Strategic Reinsurance and Explainable AI

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Abstract

This study explores the strategic determinants that impact reinsurance purchase decisions in the P&C insurance industry using the Shapley Additive exPlanations explainable artificial-intelligence (XAI) framework, or SHAP library. Key determinants such as financial considerations, competition, and industry demand for reinsurance are considered to identify their impact on different levels of ceding. The XAI process ranks these determinants based on their influence on reinsurance purchases, and identifies clear relationships between these determinants and ceding levels. For instance, an increase in writing a specific product type can lead to a lower incentive to hedge more within that product type. Additionally, this methodology also reveals more complex relationships between determinants and reinsurance purchases based on their values. Finally, the study includes a machine learning significance test for each determinant impacting insurance purchases.

Keywords: risk management, insurance, machine learning, artificial intelligence, explainable AI, property and casualty insurance

JEL Classifications: G22, G32

I. Introduction

The use of artificial intelligence (AI) in financial economics has increased tremendously in recent years. For example, machine learning, or deep learning, has been used to analyze mortgage risk (Sirignano, Sadhwani, and Giesecke; 2016), portfolio selection (Heaton, Polson, and Witte; 2017), and analyze large pools of loans (Sirignano and Giesecke; 2019). In the insurance industry, Brockett et al. (1994) and Brockett et al. (2006) utilized artificial neural networks (ANN) to predict insurer's insolvency. Additionally, Hejazi and Jackson (2016), Wüthrich and Merz (2019) and Wüthrich (2019) applied ANN models in an actuary framework. Most prior AI studies attempt to predict outcomes based on AI's non-linear advantage over widely used classical regression analysis and superior accuracy in making predictions. However, the explanation of independent variables, or so-called "features", in the AI setting have previously not been explainable. The AI model, such as ANNs, can be thought of as "black boxes" built on different (hidden) layers and neurons. In recent years, researchers have started to open these black boxes using several methodologies. This study aims to use the ANN models to implement existing econometric techniques to explain insurers demand for reinsurance focusing on managerial strategic decision making. More importantly, we try to open the AI "black box" using explainable AI. This study uses the SHapley Additive exPlanations (SHAP) methodology introduced by Lundberg and Lee (2017) to complement the ANN model. SHAP allocates each variable's influence on the overall prediction based on Shapley's values using a game-theoretical approach.

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According to Modigliani and Miller (1958), insurers would not need to consider purchasing reinsurance in a frictionless world. However, later literature considers frictions that lead to different levels of firm hedging. Determinants that have been shown to lead to different insurer ceding levels include taxes (Smith and Stulz (1985)), external cost of financing (Froot, Scharfstein, and Stein (1993), and Froot and Stein (1998)), the reinsurance market (Cole and McCullough (2006)), and competition and market structure (MacKay and Phillips (2005)), Adam, Dasgupta, and Titman (2007), Rampini, Sufi, and Viswanathan (2014), and Nettayanun (2014)). We include these determinants in our analysis as independent variables and use the level of reinsurance purchases as a risk management measure, with a particular emphasis on competition and strategic risk management.

Explainable AI (XAI) can explain reinsurance purchases in the property and casualty (P&C) industry. Most prior research employs various econometric approaches to explain reinsurance purchases, identifying the following top ten product type influences: commercial long-tail (*CL*), commercial short-tail (*CS*), personal short-tail (*PS*), and personal long-tail (*PL*), leverage, brokerage expense position compared to its peers, size, ownership structure, and number of companies in the industry. Additionally, the SHAP library can reveal more complex relationships. For example, broker expenditure comparisons to peers show a positive relationship with ceding level (SHAP values of 0 to 0.2[3]). This relationship increases as SHAP values increase as predicted by Maksimovic and Zechner (1991), MacKay and Phillips (2005), and Nettayanun (2014) that find broker or technology investment distances is associated with higher ceding levels. Furthermore, significance tests from Horel and Giesecke (2019) find six significant variables within the top ten SHAP values: leverage, ownership structure, product types (CL, CS, PS), and stock holding percentage in the portfolio. Applying these machine learning techniques can give a richer explanation of reinsurance purchase behavior in the insurance industry. The first major contribution of this study is the application of alternative techniques to analyze reinsurance data in contrast to traditional statistical methods. These techniques do not require non-linearity between dependent and independent variables, allowing for the exploration of variable interactions including visualizations. The second contribution is the use of significant tests within the machine learning framework for reinsurance data. These approaches enable the ranking of determinants importance, exploration of complex relationships, and identification of significant determinants within the machine learning framework.

We proceed as follows. Section 2 reviews related literature. Second 3 discuss XAI models and summarizes determinants/variables from previous literature that affect risk management. Section 4 discusses the dataset. Section 5 analyzes the dataset using different XAI approaches. Finally, the last section concludes the study.

II. Literature review

Recently, there have been significant developments in machine learning in the corporate finance context. For example, Colla et al. (2013) used cluster analysis, a machine learning method, to identify similarities among firms that structure their debts for public US companies. Nettayanun (2014) also used cluster analysis to identify subgroups within the insurance industry based on risk management tools such as reinsurance, investment portfolio, and leverage ratio. Amini et al. (2021) applied machine learning to predict leverage from various financial factors, arguing that these

[3] The positive SHAP values represent the positive contributions of features on labels in the model.

machine learning methods can exploit the non-linear relationships between determinants for predicting leverage. Erel et al. (2021) used machine learning for the director selection process, helping predict directors' performance. Bubb and Catan (2022) used machine learning methods with a large dataset of voting data from mutual funds to explore their relationship with corporate governance.

Korangi, Mues, and Bravo (2023) find that deep learning models outperform previous statistical models in predicting default, using data from mid-cap companies in the US over a sample period of more than 30 years. Griffin, Hirschey, and Kruger (2023) use explainable AI, specifically SHAP, to find various features that explain municipal bond market markups. Similarly, we use SHAP to explain reinsurance purchases. Studies in finance academic literature have discussed the role of artificial intelligence and machine learning in business, highlighting their impact on corporate finance and risk management. In the context of corporate finance, Babina et al. (2024) find that AI investment can directly influence firm growth through product innovation and reduce the cost of product development through process innovation.

This study addresses the gap in understanding the role of AI and machine learning in explaining dependent variables, contributing to the growing body of AI research in corporate finance literature (Hornuf and Schaefer, 2025). Specifically, we use an artificial neural network (ANN) model to explain reinsurance purchases. This study integrates the ANN model with explainable AI or interpretable machine learning techniques such as SHAP and SFIT to explain the dependent variable, reinsurance level. The input variables, or features, are based on existing variables derived from previous literature. According to Hornuf and Schaefer (2025), explainable AI can assist financial institutions better understand the ANN model and how it utilizes features to inform decisions. This study contributes to the existing literature by using alternative statistical models and techniques to analyze structural data and explain reinsurance purchases, particularly under the assumption of non-linear interactions between variables. Next, we discuss the models and variables used in the study.

III. Models and variables

Econometric techniques provide statistical predictions of how each determinant included in the model as independent variables is related to the dependent variable, however, the main assumption in ordinary least square and panel data models is that the relationships between the dependent and independent variables are linear. In contrast, an artificial neural network (ANN) relaxes this assumption by flexibly selecting an activation function in the hidden layers and neurons. Until recently, a drawback of ANN was its inability to explicitly explain how each determinant influences the dependent variable. This section illustrates the use of ANN through explainable AI (XAI) to explain reinsurance purchases. Specifically, this study uses Shapley Additive explanation (SHAP) methodology, introduced by Lundberg and Lee (2017), to explain the influence of each determinant, or independent variable, on the dependent.

