significant impact on loss ratio, with the exception of packaged ID coverage.

[Insert Table 7 here]

To underpin the competitive advantage analysis, we also compare the performance of incumbent firms with the performance of new competitors in the cyber insurance market. While the comparison has attracted some attention in the management literature (e.g., King and Tucci, 2002), we are not aware of any study that compares incumbent and new insurance firms As argued above, we expect more experienced firms to have a competitive advantage and better performance; thus incumbent firms are expected to outperform new insurers in the cyber insurance market. The results presented in Online-Appendix E confirm this conjecture, although the evidence is significant only for the subgroup excluding professional surplus insurers, re-emphasizing the competitive advantage of professional surplus insurers.

5.2. Drivers of Loss Ratio Growth

The recent growth of the U.S. cyber insurance market signals the potential for a developed cyber insurance market. However, regulators and rating agencies view rapid growth as a risk factor that adversely impacts solvency. Rapid growth is especially concerning for cyber insurers, as adverse selection and mispricing are prevalent in emerging product lines.[13] In an effort to analyze the drivers of cyber insurance loss ratios, we adopt the methodology of Barth and Eckles (2009) and run regressions of premium growth, claim frequency growth, and average claim severity growth against loss ratio growth. The regression model is:

$$Ln\_GrLossRatio_{i,t} = \alpha + \beta GrFactor_{i,t} + \theta Year\_dummy + \varepsilon_{i,t} \quad (4),$$

where the $Ln\_GrLossRatio_{i,t}$ is the logarithm of loss ratio growth of insurer *i*, defined as loss ratio in year *t* divided by loss ratio in year t-1 for each of the seven types of cyber coverage. The sample size for standalone ID theft and packaged ID theft is too small to provide meaningful results, so they have been removed from our discussion in the text. The key independent variable $GrFactor_{i,t}$ denotes the growth in the different factors tested, such as premiums growth (defined as premiums earned in year *t* divided by premiums earned in year t-1), claim frequency growth (defined as claim frequency in year *t* divided by claim frequency in year t-1), and average claim severity growth (defined as average claim severity in year *t* divided by average claim severity in year t-1). To reduce the impact of outliers, we winsorize both dependent variables and independent variables at the 2_pctl and 98_pctl.[14]

Panel A of Table 8 presents the relationship between premium growth and changes in loss ratios. Premium growth has a significant negative relationship with overall loss ratio growth for both standalone and packaged policies, suggesting that the increase in cyber premium is not a driver of increase in underwriting risk. The negative relationship is consistent

[13] Credit rating agencies view rapid growth in cyber insurance and especially aggressive growth in standalone cyber coverage as having a negative impact on an insurer's credit rating (Fitch Ratings, 2016).
[14] All the ratio variables used in this study are winsorized at 2_pctl and 98_pctl to reduce the impact of outliers. We also conducted a robustness check by winsorizing at 3_pctl and 97_pctl and obtained similar results.

with the findings of Barth and Eckles (2009). One possible explanation is that as business size grows, cyber insurers may gain a deeper understanding of cyber risks, leading to greater competence in underwriting and pricing cyber risks.

Panel B of Table 8 presents the relationship between claim frequency growth and changes in loss ratios. Claim frequency growth has a significant positive relationship with cyber coverage loss ratio growth and packaged coverage loss ratio growth. Our results suggest that claim frequency growth, or the change in the number of cyber claims incurred, is an appropriate metric in evaluating excessive growth risk for packaged cyber products. However, claim frequency growth has no significant impact on standalone coverage loss ratio growth.

Panel C of Table 8 presents the relationship between claim severity growth and changes in loss ratios. Claim severity growth has a significant positive relationship with the loss ratios of all types of cyber coverage. Our results suggest that claim severity growth, or the change in the average amount of losses incurred, is a more accurate metric in evaluating excessive growth risk than claim frequency growth.

Our findings suggest that cyber insurers must not only carefully assess the interdependency of cyber risks, but also focus on policy design elements, such as policy limits and cost-sharing features. Failure to properly incentivize policyholders to practice sound network security encourages moral hazard. As noted by commentators who doubt the efficacy of cyber insurance in improving overall network security (Öğüt, Menon, and Raghunathan, 2005), consumer behavior, such as moral hazard, results in higher losses once a loss has occurred. Thus, moral hazard is detrimental to cyber insurer's profitability, especially due to higher severity driving cyber loss ratios.

[Insert Table 8 here]

6. Conclusions

Despite the challenges of unfavorable insurability conditions and unestablished loss experiences, the U.S. cyber insurance industry has grown tremendously in recent years. Increasing cyber risk awareness from the insurance industry, regulators, and policyholders signals the feasibility of a developed private cyber insurance market. Through an empirical study of cyber insurance supply in the U.S. market, we find that insurers do not participate in the cyber insurance market simply to overcome constraints on their business growth. Rather, the decision to participate can be best explained by a careful evaluation of potential competitive advantages in understanding and pricing cyber risks and by a purpose to balance risks between investment and underwriting.

Our analysis of the amount of coverage offered by cyber insurance market participants yields conclusions consistent with the hypotheses explaining cyber insurance participation. In addition, we find that reinsurance significantly impacts the amount of coverage offered, revealing that the development of the cyber reinsurance market is imperative for the healthy growth of the cyber insurance market as a whole. As innovative catastrophe modeling and acquisition of reliable loss data are inevitable externalities of an emerging risk, the lack of reinsurance capacity for cyber insurance will gradually improve as the market becomes more fully fledged. Furthermore, our analysis of other firm-specific characteristics reveal niches within different segments of the cyber insurance market. We find that such preferences do not always correspond with better performance, suggesting that insurers choose to operate in segments in which they are most effective, rather than those that are most profitable.

As a new insurance line, cyber insurance has been profitable at the industry level; however, the profitability is volatile, and performance varies across individual firms and across types of cyber insurance offered. Firm size, mutual organizational form, surplus status, and extent of diversification all demonstrate significant relationships with underwriting profitability. Additionally, we find that a short-term increase in loss ratio is more sensitive to claim severity than claim frequency and is not driven by premium growth. Our findings reinforce the severe loss potential of catastrophic cyber events, especially in standalone coverage.

Our analyses of cyber insurance profitability have produced three key insights. First, an insurer's ability to combat moral hazard through strategic policy design dictates its profitability. In this regard, we argue that the positive externalities of a developed cyber insurance market will improve general internet security. Second, since the catastrophic loss potential of interdependent cyber risks imposes solvency concerns (Baer and Parkinson, 2007), an accurate evaluation of such risks posed by underwriting cyber insurance should become part of insurer solvency regulations. Future research on establishing adequate cyber insurance reserves and capital support may encourage the development of a sustainable market (Eling and Schnell, 2018). Finally, we argue that insurers and regulators must be mindful of the negative externalities of inflated competition. The sustained profitability of packaged cyber insurance products has inevitably stimulated insurer participation; however, recent participants may not have a thorough understanding of the loss potential of cyber risks, increasing the likelihood of packaged cybersecurity products being mispriced. Although new business lines will be self-correcting as larger losses hit the market, we argue that profit-oriented market penetration may impede the development of a robust cyber insurance market.

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Table 1. Variable Descriptions and Definitions

Variable Name	Variable Description	Definition
Cyber	Cyber insurance	Dummy variable equal to 1 if an insurer offers cybersecurity insurance or identity theft insurance; 0 otherwise
Alone	Standalone cyber insurance	Dummy variable equal to 1 if an insurer offers standalone cybersecurity insurance or identity theft insurance; 0 otherwise
Packgd	Packaged cyber insurance	Dummy variable equal to 1 if an insurer offers packaged cybersecurity insurance or identity theft insurance; 0 otherwise
Alone_CB	Standalone cybersecurity insurance	Dummy variable equal to 1 if an insurer offers standalone cybersecurity insurance; 0 otherwise
Packgd_CB	Packaged cybersecurity insurance	Dummy variable equal to 1 if an insurer offers packaged cybersecurity insurance; 0 otherwise
Alone_ID	Standalone identity theft insurance	Dummy variable equal to 1 if an insurer offers standalone identity theft insurance; 0 otherwise
Packgd_ID	Packaged identity theft insurance	Dummy variable equal to 1 if an insurer offers packaged identity theft insurance; 0 otherwise
Variables measuring business growth constraint		
d_dpw	Premium growth	Direct premiums written growth from year t-1 to year t
LB_size	Relative size of lines of business that an insurer operates in	An insurer's business line fraction of total industry premium for single line insurers; weighted average of relative sizes by direct premiums written across business lines for multiline insurers
LB_conc	Concentration of lines of business that an insurer operates in	Sum of an insurer's fractions of direct premiums written across lines multiplied by line-specific Herfindahl indexes measuring industry concentration by lines
Variables measuring investment risk		
Asset_risk	Proportion of risky asset holdings	Fraction of total invested assets in common stocks and high-yield bonds (bonds rated 3-6)
Variables measuring competitive advantage		
Pwherf	Diversification across geographical areas	Complement of the Herfindahl index of direct premiums written across U.S. states and territories
Lbherf_dpw	Diversification across business lines	Complement of the Herfindahl index of direct premiums written across business lines
Surplus insurer	Surplus lines dummy	Dummy variable equal to 1 if an insurer is a professional surplus lines insurer; 0 otherwise
Surplus_aff	Surplus lines affiliation dummy	Dummy variable equal to 1 if an insurer is affiliated with professional surplus lines insurers; 0 otherwise
Other variables		
Size	Firm size	Natural logarithm of total admitted assets
Age	Age of firm	Natural logarithm of number of years since a firm's incorporation
List	Public dummy	Dummy variable equal to 1 if an insurer (or its holding company) is publicly traded; 0 otherwise
Mutual	Mutual dummy	Dummy variable equal to 1 if an insurer is a mutual or reciprocal company; 0 otherwise
Unaffiliated	Affiliation dummy	Dummy variable equal to 1 if an insurer is an unaffiliated insurer; 0 otherwise
Liab_phs	Financial leverage	Total liability/policyholder's surplus
Npw_phs	Underwriting leverage	Net premiums written/policyholder's surplus
Rating	Financial strength rating	A.M. Best's rating, ranging from 1 to 5: 1 = below B-; 2 = B, B-; 3 = B++, B+; 4 = A, A-; 5 = A++,A+
ROI	Return on invested assets	Net investment gain/total invested assets
Related_cyber	Cyber-related lines	Percentage of direct premiums in homeowner and commercial multi-peril lines
Rein_ceded	Reinsurance usage	Reinsurance premiums ceded/(direct premiums written + reinsurance assumed)
RBC_ratio	Risk-based capital ratio	Adjusted capital/Risk-based capital

Table 2. Overview of the U.S. Cyber Insurance Market, 2015-2017

Panel A: Number of firms offering cyber insurance

	N			Professional Surplus Line Insurers			Affiliated with Surplus Line Insurers		
Year	**2015**	**2016**	**2017**	**2015**	**2016**	**2017**	**2015**	**2016**	**2017**
Cyber	453	537	615	55	64	78	229	272	297
Alone	127	138	137	38	42	46	72	76	67
Packgd	376	452	549	29	37	57	192	230	267
Alone_CB	115	127	128	38	41	45	64	69	63
Alone_ID	14	14	14	0	1	3	10	10	7
Packgd_CB	228	320	402	23	33	53	109	168	198
Packgd_ID	228	234	299	9	7	8	132	129	155
P&C Industry	2628	2615	2572	151	146	146	717	714	755

Panel B: Premium size of cyber insurance

	Total DPW ($ Million)			Market Share (%): Surplus Insurers			Market Share (%): Surplus Affiliated Insurers		
Year	**2015**	**2016**	**2017**	**2015**	**2016**	**2017**	**2015**	**2016**	**2017**
Cyber	1,062.3	1,393.2	2,161.9	20.00	21.46	22.01	61.15	57.22	61.39
Alone	509.2	944.5	1,004.6	32.06	28.24	31.74	52.07	58.31	53.06
Packgd	553.1	448.7	1,157.3	8.90	7.18	13.56	69.51	54.92	68.63
Alone_CB	488.0	920.7	985.6	33.45	28.07	30.65	50.13	58.18	53.90
Alone_ID	21.2	23.8	19.1	0.00	34.86	88.04	96.80	63.55	9.66
Packgd_CB	395.4	280.5	976.2	12.37	11.33	16.03	75.41	56.51	71.73
Packgd_ID	157.7	168.2	181.1	0.20	0.27	0.24	54.70	52.27	51.92
P&C Industry	585,698	608,469	636,122	5.08	4.80	4.90	48.43	49.47	53.82

Panel C: Market concentration and cyber premium ratio as of insurer DPW

	HHI			Top 4 Share (%)			Mean % of DPW			Median % of DPW		
	2015	**2016**	**2017**	**2015**	**2016**	**2017**	**2015**	**2016**	**2017**	**2015**	**2016**	**2017**
Cyber	562	415	352	36.0	32.3	27.0	0.60	0.69	0.83	0.12	0.18	0.22
Alone	605	829	533	42.4	47.4	35.4	1.22	1.44	1.62	0.27	0.38	0.47
Packgd	1,187	176	697	47.6	20.4	41.9	0.32	0.38	0.52	0.09	0.12	0.16
Alone_CB	638	835	546	44.3	47.8	36.0	1.32	1.54	1.71	0.31	0.41	0.51
Alone_ID	4,570	3,110	4,266	98.0	98.0	95.5	0.19	0.28	0.24	0.01	0.02	0.04
Packgd_CB	2,228	303	966	64.6	28.8	49.6	0.36	0.41	0.59	0.07	0.09	0.12
Packgd_ID	405	379	324	31.2	30.0	28.0	0.16	0.18	0.16	0.06	0.06	0.06

Note: The table summarizes the U.S. cyber insurance market based on all firms in the industry with positive net admitted assets. The Herfindahl-Hirschman index (HHI) is calculated for each form of cyber insurance based on direct premiums written (DPW). All insurers with positive direct premiums written on each form of cyber insurance are included in the calculation. "Professional Surplus Line Insurers" are defined based on A.M. Best's definition; that is, insurers that write 50% or more of their total direct premiums on a non-admitted basis. "Surplus Affiliated Insurers" are insurers that are affiliated with professional surplus lines insurers.

Table 3. Summary Statistics of Variables

Variable	N	Mean	Median	Std Dev	5_pctl	95_pctl
d_dpw (%)	6458	6.883	3.089	28.858	-28.688	54.214
LB_size	6458	0.099	0.063	0.101	0.014	0.351
LB_conc	6458	0.021	0.02	0.011	0.008	0.035
Asset_risk (%)	6458	13.004	4.805	17.318	0	51.603
Pwherf	6458	0.452	0.496	0.39	0	0.946
Lbherf_dpw	6458	0.431	0.491	0.295	0	0.825
Surplus insurer	6458	0.063	0	0.242	0	1
Surplus_aff	6458	0.342	0	0.475	0	1
Size	6458	11.38	11.26	1.914	8.471	14.685
Age	6458	3.515	3.526	0.87	2.079	4.905
List	6458	0.250	0	0.433	0	1
Mutual	6458	0.190	0	0.392	0	1
Unaffiliated	6458	0.186	0	0.389	0	1
Liab_phs	6458	1.395	1.139	1.249	0.021	3.664
Npw_phs (%)	6458	71.002	54.714	73.087	0	222.864
Rating	6458	3.398	4	1.43	1	5
ROI (%)	6458	2.044	2.036	1.096	0.150	3.911
Related_cyber (%)	6458	21.852	0.544	30.591	0	89.936
Rein_ceded	6458	0.581	0.494	3.837	0.000	1.000
RBC_ratio	6458	27.869	5.280	56.019	1.474	148.194

Note: The number of observations is based on the sample with non-missing values of all the variables specified in the table. Definitions of the variables are provided in Table 1.

Table 4. Logistic Regression: Determinants of Cyber Insurance Offering

Panel A: For all insurers

	Cyber	Alone	Packgd	Alone_CB	Alone_ID	Packgd_CB	Packgd_ID
d_dpw	0.006***	0.009***	0.005***	0.010***	-0.020**	0.006***	0.004*
	(0.002)	(0.003)	(0.002)	(0.003)	(0.010)	(0.002)	(0.002)
LB_size	-4.800***	-7.567***	-3.883***	-8.289***	-3.554	-7.853***	0.780
	(1.141)	(1.580)	(1.309)	(1.724)	(3.227)	(2.568)	(1.213)
LB_conc	-6.471	-30.863**	-3.663	-28.196**	-36.184*	-29.937**	15.102
	(8.562)	(12.972)	(9.475)	(13.360)	(21.951)	(13.504)	(13.498)
Asset_risk	-0.022***	-0.019***	-0.021***	-0.021***	-0.001	-0.021***	-0.021**
	(0.005)	(0.005)	(0.005)	(0.006)	(0.020)	(0.006)	(0.008)
Pwherf	0.603***	0.819**	0.557**	0.681**	2.159*	0.450*	0.740**
	(0.200)	(0.358)	(0.240)	(0.331)	(1.214)	(0.257)	(0.296)
Lbherf_dpw	2.456***	2.132***	2.293***	2.495***	-0.182	2.689***	2.701***
	(0.289)	(0.491)	(0.323)	(0.474)	(1.401)	(0.457)	(0.537)
Surplus	0.428**	1.125***	-0.079	1.200***	0.047	-0.022	-0.927***
insurer	(0.189)	(0.208)	(0.186)	(0.216)	(0.499)	(0.199)	(0.307)
Size	0.327***	0.505***	0.237***	0.545***	0.190	0.250***	0.267***
	(0.056)	(0.082)	(0.062)	(0.094)	(0.116)	(0.072)	(0.083)
Age	-0.060	-0.094	-0.000	-0.092	0.119	-0.065	-0.003
	(0.111)	(0.178)	(0.136)	(0.185)	(0.579)	(0.148)	(0.145)
List	0.266	0.251	0.177	0.301	-0.016	0.136	-0.014
	(0.242)	(0.323)	(0.268)	(0.338)	(0.670)	(0.293)	(0.398)
Mutual	0.480***	-0.901*	0.561***	-1.166**	0.030	0.792***	0.221
	(0.176)	(0.465)	(0.204)	(0.456)	(0.971)	(0.221)	(0.248)
Unaffiliated	-0.447**	-0.345	-0.568***	-0.196	-1.366**	-0.522***	-0.408*
	(0.178)	(0.351)	(0.181)	(0.410)	(0.581)	(0.195)	(0.241)
Liab_phs	0.002	-0.270**	0.019	-0.262**	-0.231	0.099	0.069
	(0.078)	(0.131)	(0.086)	(0.130)	(0.294)	(0.099)	(0.111)
Npw_phs	-0.004***	-0.006**	-0.002	-0.006**	-0.000	-0.003	-0.002
	(0.002)	(0.003)	(0.002)	(0.003)	(0.006)	(0.002)	(0.002)
Rating	0.096	-0.229*	0.202*	-0.236*	-0.226	0.267**	0.243
	(0.108)	(0.131)	(0.104)	(0.141)	(0.249)	(0.113)	(0.168)
ROI	0.087	-0.123	0.156*	-0.178	0.568**	0.200**	0.103
	(0.084)	(0.142)	(0.084)	(0.155)	(0.272)	(0.092)	(0.112)
Related_cyber	0.015***	-0.017**	0.020***	-0.025***	0.015	0.008**	0.036***
	(0.003)	(0.008)	(0.003)	(0.010)	(0.012)	(0.004)	(0.004)
Rein_ceded	-0.001	-0.012	0.003	-0.016	0.015*	0.003	0.005
	(0.009)	(0.009)	(0.007)	(0.010)	(0.008)	(0.010)	(0.005)
RBC_ratio	0.003	0.000	0.003*	0.001	-0.005	0.001	0.005**
	(0.002)	(0.003)	(0.002)	(0.003)	(0.006)	(0.002)	(0.002)
year=2016	0.302***	0.144	0.294***	0.180	-0.018	0.499***	0.026
	(0.074)	(0.099)	(0.084)	(0.110)	(0.155)	(0.123)	(0.057)
year=2017	0.586***	0.122	0.667***	0.188	-0.061	0.885***	0.418***
	(0.094)	(0.164)	(0.102)	(0.177)	(0.449)	(0.133)	(0.120)
Constant	-6.762***	-7.007***	-7.024***	-7.531***	-8.594***	-7.190***	-9.851***
	(0.915)	(0.916)	(0.911)	(1.064)	(2.364)	(0.840)	(1.227)
N	6458	6458	6458	6458	6458	6458	6458
Pseudo R-sq	0.274	0.295	0.255	0.323	0.174	0.288	0.259

Note: Heteroscedasticity-consistent standard errors (allowing for clustering at the group level) are in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. Definitions of the dependent variables and the independent variables are provided in Table 1. The dependent variables are dummy variables indicating offering or not offering each form of cyber insurance.

Table 5. OLS Regressions for Cyber Insurance Premium Volume

Panel A: For all cyber insurers

	Cyber	Alone	Packgd	Alone_CB	Alone_ID	Packgd_CB	Packgd_ID
d_dpw	0.010**	0.002	0.012**	-0.001	-0.001	0.010*	0.013*
	(0.004)	(0.006)	(0.005)	(0.006)	(0.045)	(0.006)	(0.006)
Asset_risk	-0.011*	-0.025*	-0.010*	-0.026*	-0.079	-0.010	-0.000
	(0.006)	(0.013)	(0.005)	(0.014)	(0.048)	(0.008)	(0.009)
Pwherf	0.664***	1.205	0.692***	1.592**	3.948	0.741**	0.078
	(0.246)	(0.755)	(0.220)	(0.719)	(2.907)	(0.304)	(0.272)
Lbherf_dpw	-0.170	1.833*	-0.548	1.574	-0.411	-0.774*	-0.191
	(0.429)	(0.936)	(0.483)	(1.050)	(2.488)	(0.458)	(0.877)
Surplus	0.155	1.151***	-1.084***	1.064***	-2.033**	-0.596	-1.726***
insurer	(0.276)	(0.283)	(0.343)	(0.293)	(0.739)	(0.371)	(0.591)
Size	0.803***	0.567***	0.750***	0.480***	0.566**	0.552***	0.768***
	(0.063)	(0.147)	(0.076)	(0.141)	(0.255)	(0.094)	(0.108)
Age	0.070	0.363	-0.022	0.480*	-1.300	0.204	-0.183
	(0.152)	(0.262)	(0.158)	(0.248)	(1.081)	(0.157)	(0.249)
List	0.151	0.126	0.082	0.158	2.367	0.181	0.232
	(0.214)	(0.355)	(0.226)	(0.376)	(2.321)	(0.302)	(0.266)
Mutual	-0.006	-2.057***	0.404**	-1.608**	-3.711***	0.588**	0.397
	(0.222)	(0.733)	(0.203)	(0.786)	(1.160)	(0.258)	(0.355)
Unaffiliated	0.631***	0.935	0.524***	0.598	10.543	0.605**	0.482**
	(0.207)	(0.740)	(0.175)	(0.718)	(5.919)	(0.241)	(0.221)
Liab_phs	-0.043	-0.011	0.033	0.104	-0.121	-0.016	-0.004
	(0.094)	(0.244)	(0.093)	(0.261)	(0.857)	(0.097)	(0.160)
Npw_phs	-0.006***	-0.009	-0.005**	-0.011*	-0.012	-0.003	-0.003
	(0.002)	(0.006)	(0.002)	(0.006)	(0.030)	(0.003)	(0.002)
Rating	-0.157	-0.473**	-0.090	-0.493**	1.162	-0.177	0.079
	(0.132)	(0.192)	(0.132)	(0.186)	(2.211)	(0.205)	(0.157)
ROI	-0.280***	-0.449**	-0.134	-0.359*	-1.684	0.024	-0.359*
	(0.106)	(0.176)	(0.118)	(0.180)	(1.013)	(0.145)	(0.184)
Related_cyber	0.005	-0.016	0.010**	-0.017	0.031**	-0.005	0.023***
	(0.004)	(0.013)	(0.004)	(0.015)	(0.014)	(0.005)	(0.006)
Rein_ceded	1.355***	0.492	1.465***	0.335	2.759	1.189**	1.783***
	(0.367)	(0.714)	(0.362)	(0.755)	(3.959)	(0.508)	(0.391)
RBC_ratio	-0.005***	-0.009*	-0.004**	-0.008	-0.096**	-0.004*	-0.003
	(0.002)	(0.005)	(0.002)	(0.005)	(0.037)	(0.002)	(0.002)
year=2016	0.239**	0.548**	0.211*	0.495*	-0.443	0.274	0.067
	(0.115)	(0.253)	(0.124)	(0.282)	(0.383)	(0.171)	(0.127)
year=2017	0.336**	0.537**	0.362**	0.509*	-1.426	0.475**	-0.147
	(0.133)	(0.266)	(0.151)	(0.295)	(1.082)	(0.206)	(0.169)
Constant	-4.351***	-1.277	-4.395***	-0.734	0.970	-2.640**	-5.441***
	(1.040)	(1.682)	(1.046)	(1.594)	(12.842)	(1.060)	(1.607)
N	1567	397	1343	366	41	935	739
Adj R-sq	0.331	0.359	0.328	0.328	0.704	0.228	0.302