This study implements an artificial neural network model using TensorFlow from the Google Collaboration platform. In the ANN model, the dependent variable, *Cede,* is the "label", and the independent variables are the "features". The model also includes an intercept variable. The implementation is similar to an econometric analysis setting and is also used for significance tests in the next section. The construction of ANN follows Gu, Kelly, and Xiu (2020) closely, using a sequential model with two hidden layers in the Keras library, which provides an optimal construction. The complexity of the model can increase with a higher number of layers and neurons. The number of neurons follows the geometric pyramid rule from Master (1993), similar to Gu, Kelly, and Xiu (2020). Each hidden layer should have $\sqrt{n \times m}$ neurons where n is the number of input neurons and m is the number of output neurons. Using our 37,447 observations in this analysis, this leads to a first layer number of 8 neurons and second layer of 3 neurons. To avoid outlier problems, most of the variables included in the model must be in a similar scale. Most variables range from 0 to 1, however, some variables need further scaling by subtracting the average of that variable and dividing by its standard deviation. The model uses 80% of the data as a training sample and the remaining 20% as a testing sample to adjust for overfitting the model. The activation function for each neuron is a sigmoid function, which gives the lowest mean square error (MSE). Each type of neuron network is dense, meaning all the neurons are connected.

To understand how each independent variable (feature) influences the dependent variable (label), *cede*, we use SHapley Additive exPlanations (SHAP)[4] introduced by Lundberg and Lee (2017). SHAP is derived from Shapley values from game theory that explain how each player contributes to the game's optimal solution. Lundberg and Lee (2017) implement SHAP using the same principles as Shapley values. The SHAP method is also applied using local data to explain each prediction label, referred to as local interpretable model agnostic explanations (LIME) by Ribeiro, Singh, and Guestrin (2016). In this study, we use DeepExplainer to explain the independent variable (features).

Next, we discuss the independent variables (features) and the dependent variable (label) in an artificial neural network model econometric setting. These variables are derived from both prior theoretical and empirical studies. The dependent variable (label) is $Cede_{it}$, which is the level of reinsurance purchased by the i^{th} insurer in the property and casualty insurance industry at time t. It is defined as the reinsurance ceded divided by the net premium written. This study selects the following independent variables (features) based on the availability of P&C insurance industry data in the SNL database.

Taxes

Smith and Stulz (1985), Stulz (1996), and Graham and Smith (1999) argue that taxes influence risk management activities, with convex tax schedules leading to more strategic hedging to reduce firm net income volatility. For example, during years of high net income, firms protect that income from high tax rates leading to increased firm value. However, Tufano (1996), Cole and McCullough (2006), and Nettayanun (2014) do not find any relationship between tax variables and reinsurance purchases. We define the variable *Tax* as federal and foreign income taxes divided by the book value of assets to measure the tax impact on hedging behavior. Based on previous literature, this study expects a positive relationship between tax and insurance purchasing levels.

Product Type

Adam, Dasgupta, and Titman (2007) argue that the elasticity of demand and the convexity of production costs influence different firm hedging levels. Also, Winter (1994) suggests that each line of insurance business exhibit different reinsurance demand due to varying reinsurance pricing

[4] More details in Lundberg et al. (2018) and the complete explanation and open-source codes are at https://github.com/slundberg/shap.

levels. Consequently, different exposure levels to insurance products can lead to different hedging levels. Mayers and Smith (1990), Cole and McCullough (2006) and Nettayanun (2014) include product types in their analysis of reinsurance levels. Following Phillips, Cummins, and Allen (1998) and Nettayanun (2014), we use four product types of insurance in the property and casualty (P&C) insurance industry: personal short-tail, personal long-tail, commercial short-tail, and commercial long-tail, as detailed in Table A1. Each product exposure is defined as the net premium written in each category divided by total net premium written. The product-type variables for personal short-tail, personal long-tail, commercial short-tail, and commercial long-tail are *PS*, *PL*, *CS*, and *CL*, respectively.

Leverage

Leverage can have either a positive or negative relationship with reinsurance levels. Cole and McCullough (2006) and Hoyt and Liebenberg (2011) use leverage as an independent variable for insurer's reinsurance level. Low leverage can be a substitute for a firm's reinsurance purchases. A firm in distress purchases more reinsurance because of higher uncertainty regarding the firm. Conversely, Rampini, Sufi, and Viswanathan (2014) use a dynamic risk management model to show that firms need capital to be used as collateral for hedging. Therefore, we can expect lower (higher) levels of risk management if the firm has higher (lower) leverage. We measure *Leverage* as the book value of debt divided by the book value of total asset.

Positioning

Strategic positioning of insurers can lead to different risk management strategies. According to Maksimovic and Zechner (1991), the level of technology investment by a firm can act as a natural hedge. For example, if a firm has a similar level of technology investment compared to the industry average, it will not need to hedge as much. MacKay and Phillips (2005) and Nettayanun (2014) use an empirical study to show the relationship between these positioning variables in different industries and firm hedging levels. In the property and casualty insurance industry, we identify four key expenses as technologies that insurance companies need to invest in: agent expenses, brokerage expenses, equipment expenses, and salary expenses. Similar to MacKay and Phillips (2005) and Nettayanun (2014), we define positioning on each technology as,

$$Pos_{i,t} = \frac{|TechExpense_{i,t} - median(\forall_j TechExpense_{i,j,t})|}{range[|TechExpense_{i,t} - median(\forall_j TechExpense_{i,j,t})|]} \quad (1)$$

where index i and j are insurers within the property and casualty insurance industry in year t. $Pos_{i,t}$ measures the difference in each firm's technology investment level from the median industry level in each year. The positions of these technologies are represented by *AgentPos*, *BrokerPos*, *EquipPos*, and *SalaryPos*.

Profitability

Myers (1977) and Mayers and Smith (1987) show that improper risk management can lead to an underinvestment problem. Profitable insurers typically do not require as much reinsurance purchases. Consequently, we expect a negative relationship between profitability and firm ceding levels. Mayers and Smith (1990), Powell and Sommer (2007), Cole and McCullough (2006), and Nettayanun (2014) also include profitability to capture underinvestment problems. We use return on assets (ROA) to capture the underinvestment problem and expect ROA to have a negative relationship with ceding levels.

Size

There are two conflicting conclusions found in the literature regarding the impact firm size has on risk management levels. Tufano (1996) and Froot, Sharfstein, and Stein (1993) suggest that smaller firms hedge more due to higher agency costs and asymmetric information related to financing activities. Mayers and Smith (1990) and Hoyt and Khang (2000) also find a negative relationship between firm size and reinsurance purchases. Conversely, Liu and Parlour (2009) introduce a model where larger firms hedge more because they have a higher probability of winning new businesses compared to smaller firms. Firms hedge less if they lack sufficient capital or resources to acquire or expect to win new business through bidding, as this could result in an over-hedged position. The hedging efforts of smaller firms having a lower chance of winning new business through bidding would be wasted. To win new business, firms will increase their bid efforts. Stulz (1996) also finds that larger firms have higher hedging levels than smaller firms. We capture the size effect using the natural log of the book value of assets, *LnAsset*.

Diversification

Diversification plays a significant role in risk management and can be used as a substitute for reinsurance purchases. By diversifying risks through selling in different regions or various product types, insurer can reduce risk and potentially lessen the need for reinsurance. Froot (2007) and Nettayanun (2014) find that focusing on specific lines of insurance products can reduce reinsurance purchases. For example, an insurance company that excels in automobile insurance can manage this risk effectively with a lower cost of capital. The cost of insuring other product lines through additional reinsurance might be too high. Therefore, insurers might benefit from reducing diversification and concentrating their efforts on automobile insurance. This study measures the level of concentration for each firm using a measurement similar to the Herfindahl index, as described by Choi and Weiss (2005), Cole and McCullough (2006), and Leverty and Grace (2010) defined as,

$$Diversification_{it} = 1 - \sum_{j=1}^{n} (\%\ share\ of\ net\ premium\ written\ in\ product\ type\ j\ for\ company\ i\ at\ time\ t)^2 \tag{2}$$

where n is the total number of product types[5]. The more concentrated an insurer is, the lower their diversification index will be, ranging from 0 to 1. Cole and McCullough (2006) found that insurers with a higher diversification index tend to buy less reinsurance.

[5] In Thailand, there are 4 product types classified by OIC: Fire, Marine, Automobile, and Miscellaneous.

Industry's Reinsurance Demand

The overall industry level of hedging influences an individual firm's level of hedging decisions, as suggested by Nain (2004) and Adam, Dasgupta, and Titman (2007). For example, if the industry-wide hedging level is high, but a particular firm within that industry has minimal hedging, the firm may benefit more than the industry as a whole if there are no adverse shocks. Conversely, if an adverse shock impacts the industry, the firm with minimal hedging may be worse off. To capture this determinance, we use the industry median hedging level, *IndustryCede*.

Intensity of Competition

There are mixed results regarding how the number of competitors in an industry impact reinsurance purchase. Mello and Ruckes (2005) and Adam and Nain (2013) argue that the number of firms negatively correlate with hedging. According to Mello and Ruckes (2005), firms using less hedging can benefit more during periods of higher cash-flows. Conversely, Allayannis and Ihrig (2001) and Adam, Dasgupta, and Titman (2007) suggest that firms tend to hedge more in competitive markets, as it becomes harder to adjust costs within such markets. Nettayanun (2014) also find that a higher number of insurers in an industry leads to higher reinsurance levels for individual insurers within that industry. We measure the number of competitors within an industry in each year using the variable *NumComp*. Additionally, we capture the level of industry competition in each year using the Herfindahl index, similar to Liebenberg and Sommer (2008), Nettayanun (2014), and Caporale, Cerrato and Zhang (2017), defined as,

$$Herfindahl_t = \sum_{i=1}^{n} \left(\frac{NPW_{it}}{Total\ NPW_t}\right)^2. \qquad (3)$$

NPW_{it} is the net premium written for insurer i at year t. $Total\ NPW_t$ is the total net premium written for year t. The value of the Herfindahl index ranges from zero to one with values closer to one (zero) indicating low (high) levels of competition.

Market Share

According to Mello and Ruckes (2005), competitive advantages that firms gain through having high power within an industry induces lower levels of risk management in those firms. Firms with a competitive advantage can charge higher prices than their competitors, resulting in a stronger financial position within the industry and lower hedging levels being used within these high-power firms. Additionally, Sommer (1996) argues that more prominent firms tend to have a healthier financial position than smaller firms. This serves as a positive signal for customers that buy more policies from these prominent firms. It can also increase insurance prices, reducing insolvency risk and leading to lower ceding levels. Therefore, market share can have a negative relationship with the level of risk management used at insurance firms. Nettayanun (2014) also finds that market share has a negative relationship with risk management levels among P&C insurers from 1989 to 2009. We use *MarketShare* to capture the market share of each insurer, defined as,

$$MarketShare_{it} = \frac{NPW_{it}}{Total\ NPW_t}, \qquad (4)$$

where NPW_{it} is the net premium written for company i in year t. $Total\ NPW_t$ is the total net premium written for year t.

Ownership Structure

Caporale, Cerrato and Zhang (2017) find that ownership structure can play a significant role in risk management decisions. According to Mayers and Smith (1981), Lamm-Tennat and Starks (1993), and Pottier and Sommer (1997), stock companies tend to engage in riskier lines of business. Cole and McCullough (2006) find that stock companies engage in lower reinsurance purchases since they have easier access to capital markets and lower risk in acquiring capital when in financial distress. Nettayanun (2014) finds that ownership structure has a positive relationship with reinsurance purchases using a random effects regression model. However, the relationship does not exist when using a fixed effect regression model from 1989 to 2009. Thus, it is interesting to see how ownership structure impacts reinsurance repurchases. The organizational form of firms found in the SNL dataset include stock companies, mutual companies, Lloyds organizations, reciprocal exchanges, risk retention groups, US branches of an alien insurers, and syndicates. The majority of these firms are listed as stock insurers. Therefore, we label the *Stock* variable as 1 if the company is a stock company, and 0 otherwise.

Substitution of Risk

We also control for the substitution of risk in insurance portfolios, similar to the approach of MacKay and Phillips (2005). *StockHolding* is defined as the stock investment in the insurer's portfolio divided by the total admitted assets in the invested portfolio. Higher stock investment implies greater risk for the firm, leading these insurers to hedge more due to the higher risks associated with their investments. In the 3SLS setting, Nettayanun (2014) finds that *StockHolding* has a positive relationship with the ceding level of insurers.

IV. Data

We obtain property and casualty insurance firm-year level data from the SNL dataset from 1996 to 2020. The study focuses on the property and casualty insurance industry due to its unique nature in managing risk management through reinsurance purchases. To reduce anomalies within the data, only firms with net premium written greater than zero are included. We truncate the data on the dependent variable, *Cede*, to values between 0 and 1 to avoid outliers. We also truncate the data on the independent variables *StockHolding* and *Diversification* to fall between 0% and 100%. All variables are winsorized at the 1% level. The variables *NumComp* and *LnAsset* are normalized because their magnitudes are large compared to other variables. The final dataset consists of 37,447 observations from 1996 to 2020.

Table 1 reports summary statistics for all variables used in our analysis. From 1996 to 2020 the mean (median) *Cede* dependent variable was 0.004 (0.000), indicating insurers ceded about 0.4% of net premiums written on average, but only 0.000% at the median level. The commercial long-tail makes up the largest segment of insurance with a mean (median) of 39.3% (19.9%). The mean market share of insurers is 0.000 implying these insurers have a low average level of market share. However, there are some large insurers in our data with the maximum market share reported as 3.2%. The mean (median) *Diversification* is 30.7% (36.6%). There are also a high proportion of insurers that are stock companies as the average *Stock* is 67.6%.

Table 1. Summary Statistics

Variable	Mean	Median	Std. Dev.	Min	Max
Cede	0.004	0.000	0.027	0.000	0.975
PS	0.236	0.110	0.281	-0.190	1.000
PL	0.119	0.000	0.216	-0.267	1.000
CS	0.251	0.105	0.327	-0.226	1.000
CL	0.393	0.199	0.416	-0.381	1.000
MarketShare	0.000	0.000	0.001	0.000	0.032
Diversification	0.307	0.366	0.262	0.000	1.000
NumComp	2098.10	2146.00	146.94	1782.00	2266.00
Herfindahl	0.015	0.015	0.001	0.014	0.018
AgentPos	0.006	0.000	0.036	0.000	0.998
BrokerPos	0.016	0.009	0.029	0.000	0.844
EquipPos	0.023	0.008	0.048	0.000	0.996
SalaryPos	0.048	0.031	0.065	0.000	0.967
ROA	0.018	0.023	0.093	-2.120	8.724
Tax	0.008	0.004	0.023	-1.555	0.844
Leverage	0.523	0.561	0.215	-0.406	6.015
LnAsset	10.855	10.805	1.903	4.382	17.703
IndCede	0.000	0.000	0.000	0.000	0.000
Stock	0.676	1.000	0.468	0.000	1.000
StockHolding	0.125	0.052	0.172	0.000	1.000