Note: Heteroscedasticity-consistent standard errors (allowing for clustering at the group level) are in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. Definitions of the independent variables are provided in Table 1. The OLS regression model is: $Ln\_DPW_{i,t} = \alpha + \beta X_{i,t-1} + \theta Year\_dummy + \varepsilon_{i,t}$, where $Ln\_DPW_{i,t}$ is the logarithm of one plus the direct premiums written in each form of cyber insurance as indicated in the table, $X_{i,t-1}$ represents observed variables relating to insurer *i*'s premiums written on cyber insurance, and $\varepsilon_{i,t}$ is an error term.

Table 6. Cyber Insurance Performance

Panel A: Industry aggregate loss ratio

	Pure Loss Ratio (%)			Loss Ratio with Defense and Cost Containment (%)		
	2015	**2016**	**2017**	**2015**	**2016**	**2017**
Cyber	36.1	36.6	18.8	40.7	44.7	25.4
Alone	44.3	36.2	29.2	52.3	45.5	37.9
Packgd	29.4	37.4	7.4	31.2	43.0	11.5
Alone_CB	42.6	35.3	29.8	50.6	44.9	38.6
Alone_ID	75.9	64.7	0.9	83.1	66.6	3.0
Packgd_CB	41.3	44.6	15.6	43.9	54.0	20.9
Packgd_ID	2.8	26.9	0.0	2.9	27.0	0.0

Panel B: Firm-level loss ratio distribution by form of cyber insurance (%)

	Pure Loss Ratio (%)			Loss Ratio with Defense and Cost Containment (%)		
Cyber	**2015**	**2016**	**2017**	**2015**	**2016**	**2017**
25_pctl	0	0	0	0	0	0
50_pctl	0	0	0	0	0	0
75_pctl	1.2	3.5	2.4	2.5	5.5	3.3
90_pctl	28.5	34.9	29.0	35.2	48.6	41.9
95_pctl	60.8	77.6	65.0	65.5	100.9	75.9
Alone	**2015**	**2016**	**2017**	**2015**	**2016**	**2017**
25_pctl	0	0	0	0	0	0
50_pctl	0	3.2	2.0	1.9	4.2	11.5
75_pctl	28.5	31.2	32.3	33.5	43.5	42.7
90_pctl	64.8	65.0	62.3	73.9	65.8	69.1
95_pctl	125.7	99.4	71.3	138.0	110.6	95.2
Packgd	**2015**	**2016**	**2017**	**2015**	**2016**	**2017**
25_pctl	0	0	0	0	0	0
50_pctl	0	0	0	0	0	0
75_pctl	0.1	0.4	0.7	0.2	0.6	1.5
90_pctl	7.3	18.5	13.4	11.0	25.6	19.2
95_pctl	28.8	47.7	51.8	32.3	59.0	74.4
Alone_CB	**2015**	**2016**	**2017**	**2015**	**2016**	**2017**
25_pctl	0	0	0	0	0	0
50_pctl	0	3.8	5.4	1.9	6.3	13.7
75_pctl	33.8	31.9	34.8	39.5	44.3	45.0
90_pctl	64.8	65.0	62.8	73.9	65.5	70.7
95_pctl	145.1	85.9	71.3	149.2	104.7	95.2
Alone_ID	**2015**	**2016**	**2017**	**2015**	**2016**	**2017**
25_pctl	0	0	0	0	0	0
50_pctl	1.4	0.1	0.0	1.4	0.1	0.0
75_pctl	3.3	5.5	5.1	3.3	5.5	5.1
90_pctl	24.5	69.0	5.2	24.5	69.0	5.2
95_pctl	118.0	118.0	5.4	118.0	118.0	5.4
Packgd_CB	**2015**	**2016**	**2017**	**2015**	**2016**	**2017**
25_pctl	0	0	0	0	0	0
50_pctl	0	0	0	0	0	0
75_pctl	0.0	2.5	3.2	0.2	3.3	4.0
90_pctl	11.7	27.3	27.8	17.8	32.4	40.8
95_pctl	29.3	57.1	84.7	34.5	75.6	103.9
Packgd_ID	**2015**	**2016**	**2017**	**2015**	**2016**	**2017**
25_pctl	0	0	0	0	0	0
50_pctl	0	0	0	0	0	0
75_pctl	0	0	0	0	0	0
90_pctl	0.75	0.40	0.04	0.75	0.40	0.04
95_pctl	8.55	0.66	1.99	8.55	0.66	1.99

Note: The "pure loss ratio" is defined as the sum of loss and loss-adjusting expenses incurred divided by premiums earned. The 2017 cyber data do not have separate reporting on adjusting expenses.

Table 7. OLS Regressions for Cyber Insurance Performance

Panel A.1. Pure loss ratio–All insurers

	Cyber	Alone	Packgd	Alone_CB	Alone_ID	Packgd_CB	Packgd_ID
Size	0.155***	0.236***	0.106***	0.277***	-0.022	0.161***	0.029
	(0.033)	(0.058)	(0.029)	(0.061)	(0.123)	(0.038)	(0.025)
Age	-0.048	-0.099	-0.063	-0.087	0.013	0.020	-0.081**
	(0.074)	(0.237)	(0.060)	(0.248)	(0.342)	(0.080)	(0.039)
List	0.073	-0.199	0.149	-0.168	-1.180	0.112	0.065
	(0.172)	(0.349)	(0.152)	(0.362)	(1.644)	(0.171)	(0.085)
Mutual	-0.252**	-1.211***	-0.002	-1.259***	-1.556	-0.249*	0.028
	(0.120)	(0.267)	(0.101)	(0.322)	(1.087)	(0.131)	(0.053)
Unaffiliated	0.330***	0.691*	0.209**	0.442	2.262	0.219*	0.095**
	(0.092)	(0.393)	(0.093)	(0.448)	(1.431)	(0.128)	(0.040)
Pwherf	0.613***	0.636	0.537***	0.512	2.487*	0.430**	0.116
	(0.134)	(0.493)	(0.125)	(0.533)	(1.178)	(0.186)	(0.101)
Lbherf_dpw	-0.817**	-0.222	-0.898***	-0.855	2.806	-1.554***	-0.274*
	(0.320)	(0.853)	(0.334)	(0.903)	(1.584)	(0.414)	(0.158)
Surplus	0.591***	0.527**	-0.025	0.509**	0.886	-0.051	-0.275***
insurer	(0.200)	(0.236)	(0.199)	(0.242)	(0.710)	(0.220)	(0.103)
year=2016	0.184**	0.293	0.143	0.303	-0.259	0.244*	-0.105
	(0.089)	(0.186)	(0.090)	(0.196)	(0.365)	(0.126)	(0.063)
year=2017	0.087	0.113	0.149	0.186	-0.475	0.303**	-0.093
	(0.100)	(0.236)	(0.100)	(0.256)	(0.506)	(0.122)	(0.081)
Constant	-0.932**	-1.553*	-0.402	-1.605*	-1.522	-0.793**	0.259
	(0.429)	(0.833)	(0.341)	(0.843)	(2.010)	(0.391)	(0.262)
N	1552	392	1332	362	41	934	722
Adj R-sq	0.117	0.085	0.074	0.084	0.204	0.108	0.034

Panel A.2. Pure loss ratio–Excluding professional surplus insurers

	Cyber	Alone	Packgd	Alone_CB	Alone_ID	Packgd_CB	Packgd_ID
Size	0.143***	0.228***	0.102***	0.284***	0.022	0.155***	0.025
	(0.031)	(0.063)	(0.028)	(0.062)	(0.121)	(0.036)	(0.025)
Age	-0.081	-0.253	-0.104*	-0.236	-0.158	-0.014	-0.081*
	(0.067)	(0.290)	(0.058)	(0.307)	(0.421)	(0.073)	(0.041)
List	0.068	-0.173	0.113	-0.074	-0.780	0.051	0.090
	(0.181)	(0.395)	(0.155)	(0.404)	(1.596)	(0.171)	(0.087)
Mutual	-0.128	-1.076***	0.059	-1.350***	-1.302	-0.153	0.002
	(0.109)	(0.241)	(0.103)	(0.312)	(1.033)	(0.136)	(0.058)
Unaffiliated	0.348***	0.483	0.212**	-0.000	2.237	0.242*	0.070*
	(0.101)	(0.461)	(0.101)	(0.532)	(1.679)	(0.145)	(0.041)
Pwherf	0.601***	0.748	0.533***	0.734	1.492	0.386**	0.162
	(0.138)	(0.451)	(0.135)	(0.447)	(1.619)	(0.182)	(0.099)
Lbherf_dpw	-1.058***	-0.562	-0.993***	-1.324	2.269	-1.705***	-0.277*
	(0.330)	(0.911)	(0.348)	(0.930)	(1.669)	(0.452)	(0.154)
Surplus_aff	0.217	0.060	0.084	-0.397	0.611	0.221	-0.104**
	(0.151)	(0.451)	(0.127)	(0.570)	(0.817)	(0.140)	(0.048)
year=2016	0.135	0.206	0.165*	0.245	-0.426	0.286**	-0.111*
	(0.084)	(0.181)	(0.091)	(0.192)	(0.330)	(0.125)	(0.066)
year=2017	0.102	0.276	0.177*	0.379	-0.356	0.361***	-0.101
	(0.102)	(0.237)	(0.103)	(0.258)	(0.513)	(0.124)	(0.084)
Constant	-0.631	-0.803	-0.198	-0.746	-0.930	-0.622	0.343
	(0.402)	(0.926)	(0.369)	(0.951)	(1.848)	(0.409)	(0.282)
N	1362	268	1214	240	37	829	700
Adj R-sq	0.109	0.075	0.084	0.098	0.118	0.133	0.039

Panel B.1. Loss ratio with defense and cost containment–All insurers

	Cyber	Alone	Packgd	Alone_CB	Alone_ID	Packgd_CB	Packgd_ID
Size	0.174***	0.223***	0.125***	0.262***	-0.037	0.185***	0.032
	(0.036)	(0.057)	(0.030)	(0.059)	(0.124)	(0.043)	(0.030)
Age	-0.077	-0.096	-0.098	-0.086	0.097	-0.022	-0.089*
	(0.080)	(0.251)	(0.066)	(0.264)	(0.364)	(0.092)	(0.050)
List	0.071	-0.177	0.132	-0.150	-1.103	0.107	0.053
	(0.187)	(0.366)	(0.162)	(0.380)	(1.728)	(0.184)	(0.108)
Mutual	-0.200	-1.371***	0.074	-1.419***	-1.534	-0.174	0.025
	(0.137)	(0.262)	(0.124)	(0.304)	(1.151)	(0.165)	(0.074)
Unaffiliated	0.244**	0.609	0.122	0.317	2.072	0.066	0.089
	(0.107)	(0.369)	(0.110)	(0.422)	(1.506)	(0.145)	(0.061)
Pwherf	0.679***	0.735	0.591***	0.618	2.417*	0.430**	0.162
	(0.149)	(0.441)	(0.136)	(0.471)	(1.222)	(0.216)	(0.148)
Lbherf_dpw	-1.052***	-0.244	-1.116***	-0.914	2.744	-1.854***	-0.378
	(0.347)	(0.869)	(0.362)	(0.916)	(1.699)	(0.448)	(0.256)
Surplus	0.731***	0.685**	0.056	0.652**	1.247*	0.061	-0.336**
insurer	(0.212)	(0.259)	(0.211)	(0.266)	(0.592)	(0.238)	(0.139)
year=2016	0.209**	0.307*	0.169*	0.317	-0.262	0.264**	-0.121
	(0.092)	(0.180)	(0.091)	(0.190)	(0.360)	(0.128)	(0.074)
year=2017	0.114	0.245	0.173	0.324	-0.460	0.338**	-0.116
	(0.102)	(0.233)	(0.105)	(0.252)	(0.515)	(0.132)	(0.095)
Constant	-0.871**	-1.307	-0.344	-1.309	-1.582	-0.660	0.346
	(0.433)	(0.802)	(0.359)	(0.815)	(2.188)	(0.427)	(0.362)
N	1552	392	1332	362	41	934	722
Adj R-sq	0.132	0.097	0.086	0.094	0.201	0.118	0.030

Panel B.2. Loss ratio with defense and cost containment–Excluding professional surplus insurers

	Cyber	Alone	Packgd	Alone_CB	Alone_ID	Packgd_CB	Packgd_ID
Size	0.160***	0.222***	0.119***	0.277***	0.038	0.175***	0.026
	(0.034)	(0.065)	(0.031)	(0.064)	(0.119)	(0.042)	(0.030)
Age	-0.109	-0.269	-0.138**	-0.251	-0.183	-0.051	-0.088
	(0.077)	(0.302)	(0.065)	(0.323)	(0.426)	(0.083)	(0.054)
List	0.078	-0.160	0.118	-0.058	-0.764	0.071	0.091
	(0.198)	(0.415)	(0.165)	(0.429)	(1.633)	(0.182)	(0.109)
Mutual	-0.074	-1.229***	0.134	-1.526***	-1.335	-0.069	-0.020
	(0.130)	(0.243)	(0.127)	(0.292)	(1.039)	(0.169)	(0.085)
Unaffiliated	0.255**	0.388	0.115	-0.144	2.323	0.081	0.048
	(0.113)	(0.444)	(0.113)	(0.495)	(1.679)	(0.155)	(0.060)
Pwherf	0.663***	0.701	0.596***	0.694	1.399	0.379*	0.238
	(0.155)	(0.428)	(0.149)	(0.421)	(1.689)	(0.216)	(0.156)
Lbherf_dpw	-1.327***	-0.472	-1.261***	-1.249	2.273	-2.070***	-0.377
	(0.351)	(0.925)	(0.370)	(0.940)	(1.695)	(0.476)	(0.248)
Surplus_aff	0.209	0.119	0.058	-0.373	0.701	0.221	-0.172**
	(0.172)	(0.458)	(0.144)	(0.561)	(0.861)	(0.156)	(0.079)
year=2016	0.164*	0.244	0.188**	0.282	-0.413	0.305**	-0.130*
	(0.087)	(0.183)	(0.091)	(0.195)	(0.327)	(0.125)	(0.076)
year=2017	0.126	0.458*	0.178*	0.566*	-0.335	0.368***	-0.128
	(0.103)	(0.263)	(0.105)	(0.285)	(0.519)	(0.130)	(0.098)
Constant	-0.543	-0.608	-0.073	-0.501	-1.022	-0.418	0.476
	(0.413)	(0.931)	(0.390)	(0.975)	(1.884)	(0.444)	(0.400)
N	1362	268	1214	240	37	829	700
Adj R-sq	0.118	0.080	0.099	0.100	0.113	0.147	0.040

Note: Heteroscedasticity-consistent standard errors (allowing for clustering at the group level) are in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. Definitions of the independent variables are provided in Table 1. The OLS regression model is: $Ln\_LossRatio_{i,t} = \alpha + \beta X_{i,t-1} + \theta Year\_dummy + \varepsilon_i$, where $Ln\_LossRatio_{i,t}$ is the logarithm of one plus the loss ratio in each form of cyber insurance as indicated in the table, $X_{i,t-1}$ represents observed variables relating to insurer *i*'s loss ratio on cyber insurance, and $\varepsilon_{i,t}$ is an error term.

Table 8. Regressions for Cyber Insurance Performance: Changes in the Loss Ratio

Panel A: Changes in the loss ratio vs. premium growth

	Cyber	Alone	Packgd	Alone_CB	Alone_ID	Packgd_CB	Packgd_ID
Pure Loss Ratio–All Insurers							
Log_Premium	-0.566*	-0.756**	-0.478*	-0.531**	1.004	-0.452	1.539*
growth	(0.320)	(0.343)	(0.270)	(0.255)	(0.429)	(0.270)	(0.847)
N	251	112	141	106	7	107	32
Adj R-sq	0.029	0.091	0.027	0.061	0.458	0.021	0.003
Pure Loss Ratio–Excluding Professional Surplus Insurers							
Log_Premium	-0.373	-0.722*	-0.467	-0.350*	1.004	-0.414	1.539*
growth	(0.430)	(0.414)	(0.350)	(0.204)	(0.429)	(0.378)	(0.847)
N	198	72	131	66	7	97	32
Adj R-sq	0.003	0.074	0.016	0.011	0.458	0.006	0.003
Loss Ratio with Defense and Cost Containment–All Insurers							
Log_Premium	-0.665**	-0.541**	-0.705***	-0.352**	1.106*	-0.720***	1.528*
growth	(0.267)	(0.260)	(0.231)	(0.166)	(0.417)	(0.252)	(0.716)
N	275	128	160	122	7	125	32
Adj R-sq	0.051	0.061	0.049	0.035	0.398	0.042	-0.019
Loss Ratio with Defense and Cost Containment—Excluding Professional Surplus Insurers							
Log_Premium	-0.512	-0.721*	-0.596*	-0.373*	1.106*	-0.586	1.528*
growth	(0.343)	(0.391)	(0.300)	(0.209)	(0.417)	(0.366)	(0.716)
N	215	79	146	73	7	111	32
Adj R-sq	0.018	0.092	0.027	0.015	0.398	0.016	-0.019

Panel B: Changes in the loss ratio vs. claim frequency growth

	Cyber	Alone	Packgd	Alone_CB	Alone_ID	Packgd_CB	Packgd_ID
Pure Loss Ratio–All Insurers							
Log_ Frequency	0.514**	0.032	0.856***	-0.091	N/A	0.721***	1.754***
growth	(0.200)	(0.271)	(0.229)	(0.240)	N/A	(0.209)	(0.382)
N	211	75	129	73	N/A	100	28
Adj R-sq	0.046	-0.007	0.126	0.008	N/A	0.093	0.271
Pure Loss Ratio–Excluding Professional Surplus Insurers							
Log_Frequency	0.699***	0.523	0.865***	0.283	N/A	0.753***	1.754***
growth	(0.216)	(0.330)	(0.237)	(0.255)	N/A	(0.220)	(0.382)
N	170	46	121	44	N/A	92	28
Adj R-sq	0.081	0.030	0.124	0.009	N/A	0.086	0.271
Loss Ratio with Defense and Cost Containment–All Insurers							
Log_ Frequency	0.380**	0.029	0.660***	-0.081	N/A	0.548**	1.662***
growth	(0.160)	(0.174)	(0.195)	(0.135)	N/A	(0.219)	(0.369)
N	231	87	146	85	N/A	116	28
Adj R-sq	0.026	-0.019	0.059	-0.014	N/A	0.026	0.229
Loss Ratio with Defense and Cost Containment–Excluding Professional Surplus Insurers							
Log_ Frequency	0.503**	0.280	0.645***	0.088	N/A	0.512**	1.662***
growth	(0.189)	(0.236)	(0.199)	(0.162)	N/A	(0.221)	(0.369)
N	185	52	134	50	N/A	104	28
Adj R-sq	0.045	-0.010	0.053	-0.037	N/A	0.017	0.229

Panel C: Changes in the loss ratio vs. average claim severity growth

	Cyber	Alone	Packgd	Alone_CB	Alone_ID	Packgd_CB	Packgd_ID
Pure Loss Ratio–All Insurers							
Log_ Severity	0.864***	0.808***	0.953***	0.682***	N/A	0.844***	1.101***
growth	(0.053)	(0.076)	(0.081)	(0.073)	N/A	(0.059)	(0.040)
N	211	75	129	73	N/A	100	28
Adj R-sq	0.715	0.686	0.728	0.703	N/A	0.754	0.924
Pure Loss Ratio–Excluding Professional Surplus Insurers							
Log_ Severity	0.873***	0.807***	0.925***	0.660***	N/A	0.833***	1.101***
growth	(0.061)	(0.138)	(0.082)	(0.117)	N/A	(0.062)	(0.040)
N	170	46	121	44	N/A	92	28
Adj R-sq	0.724	0.568	0.717	0.596	N/A	0.742	0.924
Loss Ratio with Defense and Cost Containment–All Insurers							
Log_ Severity	0.831***	0.689***	0.900***	0.514***	N/A	0.950***	1.092***
growth	(0.049)	(0.084)	(0.044)	(0.063)	N/A	(0.038)	(0.035)
N	231	87	146	85	N/A	116	28
Adj R-sq	0.695	0.584	0.760	0.564	N/A	0.792	0.917
Loss Ratio with Defense and Cost Containment–Excluding Professional Surplus Insurers							
Log_ Severity	0.844***	0.692***	0.886***	0.531***	N/A	0.939***	1.092***
growth	(0.054)	(0.118)	(0.045)	(0.093)	N/A	(0.040)	(0.035)
N	185	52	134	50	N/A	104	28
Adj R-sq	0.726	0.507	0.769	0.508	N/A	0.807	0.917

Note: Heteroscedasticity-consistent standard errors (allowing for clustering at the group level) are in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. Panel A runs the OLS regression model $Ln\_GrLossRatio_{i,t} = \alpha + \beta Ln\_GrPE_{i,t} + \theta Year\_dummy + \varepsilon_{i,t}$, where the $Ln\_GrLossRatio_{i,t}$ is the logarithm of loss ratio growth of insurer *i* (defined as loss ratio in year *t* divided by loss ratio in year *t*-1) in each form of cyber insurance as indicated in the table. The independent $Ln\_GrPE_{i,t}$ is the logarithm of premiums earned growth of insurer *i* (defined as premiums earned in year *t* divided by premiums earned in year *t*-1) in each form of cyber insurance as indicated in the table. Similarly, Panel B runs the OLS regression model $Ln\_GrLossRatio_{i,t} = \alpha + \beta Ln\_GrClaimF_{i,t} + \theta Year\_dummy + \varepsilon_{i,t}$, and Panel C runs the OLS regression model $Ln\_GrLossRatio_{i,t} = \alpha + \beta Ln\_GrClaimS_{i,t} + \theta Year\_dummy + \varepsilon_{i,t}$,where $Ln\_GrClaimF_{i,t}$ represents the logarithm of claim frequency growth of insurer *i* (defined as claim frequency in year *t* divided by claim frequency in year *t*-1), and $Ln\_GrClaimS_{i,t}$ represents the logarithm of growth of average claim severity of insurer *i* (defined as average claim severity in year *t* divided by average claim severity in year *t*-1) in each form of cyber insurance as indicated in the table. Year dummy of 2017 and constant term are included in the regressions but not reported.