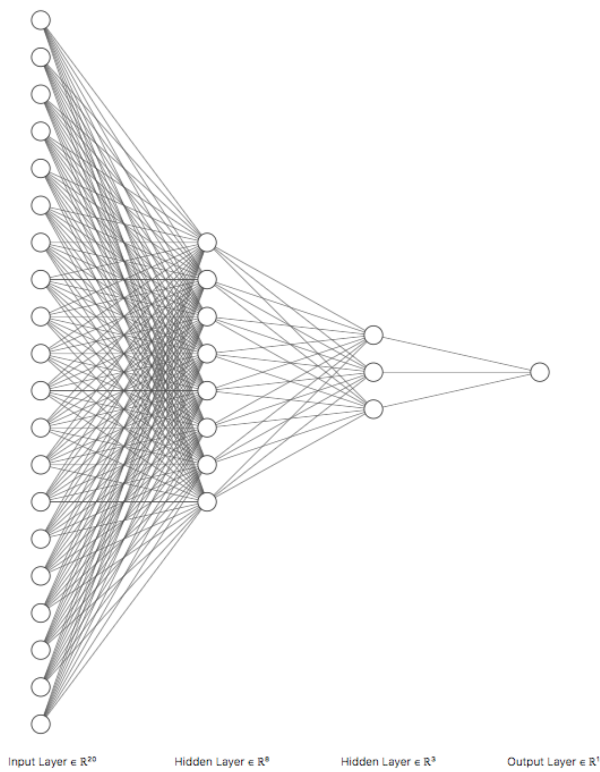
Note: This table reports summary statistics for all variables used in our study. There are 37,447 firm-year observations from 1996 to 2020. The explanations of each variable are as follows: *Cede* is defined by the premium ceded divided by net premium written. *PS* (personal short-tail), *PL* (personal long-tail), *CS* (commercial short-tail) and *CL* (commercial long-tail*)* are the product type variables, defined as the net premium written on each product type divided by net premium written on all product lines for each insurer. *MarketShare* is the market share of each insurer in a particular year defined by the net premium written divided by the total net premium written of the industry in that year. *Diversification* is one minus the Herfindahl index calculated based on each product type offered by each insurer. The Herfindahl index for the industry in each year is calculated using the net premium written from each insurer. *AgentPos*, *BrokerPos*, *EquipPos,* and *SalaryPos* are positioning variables for agent, broker, equipment, and salary, and they measure how each insurer invests in key technologies compared to its peers in the same industry. *ROA* is composed of net income divided by total book value of assets. *TAX* is total income tax divided by total book value of assets. *Leverage* is the book value of total debt divided by the book value of the total assets. *LNAsset* is the natural log of the book value of total assets with units in thousands of dollars. *IndustryCede* is the median value of cede level for all property and casualty insurers in each year. *Stock* is a dummy variable set equal to 1 if the insurer is a stock company, and 0 otherwise. *StockHolding* is defined as the stock investment in the insurer's portfolio divided by the total admitted asset in the invested portfolio.

V. Results

Global Interpretation

This study uses TensorFlow with an optimizer with default parameters for the ANN model using 64 batches and 200 epochs. The study optimizes the number of epochs based on the improvement of the loss function of the mean square error (MSE). The mean squared errors (MSE) from ANN testing sample are 7 x 10^{-4}. The diagram[6] of the ANN model is given in Figure 1.

Figure 1. Artificial Neural Network Model (ANN)



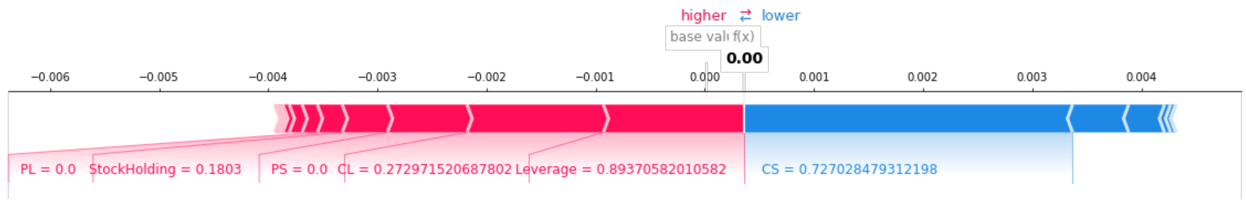
Notes: This figure shows how the ANN model is constructed. It consists of 20 independent variables (features), three hidden layers with each having ten neurons. All neurons are dense (i.e., fully connected).

After obtaining the ANN model, we can produce Shapley values for each independent variable (feature) for each observation (sample). Figure 2 illustrates the force plot from SHAPs DeepExplainer for one observation. The plot shows how each independent variable influences the SHAP value for a particular observation. Variables with red bars increase the SHAP values, while variables with blue bars decrease the SHAP values. From the figure, commercial short-tail (*CS*) is the most prominent feature that pushes the SHAP value lower. Conversely, Leverage is the most significant positive influence on SHAP values. This indicates that the levels of writing insurance in commercial short-tail (*CS*) are the most influential factors for this particular observation. Commercial long-tail (*CL*) also plays a role in explaining the ceding level in this observation, as

[6] This study generates the diagram is from http://alexlenail.me/NN-SVG/index.html.

it is the second variable that positively impacts the ceding level. We can extend the force plot for other observations in the data to analyze how each feature affects the SHAP value.

Figure 2. SHAP Force Plot



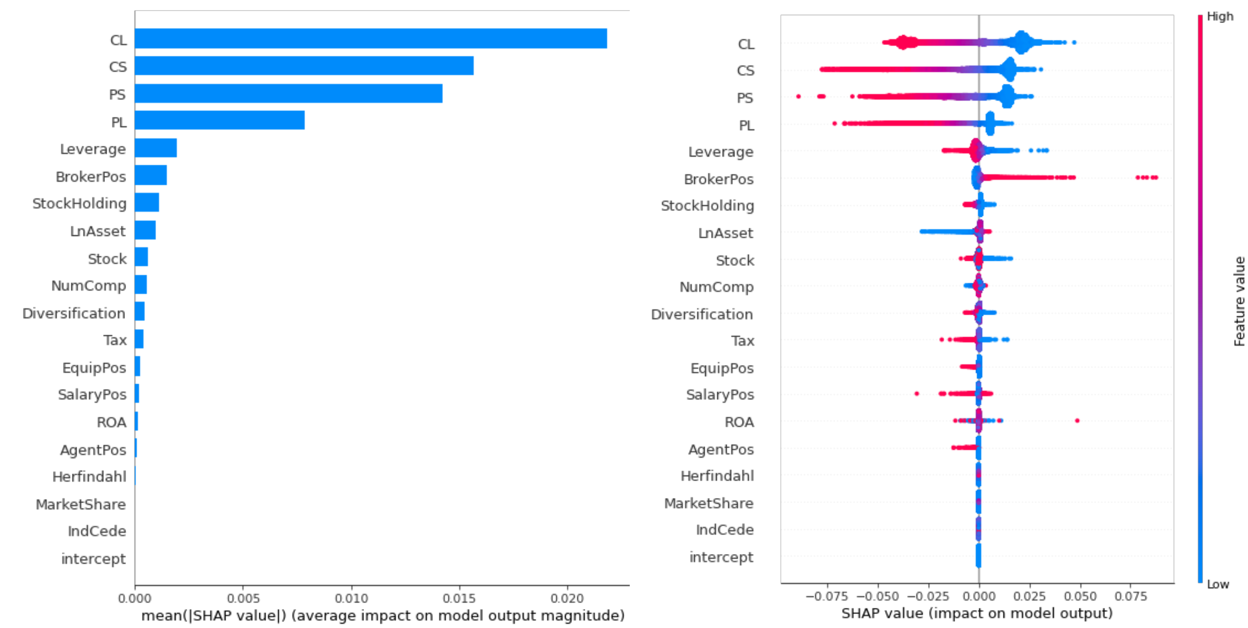
Notes: This figure shows the SHAP force plot. The red color explains how each independent variable increases the SHAP value, and the blue color explains how each independent variable decreases the SHAP value.