Cyber Insurance Supply and Performance:
An Analysis of the U.S. Cyber Insurance Market

Online-Appendix A: Literature on Cyber Risk Insurance / Contribution of this Paper

Cyber risk management and cyber insurance have received considerable attention from both academia and the insurance industry. One strand of research on cyber insurance discusses the socioeconomic merits of cyber insurance. Öğüt, Menon, and Raghunathan (2005) find that the interdependent nature of cyber risks reduces the effectiveness of self-protection, encouraging firms to purchase cyber insurance instead of investing in network security. However, they also conclude that firms do not have adequate incentive to manage network security at a socially optimal level, casting doubt on the conjecture that cyber insurance will improve network security.

Shetty et al. (2010) develop a theoretical model which addresses consumer behavior, such as moral hazard. They conclude that, while cyber insurance is effective regarding the transfer of cyber risks, a competitive cyber insurance market will not provide adequate incentive to improve network security. The proponents of cyber insurance, however, argue that despite the presence of moral hazard, a developed cyber insurance market engenders standards for best practices through establishing benchmark network security levels for cyber risk management and through incentivizing investment in self-protection (Kesan, Majuca, and Yurcik, 2005; Baer and Parkinson, 2007; Lelarge and Bolot 2009). Similarly, Biener, Eling, and Wirfs (2015) highlight two benefits of a developed cyber insurance market. First, cyber insurance coverage quantifies cyber risks, thus creating economic incentives for policyholders to practice sound network security. Second, the application process for cyber insurance causes firms to be more aware and self-protective of cyber risks.

With the consensus that, when viable, a healthy cyber insurance market will improve societal well-being and influence overall internet security, the ensuing question of interest is how a healthy cyber insurance market can be developed. In an overview of recent literature on cyber risks, Biener, Eling, and Wirfs (2015) argue that most problematic criteria regarding the insurability of cyber exposures are randomness of loss occurrence (interdependence and correlated risks), information asymmetry, and lack of reliable cyber loss data for insurance pricing. A more detailed review of the literature on these aspects is available upon request.

Despite extensive discussions on cyber risks, empirical research on cyber insurance providers is scarce. One exception is Eling and Zhu (2018), who first study the characteristics of U.S. cyber insurers using 2015 data. Our paper further contributes to this growing body of research by examining the determinants of cyber insurance offering, the participation extent, and cyber insurer performance using longitudinal data in the period 2015-2017.

Insurance companies rely heavily upon the law of large numbers and mutually independent risks to construct profitable risk pools. Baer and Parkinson (2007) find that coordinated cyber events violate the independence prerequisite since one compromised system could potentially afflict other systems in the same network. Consequently, cyber risk pools inevitably exhibit highly volatile loss experiences. The interconnectivity of computer networks is the main cause of interdependent security risks, as malicious software such as viruses and worms are able to transfer from one system to another. Furthermore, the lack of diverse options in technology protecting information technology infrastructure causes firms to be susceptible to the same vulnerabilities (Öğüt, Menon, and Raghunathan, 2005; Öğüt, Raghunathan, and Menon, 2011). In addition to the issues with interdependence, Böhme and Kataria (2006) find a high global correlation among cyber risks, further discouraging adequate risk pooling and causing insurers to include higher safety loads in premiums.

Information asymmetry, a barrier to cyber insurance supply, is not a market anomaly of cyber insurance. Adverse selection occurs within cyber insurance markets when insurers are not able to accurately evaluate the network security posture of applicants. Since firms that are more susceptible to cyber losses are more likely to purchase cyber insurance, accurate risk assessment of applicants is crucial in diversifying insurer's risk pools and projecting expected losses. Inaccurate classification of risks can result in underpriced policies and adverse loss experiences, causing profitability and solvency problems (Gordon, Loeb, and Sohail, 2003; Kesan, Majuca, and Yurcik, 2005; Baer and Parkinson, 2007).

Moral hazard occurs when firms rely solely on insurance coverage in managing cyber risks, thus relinquishing self-protective measures and increasing underwriting risk for cyber insurers. Öğüt, Menon, and Raghunathan (2005) predict that even in mature cyber insurance markets, similar moral hazard issues will persist. Conventional solutions to combat moral hazard are explored and structured to handle similar issues in cyber insurance, including offering partial coverage, setting premiums dependent upon expenditures on self-protection, monitoring policyholders' network security, offering rewards for information leading to apprehension of hackers, and reimbursing post-intrusion crisis management activities (Kesan, Majuca, and Yurcik, 2005; Baer and Parkinson, 2007).

The information asymmetry and high correlation of cyber risks create difficulties in accurately pricing cyber insurance, a topic covered in another strand of research. Pricing cyber risks faces several challenges. Specifically, the lack of actuarial data and normative standards cause insurers to over-price cyber insurance (Toregas and Zahn, 2014). In addition, cyber insurers typically develop their own underwriting standards and procedures that are not transparent to the market, adding to the difficulty in sharing information and establishing consistent underwriting benchmarks (ENISA, 2012). Acknowledging these challenges, literature in this strand proposes various solutions to model cyber-risk distributions (Böhme and Kataria, 2006; Böhme and Schwartz, 2010; Maillart and Sornette, 2010; Herath and Herath, 2011; Mukhopadhyay et al., 2013; Wheatley, Maillart, and Sornette, 2016; Eling and Loperfido 2017). However, due to the fast-evolving nature of cyber risks, continuing efforts are required to develop sophisticated models that overcome the challenges of limited actuarial data and unestablished normative standards (Shang, 2017).

Despite extensive discussions on cyber risks, empirical research on cyber insurance providers is scarce, with the exception of Eling and Zhu (2018), the first studying the characteristics of US cyber insurers using 2015 data. Our paper further contributes to this growing body of research by examining the determinants of cyber insurance offering, the participation extent, and cyber insurer performance using longitudinal data in the period 2015-2017.

Online-Appendix B:
Panel B of Table 4. Logistic Regression: Determinants of Cyber Insurance Offering

Panel B: Excluding professional surplus insurers

	Cyber	Alone	Packgd	Alone_CB	Alone_ID	Packgd_CB	Packgd_ID
d_dpw	0.007***	0.009***	0.005**	0.010***	-0.021**	0.006**	0.005
	(0.002)	(0.003)	(0.002)	(0.003)	(0.009)	(0.002)	(0.003)
LB_size	-4.166***	-7.738***	-3.392**	-8.921***	-2.086	-8.231***	1.800
	(1.249)	(1.901)	(1.432)	(2.219)	(2.077)	(2.751)	(1.387)
LB_conc	-4.311	-26.359**	-0.477	-24.457**	-24.350	-26.767**	20.237
	(8.288)	(11.695)	(9.152)	(12.095)	(20.436)	(13.191)	(12.671)
Asset_risk	-0.022***	-0.015***	-0.022***	-0.018***	0.004	-0.023***	-0.019**
	(0.005)	(0.005)	(0.006)	(0.005)	(0.022)	(0.006)	(0.008)
Pwherf	0.458**	0.599	0.447*	0.446	1.810*	0.417	0.566*
	(0.210)	(0.434)	(0.250)	(0.437)	(1.079)	(0.271)	(0.296)
Lbherf_dpw	2.474***	1.837***	2.409***	2.283***	-0.474	2.820***	2.829***
	(0.298)	(0.527)	(0.332)	(0.504)	(1.254)	(0.466)	(0.546)
Surplus_aff	**0.877*****	**1.439*****	**0.741****	**1.451*****	**1.390**	**0.193**	**1.038*****
	(0.275)	**(0.402)**	**(0.302)**	**(0.428)**	**(0.948)**	**(0.346)**	**(0.400)**
Size	0.314***	0.455***	0.235***	0.505***	0.082	0.273***	0.248***
	(0.058)	(0.083)	(0.063)	(0.095)	(0.161)	(0.075)	(0.083)
Age	-0.080	-0.063	-0.048	-0.077	0.247	-0.141	-0.020
	(0.114)	(0.168)	(0.142)	(0.173)	(0.511)	(0.160)	(0.141)
List	-0.035	-0.051	-0.071	0.021	-0.425	0.037	-0.313
	(0.284)	(0.364)	(0.314)	(0.390)	(0.705)	(0.367)	(0.419)
Mutual	0.654***	-0.608	0.757***	-0.844**	0.188	0.895***	0.423*
	(0.167)	(0.438)	(0.194)	(0.405)	(1.019)	(0.235)	(0.245)
Unaffiliated	-0.407**	-0.105	-0.527***	0.063	-1.150**	-0.507**	-0.363
	(0.178)	(0.403)	(0.189)	(0.502)	(0.525)	(0.208)	(0.238)
Liab_phs	-0.022	-0.346**	-0.001	-0.346**	-0.280	0.094	0.057
	(0.073)	(0.141)	(0.081)	(0.144)	(0.252)	(0.098)	(0.103)
Npw_phs	-0.004**	-0.004	-0.002	-0.005*	0.002	-0.003	-0.001
	(0.001)	(0.003)	(0.002)	(0.003)	(0.006)	(0.002)	(0.002)
Rating	0.017	-0.398***	0.132	-0.413***	-0.277	0.242**	0.161
	(0.100)	(0.137)	(0.096)	(0.143)	(0.272)	(0.113)	(0.148)
ROI	0.113	-0.130	0.179*	-0.207	0.660**	0.221**	0.119
	(0.094)	(0.160)	(0.094)	(0.178)	(0.274)	(0.105)	(0.125)
Related_cyber	0.017***	-0.012	0.021***	-0.021**	0.015	0.009**	0.037***
	(0.003)	(0.008)	(0.003)	(0.010)	(0.012)	(0.004)	(0.004)
Rein_ceded	-0.008	-0.025**	-0.002	-0.031**	0.012	-0.001	0.002
	(0.011)	(0.011)	(0.009)	(0.014)	(0.008)	(0.011)	(0.006)
RBC_ratio	0.002	-0.001	0.003*	0.000	-0.007	0.002	0.004**
	(0.001)	(0.004)	(0.001)	(0.004)	(0.005)	(0.002)	(0.002)
year=2016	0.304***	0.111	0.299***	0.166	-0.065	0.502***	0.051
	(0.079)	(0.104)	(0.088)	(0.117)	(0.154)	(0.129)	(0.058)
year=2017	0.564***	0.047	0.623***	0.147	-0.372	0.844***	0.423***
	(0.103)	(0.196)	(0.108)	(0.215)	(0.412)	(0.138)	(0.131)
Constant	-6.684***	-6.435***	-7.008***	-6.962***	-8.454***	-7.300***	-10.003***
	(0.920)	(0.887)	(0.906)	(1.080)	(2.005)	(0.848)	(1.297)
N	6054	6054	6054	6054	6054	6054	6054
Pseudo R-sq	0.289	0.265	0.280	0.293	0.204	0.305	0.280

Note: Heteroscedasticity-consistent standard errors (allowing for clustering at the group level) are in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. Definitions of the dependent variables and the independent variables are provided in Table 1. The dependent variables are dummy variables indicating offering or not offering each form of cyber insurance.