Figure 3 illustrates how each feature affects the reinsurance level from a global perspective using DeepExplainer and training data for calculating SHAP values. The left panel is a bar plot of the SHAP value mean absolute values for each feature across all observations. *CL*, *CS*, *PS*, *PL, Leverage*, *BrokerPos, StockHolding, LnAsset, Stock,* and *NumComp* are the top ten variables that influence reinsurance purchases according to SHAP analysis. It shows what product types are the most important in impacting the insurers ceding decisions. In addition, the analysis also shows how *Diversification*, *Tax*, *EquipPos*, *SalaryPos*, *ROA*, *AgentPos*, *Herfindahl*, *MarketShare*, and *IndCede* have influence on reinsurance purchasing levels.

The right panel of Figure 3 shows both negative and positive SHAP values for higher (red) and lower (blue) levels for each featured variable. For example, higher (red) product mix percentages in commercial long-tail, commercial short-tail, personal short-tail, and personal long-tail lines of business mostly result in negative SHAP values. This implies that firms specializing in these specific lines of business are less likely to purchase reinsurance. These results align with the explanation from Winter (1994) and Adam, Dasgupta, and Titman (2007), which suggest that product types influence firm's risk management levels.

Lower (higher) levels of leverage are associated with positive (negative) SHAP values indicating the level of leverage influences hedging decisions. Insurers tend to hedge less (more) for low (high) levels of leverage. The higher (lower) position in broker expense is associated with higher SHAP value levels. We also find that lower (higher) values of stock holdings are associated with higher (lower) reinsurance levels, and higher (lower) differences in firm's brokerage expense position from the industry median is associated with higher (lower) reinsurance levels. In addition, lower (higher) diversification insurers tend to have positive (negative) SHAP values. This is similar to the results from Froot (2007) and Nettayanum (2014). More focused insurers tend to hedge less due to their competitive advantage in the lines of business they focus in. These are the examples that we obtain by looking at the overall SHAP values in a global sense. The local interpretations by variable are in the next section.

Figure 3. SHAP-DeepExplainer



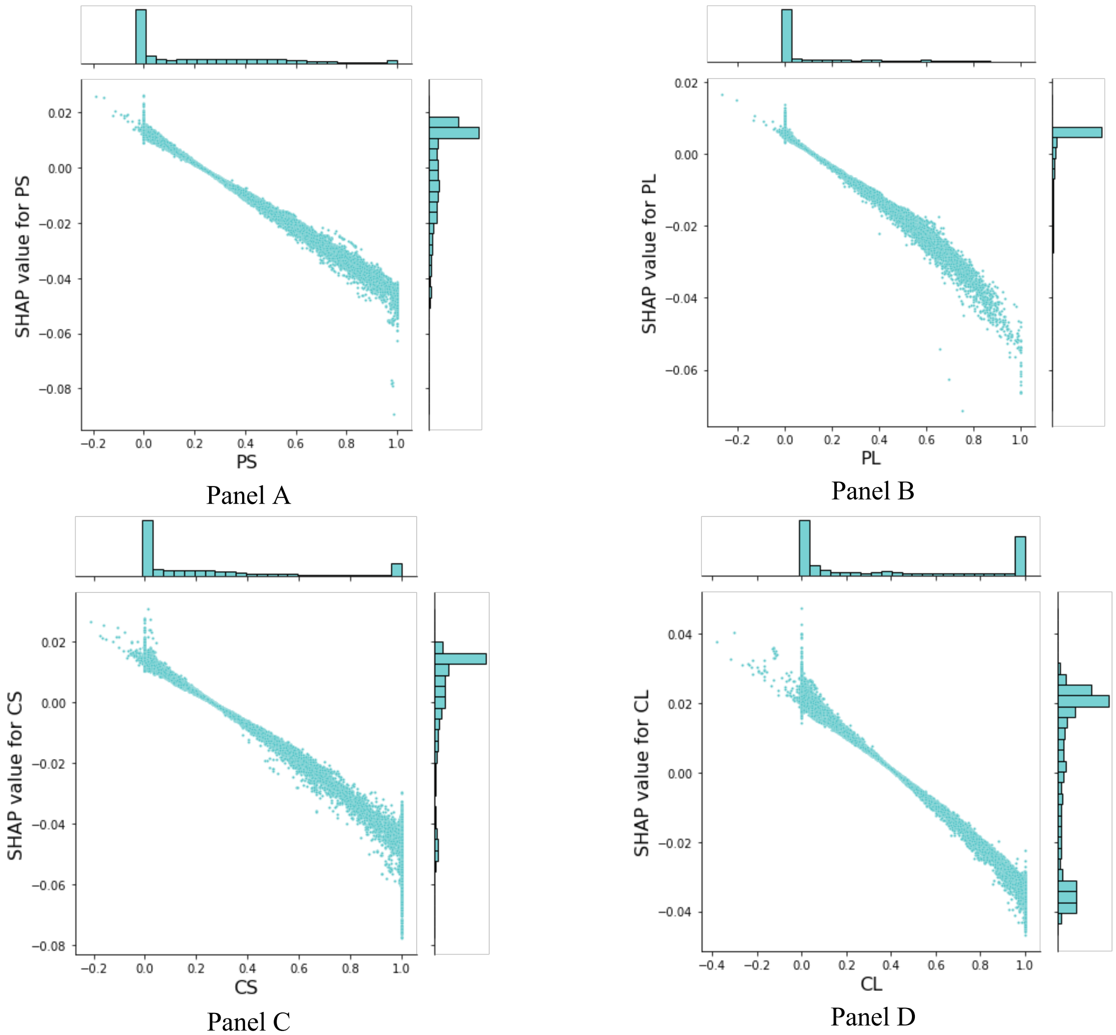
Notes: These figures show how each independent variable influences SHAP values using the overall sample from DeepExplainer in the SHAP library. The left panel is the bar plot of the absolute mean of the SHAP values from the overall sample. The right panel is the violin plot that explains how each sample affects SHAP values. The gradient color is from blue to red. The red color shows a higher value of each independent variable. The blue color exhibits a lower value of each independent variable.

Local Interpretation

After focusing on global interpretations, we now shift to explore how each feature influences insurers' ceding decisions using Shapley values as the key identifier. Figure 4 illustrates the dependence plot for the product-type variables from the SHAP library to show how ceding levels are related with each feature. These plots are similar to the partial/marginal effect of each independent variable in the econometric settings similar to Nettayanun (2014). The plots display Shapley values for all observations corresponding to the selected feature, explaining how Shapley values change when the selected feature varies. This explanation provides insight into how value levels for each feature affect reinsurance demands.

In Figure 4, the personal short-tail (*PS*), personal long-tail (*PL*), commercial short-tail (*CS*), and commercial long-tail (*CL*) are shown in panels A, B, C, and D, respectively. This figure illustrates how product type influences SHAP values, with each product type having a negative relationship with SHAP values. It also shows SHAP value coupled with histograms of each feature on top and SHAP value histograms on the side. Lower (higher) product mix percentages in each product type implies positive (negative) SHAP values. This means that the insurers tend to have more (less) ceding levels when writing a low (high) proportion of *PS*, *PL*, *CS*, or *CL* based on SHAP values. All types of products exhibit this behavior, suggesting that the types of products do not differentiate how firms hedge risk, but the level of writing in each product type does impact risk hedging. This supports Froot (2007) and Mellow and Ruckes (2005) that find insurers may hedge less if they have a competitive advantage. Our findings show that the incentive to hedge decreases for insurers that write more business in a particular business line.

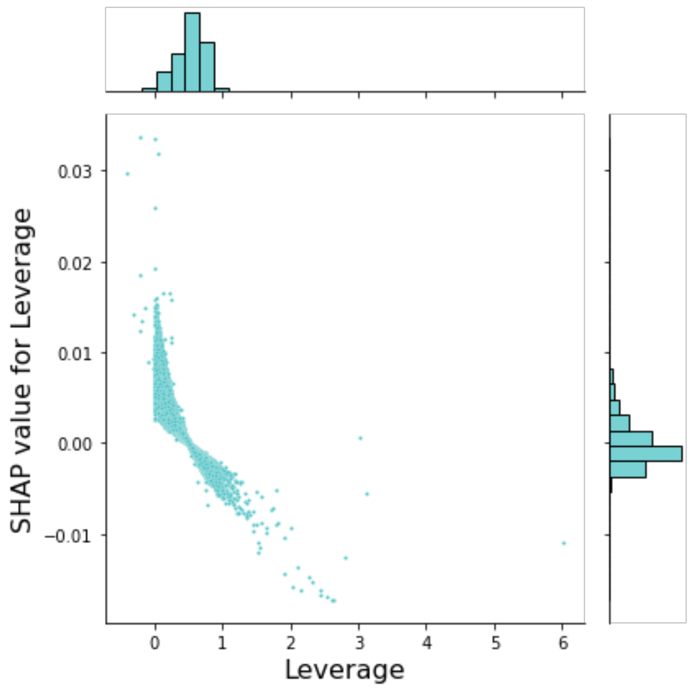
Figure 4. Dependence Plots for the Product Types



Notes: Dependence plots of SHAP values and product types. Panel A is for feature personal short-tail (*PS*) with associated feature *Stock*. Panel B is for feature personal long-tail (*PL*) with associated feature *BrokerPos*. Panel C is for feature commercial short-tail (*CS*) with associated feature *LnAsset*. Panel D is for feature commercial long-tail (*CL*) with associated feature *Stock*.

Figure 5 illustrates the dependence plot for *Leverage*. Low levels of leverage are mostly associated with positive SHAP values. Some leverage values are greater than one indicating a negative equity for insurers. This result supports Rampini, Sufi, and Viswanathan (2014) that find a higher level of leverage lowers the level of risk management activity, contrary to the opposite predictions from Cole and McCullough (2006) and Hoyt and Liebenberg (2011). Having more leverage in the company might influence insurers to cede less and retain more risk. Our analysis does not show a substitution effect between leverage and reinsurance.

Figure 5. Dependence Plot for *Leverage*

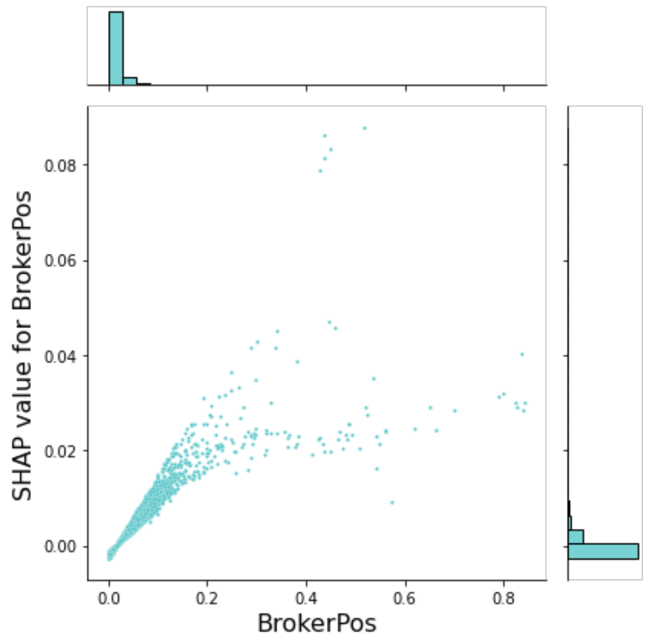


Notes: Dependence plot of SHAP values and *Leverage*.

Figure 6 illustrates the dependence plot of *BrokerPos*. Higher *BrokerPos* values tend to produce positive SHAP values. From values of *BrokerPos* from 0 to 0.2, the SHAP value accelerates upward. This is in line with Maksimovic and Zechner (1991), MacKay and Phillips (2005), and Nettayanun (2014) which find that the distance of broker expense compared to peers can positively influence ceding levels.

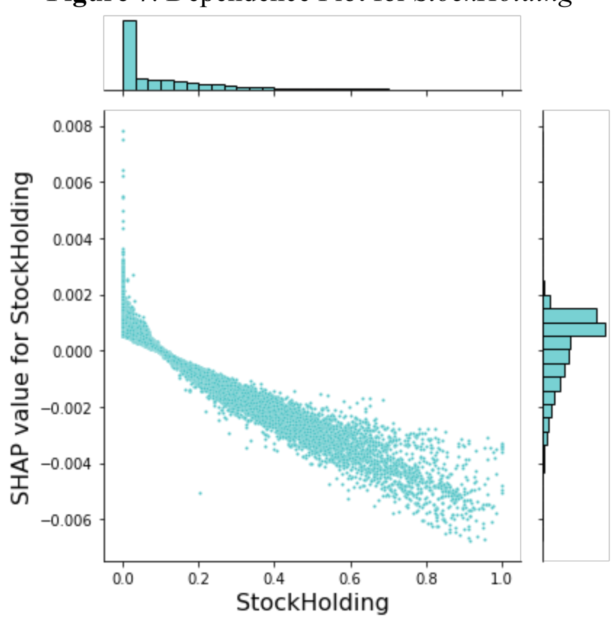
The seventh most important feature from Figure 7 is *StockHolding* which has SHAP values that are either negative or close to zero. However, some insurers with very low stock holdings have positive SHAP values. Figure 7 shows that insurers with more stock holdings have lower ceding levels, while insurers with very low stockholdings tend to have higher ceding levels. This finding does not support MacKay and Phillips (2005) substitution of risk between stockholding and reinsurance purchases. It also slightly differs from Nettayanun (2014) and MacKay and Phillips (2005) that find a positive significant relationship between stock holding and ceding levels. Figure 5 indicates that a large part of the plot has negative SHAP values, suggesting an overall negative relationship between stockholding and ceding levels.

Figure 6. Dependence Plot for *BrokerPos*



Notes: Dependence plot of SHAP values and *BrokerPos*.

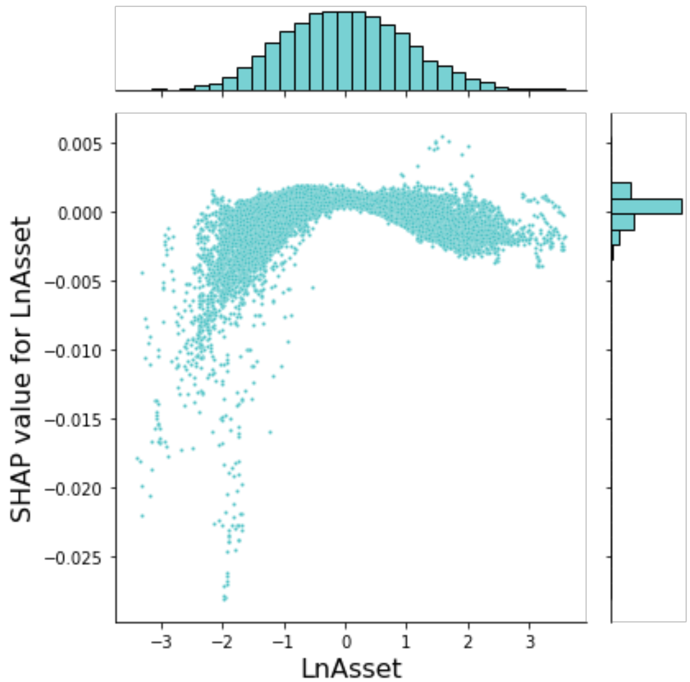
Figure 7. Dependence Plot for *StockHolding*



Notes: Dependence plot of SHAP values and *StockHolding*.