Online-Appendix C: Heckman Two-Step Regressions for Cyber Insurance Premium Volume

Panel A: For all insurers

	Cyber	Alone	Packgd	Alone_CB	Alone_ID	Packgd_CB	Packgd_ID
d_dpw	0.007***	0.005	0.008***	0.003	-0.005	0.002	-0.004
	(0.002)	(0.005)	(0.002)	(0.006)	(0.040)	(0.003)	(0.009)
Asset_risk	-0.010*	-0.029***	-0.009*	-0.029**	-0.072**	0.007	0.056**
	(0.005)	(0.011)	(0.005)	(0.012)	(0.034)	(0.006)	(0.027)
Pwherf	0.658***	1.483**	0.705***	1.715***	4.038	0.001	-1.640*
	(0.217)	(0.663)	(0.224)	(0.632)	(5.267)	(0.286)	(0.926)
Lbherf_dpw	-0.250	2.454**	-0.557	2.099	-0.295	-3.522***	-7.258**
	(0.500)	(1.152)	(0.558)	(1.382)	(1.650)	(0.557)	(3.096)
Surplus	0.164	1.506**	-1.066***	1.319**	-1.791	-0.679***	1.258
insurer	(0.184)	(0.590)	(0.192)	(0.636)	(1.345)	(0.257)	(1.541)
Size	0.788***	0.685***	0.741***	0.569**	0.615	0.369***	0.004
	(0.062)	(0.214)	(0.059)	(0.236)	(0.490)	(0.070)	(0.340)
Age	0.074	0.361*	-0.018	0.487**	-1.150*	0.302**	-0.180
	(0.085)	(0.204)	(0.086)	(0.210)	(0.656)	(0.126)	(0.312)
List	0.152	0.207	0.091	0.226	2.333***	0.052	0.277
	(0.120)	(0.277)	(0.121)	(0.297)	(0.894)	(0.170)	(0.450)
Mutual	-0.022	-2.236***	0.402**	-1.785**	-3.726***	-0.136	-0.413
	(0.186)	(0.640)	(0.205)	(0.805)	(1.287)	(0.261)	(0.712)
Unaffiliated	0.642***	0.946	0.524**	0.654	11.580*	0.919***	1.880*
	(0.245)	(0.773)	(0.258)	(0.794)	(6.719)	(0.338)	(1.027)
Liab_phs	-0.011	-0.060	0.055	0.060	-0.215	-0.067	-0.125
	(0.054)	(0.185)	(0.055)	(0.192)	(0.850)	(0.077)	(0.191)
Npw_phs	-0.006***	-0.012**	-0.005***	-0.012**	-0.008	0.001	0.001
	(0.002)	(0.005)	(0.002)	(0.006)	(0.015)	(0.002)	(0.005)
Rating	-0.161**	-0.531***	-0.091	-0.538***	1.563	-0.484***	-0.575
	(0.072)	(0.174)	(0.082)	(0.179)	(1.792)	(0.122)	(0.358)
ROI	-0.273***	-0.444***	-0.130*	-0.356**	-1.430	-0.156*	-0.663**
	(0.060)	(0.127)	(0.068)	(0.139)	(1.203)	(0.090)	(0.261)
Related_cyber	0.005	-0.020**	0.010**	-0.021*	0.034	-0.013***	-0.076*
	(0.003)	(0.008)	(0.004)	(0.011)	(0.023)	(0.003)	(0.042)
Rein_ceded	1.353***	0.471	1.473***	0.323	3.519	1.317***	1.613**
	(0.229)	(0.571)	(0.234)	(0.590)	(2.352)	(0.290)	(0.655)
RBC_ratio	-0.005***	-0.009**	-0.004***	-0.008**	-0.095***	-0.004**	-0.017**
	(0.001)	(0.004)	(0.001)	(0.004)	(0.019)	(0.002)	(0.007)
year=2016	0.227*	0.595**	0.206	0.542*	-0.348	-0.200	0.017
	(0.134)	(0.278)	(0.142)	(0.292)	(0.503)	(0.204)	(0.461)
year=2017	0.322**	0.569**	0.363**	0.551*	-1.399*	-0.330	-1.329**
	(0.148)	(0.281)	(0.174)	(0.297)	(0.758)	(0.220)	(0.662)
Constant	-4.100***	-4.067	-4.349**	-2.771	-5.056	6.569***	26.590**
	(1.471)	(4.259)	(1.826)	(4.634)	(21.889)	(1.565)	(13.407)
Mills	-0.064	0.696	0.000	0.482	0.610	-2.398***	-6.959**
	(0.393)	(1.043)	(0.475)	(1.107)	(5.376)	(0.349)	(2.862)
N	6458	6458	6458	6458	6458	6458	6458

Panel B: Excluding professional surplus insurers

	Cyber	Alone	Packgd	Alone_CB	Alone_ID	Packgd_CB	Packgd_ID
d_dpw	0.006***	0.002	0.007***	0.001	0.162	0.001	-0.003
	(0.002)	(0.006)	(0.002)	(0.007)	(0.598)	(0.004)	(0.006)
Asset_risk	-0.004	-0.020	-0.006	-0.025*	-0.082	0.015**	0.033**
	(0.005)	(0.013)	(0.006)	(0.014)	(0.374)	(0.007)	(0.015)
Pwherf	0.675***	1.582**	0.704***	1.968***	-14.587	0.000	-0.473
	(0.205)	(0.750)	(0.214)	(0.725)	(61.453)	(0.294)	(0.487)
Lbherf_dpw	-0.812	3.003**	-0.987	2.842*	10.674	-4.151***	-5.284***
	(0.535)	(1.286)	(0.623)	(1.625)	(33.314)	(0.593)	(1.595)
Surplus_aff	-0.543**	-2.505**	-0.564***	-2.713**	-16.246	-0.756***	-2.586***
	(0.215)	(1.026)	(0.219)	(1.055)	(47.391)	(0.221)	(0.627)
Size	0.726***	0.481*	0.708***	0.511*	-0.726	0.311***	0.263
	(0.063)	(0.247)	(0.062)	(0.269)	(5.672)	(0.074)	(0.180)
Age	0.042	0.022	-0.055	0.034	-2.084	0.364***	-0.175
	(0.088)	(0.268)	(0.089)	(0.286)	(8.968)	(0.138)	(0.227)
List	0.224*	0.152	0.216*	0.225	5.739	0.332*	0.888**
	(0.124)	(0.324)	(0.126)	(0.338)	(17.386)	(0.191)	(0.372)
Mutual	-0.239	-2.496***	0.187	-2.850***	-5.577	-0.481*	-0.629
	(0.203)	(0.654)	(0.237)	(0.888)	(14.343)	(0.284)	(0.531)
Unaffiliated	0.608**	1.021	0.499**	0.757	31.802	0.802**	1.367**
	(0.236)	(0.844)	(0.253)	(0.890)	(85.140)	(0.338)	(0.660)
Liab_phs	0.028	0.184	0.064	0.210	3.079	-0.059	-0.031
	(0.054)	(0.256)	(0.054)	(0.269)	(12.518)	(0.080)	(0.131)
Npw_phs	-0.006***	-0.012*	-0.005***	-0.012	0.012	0.001	-0.003
	(0.002)	(0.006)	(0.002)	(0.007)	(0.176)	(0.002)	(0.003)
Rating	-0.132*	-0.094	-0.057	-0.098	7.421	-0.450***	-0.151
	(0.071)	(0.274)	(0.079)	(0.285)	(25.141)	(0.124)	(0.196)
ROI	-0.286***	-0.234	-0.185**	-0.118	-7.324	-0.255***	-0.571***
	(0.063)	(0.170)	(0.073)	(0.190)	(19.837)	(0.097)	(0.173)
Related_cyber	0.004	-0.011	0.008	-0.011	-0.099	-0.015***	-0.047**
	(0.004)	(0.009)	(0.005)	(0.012)	(0.427)	(0.004)	(0.021)
Rein_ceded	1.295***	0.632	1.450***	0.596	7.276	1.351***	1.638***
	(0.237)	(0.706)	(0.242)	(0.742)	(28.729)	(0.293)	(0.498)
RBC_ratio	-0.004***	-0.006	-0.003***	-0.005	0.003	-0.003	-0.010***
	(0.001)	(0.006)	(0.001)	(0.006)	(0.315)	(0.002)	(0.004)
year=2016	0.168	0.602*	0.165	0.552	1.284	-0.209	-0.048
	(0.138)	(0.344)	(0.145)	(0.372)	(7.647)	(0.215)	(0.336)
year=2017	0.209	0.413	0.220	0.442	3.772	-0.440*	-1.053***
	(0.153)	(0.352)	(0.176)	(0.378)	(16.751)	(0.229)	(0.407)
Constant	-2.252	0.363	-2.741	-0.866	91.120	8.358***	16.833***
	(1.563)	(5.038)	(1.979)	(5.399)	(326.187)	(1.599)	(6.517)
Mills	-0.512	-0.442	-0.399	-0.031	-28.099	-2.802***	-4.919***
	(0.435)	(1.319)	(0.534)	(1.365)	(87.838)	(0.364)	(1.392)
N	6054	6054	6054	6054	6054	6054	6054

Note: Standard errors are in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. Definitions of the independent variables are provided in Table 1. The model is estimated using Heckman two-step regressions. The second step regression equation (reported in the table) is: $Ln\_DPW_{i,t} = \alpha + \beta X_{i,t-1} + \theta Year\_dummy + \varepsilon_{i,t}$, where $Ln\_DPW_{i,t}$ is the logarithm of one plus the direct premiums written in each form of cyber insurance as indicated in the table, $X_{i,t-1}$ represents observed variables relating to insurer *i*'s premiums written on cyber insurance, and $\varepsilon_{i,t}$ is an error term. The first step sample selection equation is: $CYBER\_OFF_{i,t} = \gamma Z_{i,t-1} + u_{i,t}$, where $CYBER\_OFF_{i,t}$ equals zero if an insurer does not offer a certain form of cyber insurance and one if an insurer has positive direct premiums written in a certain form of cyber insurance as indicated in the table. $Z_{i,t-1}$ represents the vector of variables determining cyber insurance offering. Mills is the non-selection hazard calculated from the first step selection equation.