The eighth important feature for ceding insurance is firm size, *LnAsset*, as shown in Figure 8. The relationship between size and SHAP values are negative for small insurers. For medium-sized insurers, SHAP values are close to zero or slightly positive. For larger firms, SHAP values decrease to negative values and then increase back to positive values. Therefore, the size effects on reinsurance purchases do not appear to be conclusively negative or positive, contrary to the conclusions of Froot, Scharfstein, and Stein (1993), Tufano (1996), Stulz (1996), and Liu and Parlour (2009).

Figure 8. Dependence Plot for *LnAsset*

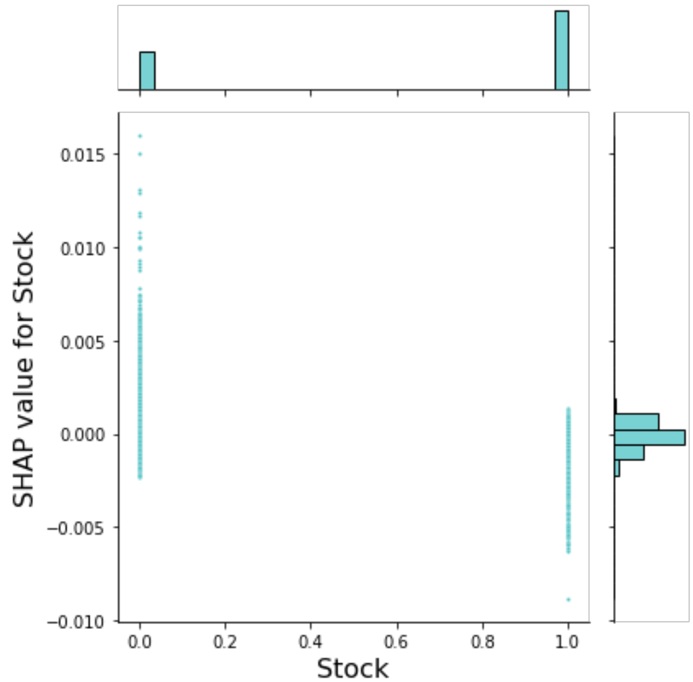


Notes: Dependence plot of SHAP values and *LnAsset*.

Figure 9 illustrates the relationship between ownership structure and ceding levels. For stock ownership companies, indicated by 1, the SHAP values range from positive to negative. The range of SHAP values is wider for other types of ownership structures, showing both positive and negative SHAP values as well. This indicates that there is no clear conclusion about the relationship between ownership structure and reinsurance purchases.

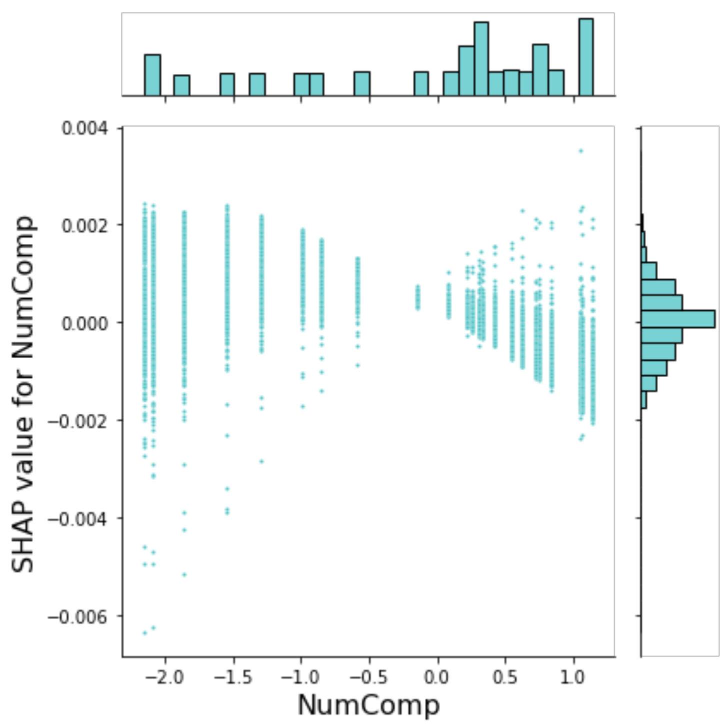
Figure 10 illustrates how the intensity of competition can influence reinsurance demand. It shows a wide range of both positive and negative SHAP values when there are either a low or high number of firms in the industry, indicating both increasing and decreasing reinsurance demand at these levels of competition. However, the influence tends to be close to zero when there is a medium number of firms in the industry, suggesting that this level of competition intensity does not influence reinsurance purchases. If we employ ordinary least squares and panel data regression, competition intensity might be found to be insignificant. The SHAP analysis provides more insight into how competition intensity impacts reinsurance purchases.

Figure 9. Dependence Plot for *Stock*



Notes: Dependence plot of SHAP values and *Stock*.

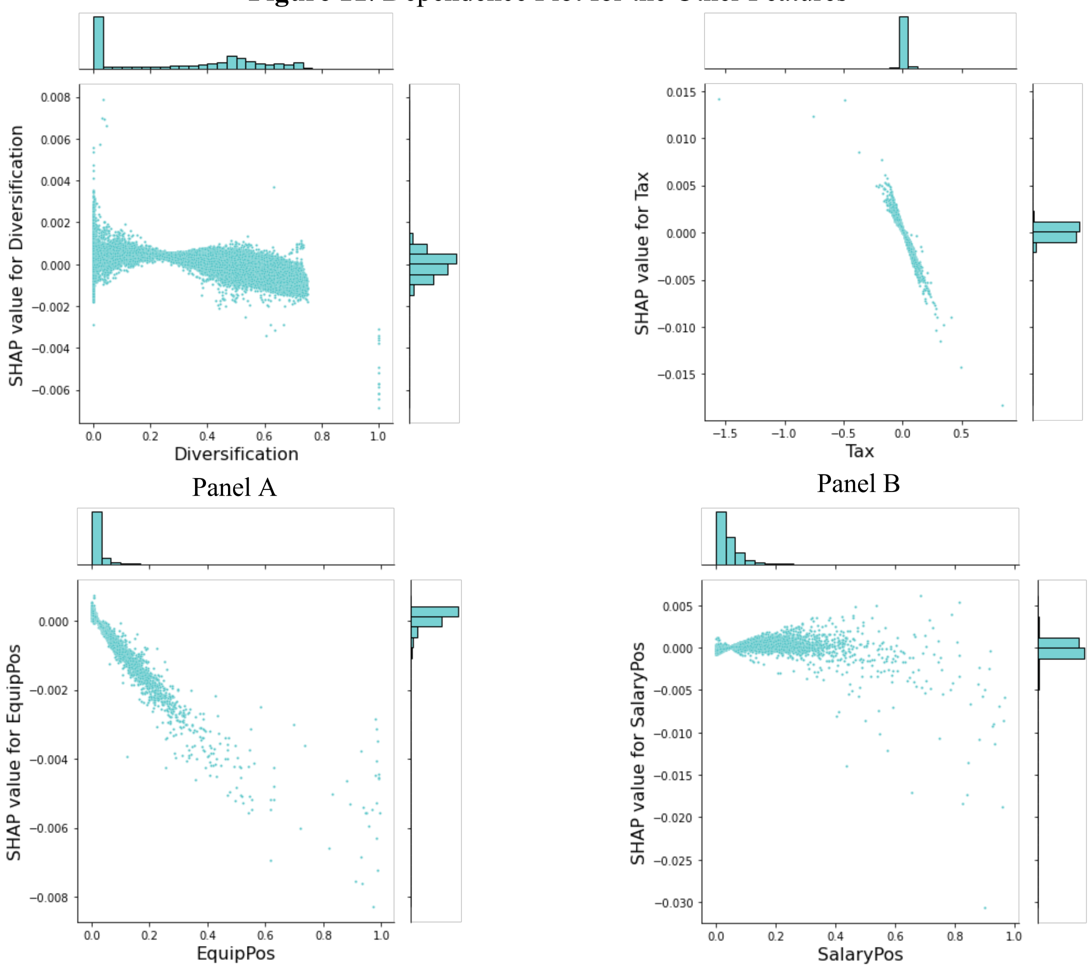
Figure 10. Dependence Plot for *NumComp*