Online-Appendix D:
Panel B of Table 5. OLS Regressions for Cyber Insurance Premium Volume

Panel B: Excluding professional surplus insurers

	Cyber	Alone	Packgd	Alone_CB	Alone_ID	Packgd_CB	Packgd_ID
d_dpw	0.011**	0.003	0.011*	-0.000	-0.020	0.010	0.010
	(0.005)	(0.009)	(0.006)	(0.011)	(0.046)	(0.007)	(0.006)
Asset_risk	-0.009	-0.023	-0.009	-0.026	-0.046	-0.007	-0.003
	(0.006)	(0.017)	(0.006)	(0.018)	(0.042)	(0.010)	(0.009)
Pwherf	0.783***	1.720*	0.782***	1.998**	3.896	0.809**	0.258
	(0.245)	(0.932)	(0.232)	(0.889)	(3.536)	(0.321)	(0.279)
Lbherf_dpw	-0.247	3.340***	-0.553	2.879**	1.559	-0.807*	-0.317
	(0.451)	(1.066)	(0.487)	(1.114)	(3.392)	(0.483)	(0.846)
Surplus_aff	**-0.342**	**-2.232*****	**-0.429**	**-2.696*****	**-1.638**	**-0.111**	**-0.738****
	(0.301)	**(0.662)**	**(0.301)**	**(0.714)**	**(1.796)**	**(0.385)**	**(0.338)**
Size	0.785***	0.557***	0.749***	0.528***	0.676*	0.508***	0.790***
	(0.065)	(0.189)	(0.076)	(0.185)	(0.321)	(0.104)	(0.112)
Age	0.020	0.010	-0.070	0.015	-0.890	0.178	-0.220
	(0.155)	(0.338)	(0.163)	(0.340)	(1.363)	(0.159)	(0.235)
List	0.203	0.149	0.190	0.230	1.165	0.291	0.330
	(0.237)	(0.399)	(0.252)	(0.432)	(2.609)	(0.346)	(0.277)
Mutual	-0.104	-2.569***	0.311	-2.864***	-3.951**	0.549**	0.320
	(0.223)	(0.572)	(0.203)	(0.768)	(1.328)	(0.245)	(0.343)
Unaffiliated	0.535***	1.038	0.424**	0.766	10.041	0.485**	0.423*
	(0.195)	(0.757)	(0.179)	(0.704)	(5.968)	(0.234)	(0.231)
Liab_phs	-0.002	0.118	0.044	0.192	-0.337	-0.011	0.017
	(0.095)	(0.239)	(0.103)	(0.239)	(0.865)	(0.099)	(0.159)
Npw_phs	-0.007***	-0.012*	-0.005**	-0.011	-0.003	-0.002	-0.004
	(0.002)	(0.007)	(0.002)	(0.008)	(0.024)	(0.003)	(0.003)
Rating	-0.127	-0.149	-0.038	-0.097	0.953	-0.161	0.162
	(0.116)	(0.218)	(0.119)	(0.218)	(1.914)	(0.191)	(0.147)
ROI	-0.277**	-0.287	-0.163	-0.155	-1.127	-0.012	-0.376**
	(0.110)	(0.221)	(0.121)	(0.237)	(0.832)	(0.145)	(0.187)
Related_cyber	0.008*	-0.012	0.011**	-0.011	0.028	-0.005	0.023***
	(0.005)	(0.016)	(0.005)	(0.019)	(0.019)	(0.006)	(0.006)
Rein_ceded	1.248***	0.598	1.412***	0.589	4.547	1.024**	1.880***
	(0.337)	(0.778)	(0.358)	(0.800)	(2.688)	(0.504)	(0.436)
RBC_ratio	-0.004**	-0.006	-0.003*	-0.004	-0.077	-0.003	-0.002
	(0.002)	(0.008)	(0.002)	(0.008)	(0.043)	(0.003)	(0.002)
year=2016	0.229**	0.602**	0.215*	0.541	-0.117	0.319*	0.031
	(0.113)	(0.288)	(0.123)	(0.331)	(0.393)	(0.176)	(0.128)
year=2017	0.309**	0.407	0.311**	0.439	-0.977	0.427*	-0.201
	(0.130)	(0.339)	(0.149)	(0.375)	(0.927)	(0.220)	(0.179)
Constant	-3.978***	-1.214	-4.197***	-0.986	-4.880	-1.955*	-5.447***
	(0.983)	(1.614)	(1.013)	(1.466)	(9.458)	(1.069)	(1.529)
N	1376	273	1225	244	37	830	716
Adj R-sq	0.346	0.344	0.338	0.311	0.704	0.227	0.302

Note: Heteroscedasticity-consistent standard errors (allowing for clustering at the group level) are in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. Definitions of the independent variables are provided in Table 1. The OLS regression model is: $Ln\_DPW_{i,t} = \alpha + \beta X_{i,t-1} + \theta Year\_dummy + \varepsilon_{i,t}$, where $Ln\_DPW_{i,t}$ is the logarithm of one plus the direct premiums written in each form of cyber insurance as indicated in the table, $X_{i,t-1}$ represents observed variables relating to insurer *i*'s premiums written on cyber insurance, and $\varepsilon_{i,t}$ is an error term.

Online-Appendix E: Incumbent vs. New Cyber Insurers

Table 9 presents our analysis of characteristics of new cyber insurers and incumbent cyber insurers. We find that the financial characteristics of new cyber insurers are, in general, very similar to the incumbents. Several differences are observed: new entrants tend to be smaller in size, possess higher asset risk, and are less diversified across geographical areas than incumbents. New entrants are less likely to be affiliated with professional surplus insurers, supporting the notion that cyber insurance has expanded into the admitted insurer market even without affiliation with surplus carriers. Meanwhile, more private and mutual insurers are entering the cyber insurance market which was previously heavily comprised of incumbent stock insurers. In addition, new entrants that offer standalone cyber coverage are more likely to be unaffiliated single insurers than the incumbent insurers, while new entrants that offer packaged cyber coverage are more likely to be professional surplus insurers than the incumbent insurers, suggesting that professional surplus insurers have observed the opportunity presented by the immense growth of the packaged cyber insurance market and thus have expanded into the market to compete with admitted insures.

Table 10 presents regression results for the determinants of cyber insurance participation for the sample excluding incumbent insurers. Our results are similar to those of the all insurer sample (Table 4 of the paper), lending further support to our cyber insurance participation hypotheses. Table 11 presents regression results that compare the premium volume offered by new cyber insurers and incumbent insurers. We find that the control variables carry signs and significances that are consistent with our previous analysis for the all insurer sample (Table 5 of the paper). In addition, it is noteworthy that new entrants tend to write smaller amounts of premium in both standalone coverage and packaged coverage. Table 12 presents an overview of the performance of new cyber insurers and incumbents at an aggregate level and Table 13 presents regression results on the performance of new cyber insurers and incumbent insurers. We find that new cyber insurers, in general, tend to have higher loss ratios than incumbents, suggesting that new entrants may lack the underwriting experience in contrast to incumbents. However, further analysis in Table 13 reveals that only a subgroup of new insurers excluding professional surplus insurers show a weakly significant higher loss ratio and thus inferior performance.

Table 9. Characteristics of New Writers vs. Incumbents (Mean Value)

Variable	**New _Cyber**	**Incum _Cyber**	**Diff (N-I)**	**New _Alone**	**Incum _Alone**	**Diff (N-I)**	**New _Packgd**	**Incum_ Packgd**	**Diff (N-I)**
d dpw (%)	6.619	7.113	-0.494	12.027	9.62	2.407	7.282	6.482	0.800
LB size	0.066	0.063	0.003	0.05	0.044	0.006	0.066	0.067	-0.001
LB conc	0.019	0.019	0.000	0.016	0.016	0.000	0.019	0.019	0.000
Asset risk	15.27	11.669	3.601***	15.021	14.183	0.838	16.499	11.034	5.465***
Pwherf	0.564	0.64	-0.076***	0.682	0.792	-0.110**	0.578	0.615	-0.037
Lbherf dpw	0.613	0.623	-0.010	0.593	0.628	-0.035	0.629	0.624	0.005
Surplus	0.119	0.121	-0.002	0.241	0.333	-0.092	0.144	0.075	0.069***
Surplus aff	0.49	0.645	-0.155***	0.722	0.87	-0.148***	0.521	0.606	-0.085**
Size	12.125	12.394	-0.269*	12.751	12.965	-0.214	12.234	12.287	-0.053
Age	3.824	3.833	-0.009	3.738	3.687	0.051	3.801	3.899	-0.098
List	0.281	0.39	-0.109***	0.444	0.486	-0.042	0.284	0.375	-0.091**
Mutual	0.276	0.187	0.089***	0.185	0.028	0.157***	0.265	0.212	0.053*
Unaffiliated	0.095	0.062	0.033	0.148	0.023	0.125***	0.079	0.065	0.014
Liab phs	1.351	1.382	-0.031	1.472	1.333	0.139	1.296	1.385	-0.089
Npw phs	58.488	57.908	0.580	54.502	47.163	7.339	56.555	61.046	-4.491
Rating	4.033	4.156	-0.123*	3.870	4.236	-0.366**	4.126	4.161	-0.035
ROI (%)	2.265	2.413	-0.148*	2.362	2.408	-0.046	2.275	2.437	-0.162**
Related_cyber (%)	31.623	30.877	0.746	16.909	11.073	5.836	30.83	35.684	-4.854**
Rein ceded	0.618	0.632	-0.014	0.60739	0.663	-0.055	0.624	0.626	-0.003
RBC ratio	25.60	35.672	-10.07***	19.4794	24.172	-4.693	24.705	38.785	-14.08***
N	210	915		54	216		215	758	

Note: The table shows the mean value of the characteristics of new cyber insurers and incumbents in 2016 and 2017. The statistical significances of the mean differences "Diff(N-I)" are based on t-test. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. Summary statistics based on median value return similar results and thus are not reported.

Table 10. Logistic Regression of Determinants of New Cyber Writers

	All insurers			Excluding professional surplus insurers		
	Cyber	**Alone**	**Packgd**	**Cyber**	**Alone**	**Packgd**
d_dpw	0.004	0.012*	0.003	0.005	0.011	0.004
	(0.003)	(0.007)	(0.004)	(0.003)	(0.009)	(0.004)
LB_size	-3.704	-11.604***	-1.875	-2.942	-10.471***	-1.165
	(2.448)	(3.498)	(2.727)	(2.173)	(3.069)	(2.403)
LB_conc	-13.533	-12.713	-19.722	-13.947	-3.675	-22.857
	(11.656)	(22.945)	(15.522)	(10.550)	(14.932)	(14.326)
Asset_risk	-0.007	-0.027**	-0.004	-0.008	-0.026**	-0.007
	(0.007)	(0.011)	(0.007)	(0.007)	(0.011)	(0.008)
Pwherf	0.395	0.953	0.281	0.423	1.311*	0.302
	(0.280)	(0.617)	(0.292)	(0.295)	(0.677)	(0.324)
Lbherf_dpw	2.789***	2.280***	2.985***	2.720***	2.524***	3.027***
	(0.453)	(0.840)	(0.547)	(0.438)	(0.798)	(0.529)
Surplus	0.437	1.533***	0.206			
insurer	(0.278)	(0.391)	(0.354)			
Surplus_aff				0.449	2.644***	0.207
				(0.354)	(0.695)	(0.390)
Size	0.208***	0.487***	0.134*	0.191**	0.420**	0.130
	(0.076)	(0.157)	(0.078)	(0.076)	(0.166)	(0.081)
Age	-0.148	0.016	-0.182	-0.144	-0.226	-0.174
	(0.147)	(0.323)	(0.165)	(0.155)	(0.317)	(0.175)
List	0.015	0.331	-0.159	-0.206	-0.143	-0.258
	(0.316)	(0.658)	(0.363)	(0.361)	(0.595)	(0.425)
Mutual	0.788***	-0.250	0.877***	0.893***	0.531	0.942***
	(0.286)	(0.652)	(0.305)	(0.311)	(0.488)	(0.342)
Unaffiliated	-0.526*	0.664	-0.780***	-0.560**	1.432	-0.829***
	(0.287)	(0.765)	(0.256)	(0.267)	(0.987)	(0.245)
Liab_phs	0.082	0.170	0.046	0.072	0.073	0.048
	(0.068)	(0.172)	(0.070)	(0.067)	(0.188)	(0.071)
Npw_phs	-0.005**	-0.006	-0.004*	-0.004**	-0.002	-0.004*
	(0.002)	(0.004)	(0.002)	(0.002)	(0.003)	(0.002)
Rating	0.134	-0.229	0.249	0.107	-0.552***	0.244
	(0.143)	(0.186)	(0.154)	(0.144)	(0.153)	(0.165)
ROI	0.081	0.100	0.083	0.119	0.182	0.119
	(0.122)	(0.270)	(0.134)	(0.124)	(0.245)	(0.139)
Related_cyber	0.012***	-0.010	0.016***	0.013***	-0.020	0.017***
	(0.003)	(0.011)	(0.004)	(0.003)	(0.015)	(0.004)
Rein_ceded	0.003	-0.013	0.005	-0.001	-0.033*	0.003
	(0.006)	(0.013)	(0.005)	(0.008)	(0.018)	(0.005)
RBC_ratio	-0.001	-0.000	-0.001	-0.001	0.002	-0.001
	(0.002)	(0.003)	(0.003)	(0.002)	(0.004)	(0.003)
year=2017	0.164	-0.368	0.349	0.160	-0.297	0.262
	(0.251)	(0.514)	(0.272)	(0.261)	(0.568)	(0.281)
Constant	-6.500***	-10.102***	-6.394***	-6.485***	-9.698***	-6.520***
	(1.022)	(2.456)	(0.988)	(1.058)	(2.613)	(1.048)
N	3375	3375	3375	3219	3219	3219
Pseudo R-sq	0.182	0.262	0.180	0.183	0.280	0.187

Note: The regression sample includes new cyber insurers and insurers that do not offer cyber insurance in 2016 and 2017. Heteroscedasticity-consistent standard errors (allowing for clustering at the group level) are in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. Definitions of the dependent variables and the independent variables are provided in Table 1. The dependent variables are dummy variables indicating if a firm is a new cyber insurer or not for each form of cyber insurance.

Table 11. OLS Regressions for Cyber Insurance Premium Volume: New vs. Incumbents

	All insurers			Excluding professional surplus insurers		
	Cyber	Alone	Packgd	Cyber	Alone	Packgd
New_Cyber	-1.232***			-1.233***		
	(0.202)			(0.202)		
New_Alone		-0.973**			-1.182***	
		(0.393)			(0.426)	
New_Packgd			-0.871***			-1.030***
			(0.216)			(0.216)
d_dpw	0.008**	0.004	0.010**	0.008**	-0.001	0.010**
	(0.004)	(0.006)	(0.004)	(0.004)	(0.009)	(0.004)
Asset_risk	-0.008	-0.028**	-0.006	-0.005	-0.024	-0.006
	(0.005)	(0.014)	(0.005)	(0.006)	(0.017)	(0.005)
Pwherf	0.668***	1.085	0.740***	0.748***	1.721*	0.790***
	(0.242)	(0.781)	(0.226)	(0.244)	(0.965)	(0.244)
Lbherf_dpw	0.084	2.669***	-0.305	-0.018	4.034***	-0.285
	(0.418)	(0.941)	(0.471)	(0.450)	(1.176)	(0.494)
Surplus insurer	0.286	1.244***	-0.860**			
	(0.283)	(0.307)	(0.369)			
Surplus_aff				-0.258	-2.334***	-0.302
				(0.323)	(0.710)	(0.327)
Size	0.771***	0.603***	0.704***	0.750***	0.611***	0.709***
	(0.063)	(0.151)	(0.079)	(0.065)	(0.193)	(0.079)
Age	0.093	0.337	0.035	0.052	-0.006	-0.002
	(0.154)	(0.306)	(0.152)	(0.148)	(0.348)	(0.153)
List	-0.102	-0.104	-0.206	-0.015	-0.118	-0.073
	(0.226)	(0.395)	(0.243)	(0.255)	(0.494)	(0.274)
Mutual	-0.102	-1.680	0.216	-0.188	-2.208**	0.154
	(0.215)	(1.072)	(0.201)	(0.214)	(0.950)	(0.192)
Unaffiliated	0.672***	1.261	0.564***	0.560***	1.416	0.467**
	(0.224)	(0.848)	(0.188)	(0.204)	(0.881)	(0.199)
Liab_phs	-0.019	-0.116	0.049	0.018	0.089	0.042
	(0.065)	(0.235)	(0.061)	(0.061)	(0.224)	(0.066)
Npw_phs	-0.006***	-0.009	-0.005**	-0.007***	-0.012	-0.005**
	(0.002)	(0.007)	(0.002)	(0.002)	(0.009)	(0.002)
Rating	-0.143	-0.634***	-0.047	-0.129	-0.318	-0.020
	(0.130)	(0.189)	(0.133)	(0.110)	(0.218)	(0.115)
ROI	-0.266**	-0.270	-0.130	-0.267**	-0.143	-0.175
	(0.106)	(0.188)	(0.119)	(0.108)	(0.197)	(0.120)
Related_cyber	0.006	-0.014	0.011**	0.008*	-0.015	0.012***
	(0.004)	(0.012)	(0.004)	(0.005)	(0.014)	(0.005)
Rein_ceded	1.278***	0.397	1.419***	1.170***	0.288	1.391***
	(0.387)	(0.792)	(0.377)	(0.348)	(0.855)	(0.365)
RBC_ratio	-0.005***	-0.006	-0.004***	-0.005***	0.003	-0.004**
	(0.002)	(0.006)	(0.002)	(0.002)	(0.009)	(0.002)
year=2017	0.053	-0.045	0.109	0.046	-0.184	0.058
	(0.081)	(0.151)	(0.100)	(0.082)	(0.197)	(0.094)
Constant	-3.742***	-0.902	-3.965***	-3.274***	-0.857	-3.713***
	(1.040)	(1.596)	(1.090)	(0.955)	(1.573)	(1.055)
N	1125	270	973	989	185	885
Adj R-sq	0.371	0.355	0.355	0.391	0.347	0.379

Note: The regression sample includes new cyber insurers and incumbents in 2016 and 2017. Heteroscedasticity-consistent standard errors (allowing for clustering at the group level) are in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. Definitions of the dependent variables and the independent variables are provided in Table 1.

Table 12. Cyber Insurance Performance: New vs. Incumbents (in Aggregate)

	Pure Loss Ratio (%)			Loss Ratio with Defense and Cost Containment (%)		
	Cyber	**Alone**	**Packgd**	**Cyber**	**Alone**	**Packgd**
2016						
New	262.34	72.26	553.76	268.39	78.28	559.86
Incumbent	24.29	34.45	2.71	32.53	43.92	8.35
2017						
New	41.56	42.98	36.65	42.08	43.30	37.86
Incumbent	16.38	26.89	5.95	23.54	36.95	10.24

Note: The "pure loss ratio" is defined as the sum of loss and loss-adjusting expenses incurred divided by premiums earned. The 2017 cyber data do not have separate reporting on adjusting expenses.

Table 13. OLS Regressions for Cyber Insurance Performance: New vs. Incumbents

Panel A: Pure loss ratio

	All insurers			Excluding professional surplus insurers		
	Cyber	**Alone**	**Packgd**	**Cyber**	**Alone**	**Packgd**
New_Cyber	0.288			0.329*		
	(0.180)			(0.172)		
New_Alone		0.251			0.231	
		(0.372)			(0.386)	
New_Packgd			0.200			0.207
			(0.149)			(0.160)
Size	0.151***	0.181**	0.099***	0.141***	0.171**	0.098***
	(0.036)	(0.068)	(0.033)	(0.035)	(0.072)	(0.034)
Age	-0.039	-0.007	-0.070	-0.086	-0.129	-0.124*
	(0.079)	(0.247)	(0.065)	(0.070)	(0.293)	(0.064)
List	0.017	-0.322	0.120	-0.015	-0.350	0.074
	(0.191)	(0.391)	(0.182)	(0.199)	(0.429)	(0.191)
Mutual	-0.331***	-1.543***	-0.045	-0.153	-1.375***	0.066
	(0.126)	(0.360)	(0.115)	(0.122)	(0.389)	(0.120)
Unaffiliated	0.351***	0.498	0.229**	0.413***	0.531	0.268**
	(0.096)	(0.389)	(0.099)	(0.106)	(0.411)	(0.107)
Pwherf	0.714***	0.513	0.672***	0.686***	0.781	0.639***
	(0.161)	(0.511)	(0.149)	(0.153)	(0.479)	(0.147)
Lbherf_dpw	-0.769**	0.197	-0.928**	-0.995***	-0.145	-0.988**
	(0.359)	(0.875)	(0.387)	(0.377)	(0.990)	(0.408)
Surplus	0.606***	0.513*	-0.182			
insurer	(0.216)	(0.279)	(0.211)			
Surplus_aff				0.368**	0.210	0.211
				(0.163)	(0.503)	(0.150)
year=2017	-0.089	-0.150	0.001	-0.025	0.081	0.008
	(0.086)	(0.233)	(0.078)	(0.084)	(0.240)	(0.084)
Constant	-0.844**	-1.016	-0.217	-0.668*	-0.685	-0.077
	(0.425)	(0.865)	(0.386)	(0.402)	(0.971)	(0.423)
N	1115	267	964	980	182	877
Adj R-sq	0.124	0.074	0.077	0.124	0.066	0.091

Panel B: Loss ratio with defense and cost containment

	All insurers			Excluding professional surplus insurers		
	Cyber	**Alone**	**Packgd**	**Cyber**	**Alone**	**Packgd**
New_Cyber	0.229			0.294*		
	(0.187)			(0.178)		
New_Alone		0.038			0.082	
		(0.376)			(0.391)	
New_Packgd			0.206			0.199
			(0.154)			(0.164)
Size	0.172***	0.162**	0.119***	0.162***	0.165**	0.116***
	(0.039)	(0.066)	(0.035)	(0.038)	(0.076)	(0.036)
Age	-0.072	-0.027	-0.099	-0.112	-0.160	-0.151**
	(0.084)	(0.264)	(0.072)	(0.077)	(0.315)	(0.069)
List	-0.009	-0.338	0.081	-0.022	-0.364	0.069
	(0.205)	(0.411)	(0.190)	(0.216)	(0.467)	(0.199)
Mutual	-0.263*	-1.634***	0.040	-0.085	-1.466***	0.157
	(0.142)	(0.370)	(0.137)	(0.144)	(0.413)	(0.144)
Unaffiliated	0.236**	0.433	0.114	0.294**	0.414	0.145
	(0.110)	(0.347)	(0.114)	(0.116)	(0.385)	(0.117)
Pwherf	0.767***	0.588	0.719***	0.724***	0.640	0.691***
	(0.180)	(0.478)	(0.159)	(0.175)	(0.493)	(0.161)
Lbherf_dpw	-1.016***	0.295	-1.174***	-1.300***	0.017	-1.284***
	(0.384)	(0.870)	(0.413)	(0.394)	(1.000)	(0.427)
Surplus	0.751***	0.618**	-0.089			
insurer	(0.224)	(0.302)	(0.226)			
Surplus_aff				0.371**	0.286	0.188
				(0.184)	(0.509)	(0.165)
year=2017	-0.090	-0.040	-0.008	-0.031	0.223	-0.014
	(0.090)	(0.215)	(0.085)	(0.086)	(0.228)	(0.089)
Constant	-0.748*	-0.588	-0.144	-0.558	-0.344	0.064
	(0.437)	(0.818)	(0.399)	(0.412)	(0.956)	(0.433)
N	1115	267	964	980	182	877
Adj R-sq	0.133	0.083	0.086	0.127	0.070	0.101

Note: Heteroscedasticity-consistent standard errors (allowing for clustering at the group level) are in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. Definitions of the independent variables are provided in Table 1. The OLS regression model is: $Ln\_LossRatio_{i,t} = \alpha + \beta X_{i,t-1} + \theta Year\_dummy + \varepsilon_i$, where $Ln\_LossRatio_{i,t}$ is the logarithm of one plus the loss ratio in each form of cyber insurance as indicated in the table, $X_{i,t-1}$ represents observed variables relating to insurer i's loss ratio on cyber insurance, and $\varepsilon_{i,t}$ is an error term.