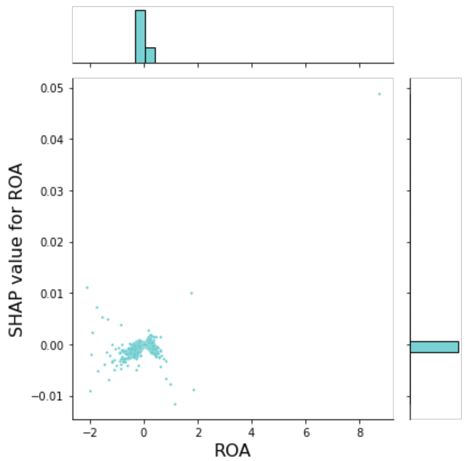


Notes: Dependence plot of SHAP values and *NumComp*.

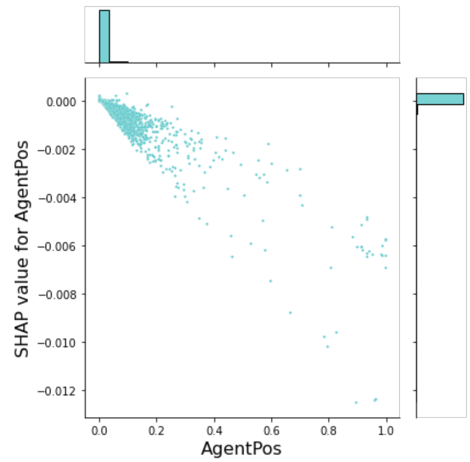
The other features ranked from 11 to 19 are shown in Figure 11. There are some interesting patterns in the dependence plot of *Herfindahl* and *IndCede*. The relationship between these variables and ceding levels, based on SHAP values, centers around zero. However, very low and very high values of these variables result in a wider range of SHAP values. Therefore, the relationship between these features and ceding levels is not conclusive for *Herfindahl* or *IndCede*. *EquipPos*, *SalaryPos*, and *AgentPos* also exhibit interesting patterns in their SHAP values. Very low values of *EquipPos*, *SalaryPos*, and *AgentPos* produce SHAP values close to zero, but the range of SHAP values become wider for higher values in these variables. Consequently, the conclusion regarding a negative or positive relationship with ceding for these features is also not conclusive.

Figure 11. Dependence Plot for the Other Features

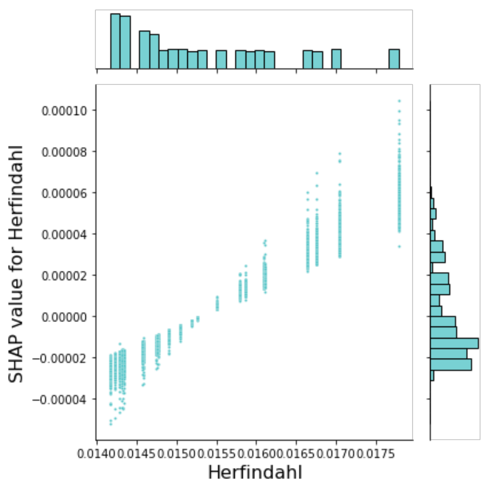




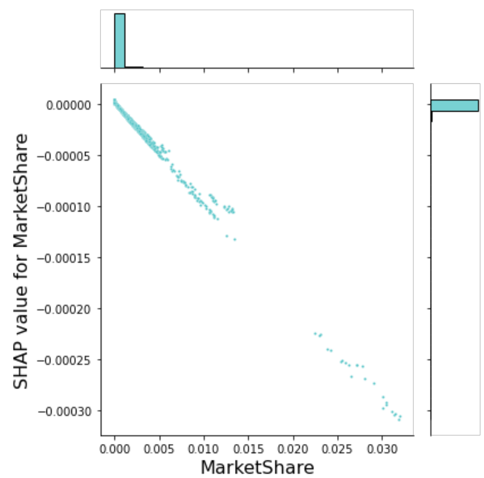
Panel E



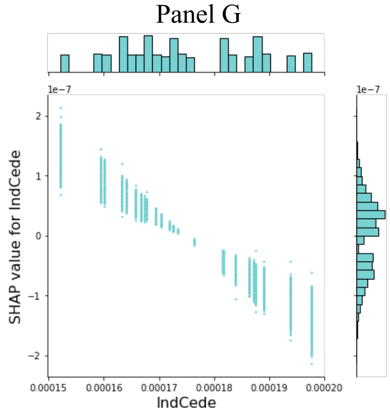
Panel F



Panel G



Panel H



Panel I

Notes: Dependence plots of SHAP values and different features. Panel A is for feature *Diversification*. Panel B is for feature *Tax*. Panel C is for feature *EquipPos*. Panel D is for feature *SalaryPos*. Panel E is for feature *ROA*. Panel F is for feature *AgentPos*. Panel G is for feature *Herfindahl*. Panel H is for feature *MarketShare*. Panel I is for feature *IndCede*.

Overall, the SHAP framework provides valuable insights into the relationship between variables/features that have been studied in previous literature. First, the framework offers a ranking of the importance of each variable's impact on ceding level. Second, it provides a more comprehensive understanding of the relationships between the variables and ceding levels, conditioned on the value of each variable itself.

Significance Tests of Features

To our knowledge, this study is the first to explore the significance of each variable's impact on reinsurance demand/ceding using machine learning. We follow Horel and Giesecke (2019) to show the significance of each variable included in the model. The method is the latest development in explainable AI for explaining any machine learning approaches. Horel and Giesecke (2020) also have significance tests for neural networks, but their method is limited to single-layer neural network. Another significance tests methodology, single feature introduction test (SFIT), proposed by Horel and Giesecke (2019), can be implemented using any machine learning approaches. There are two advantages to using this method. First, it does not assume the distribution of the features and is applicable to various model specifications. Second, it can be applied to both regression and classification analysis. Furthermore, it accounts for the significance of correlated features. For example, if X_1 and X_2 are highly correlated, other methods might identify only one of them as significant. However, SFIT can identify both variables as significant. This is accomplished by comparing the loss between a model that includes only a constant and a model that includes the feature of interest. After this is completed for all features, the median (m-statistics) loss is calculated from all of the losses accumulated from the data. The significance of each feature can then be determined using the distribution of the m-statistics that are greater than zero. This distribution follows a binomial distribution with *n* is the number of test observations and probability of ½. The implementation of this method can be found on GitHub[7].

Table 2. Significant Variables

Variable	m-statistics
Leverage	0.00872
CL	0.00788
CS	0.00438
PS	0.00423
Stock	0.00240
StockHolding	0.00030
ROA	0.00001

Note: This table reports SFIT m-statistics values for significant variables at a 0.1 level of significance.

Table 2 presents the significant variables from the SFIT test at a 0.1 level of significance, ranked in descending order based on m-statistics. *Leverage* is identified as the most significant variable, followed by *CL*, *CS*, *PS*, *Stock*, *StockHolding*, and *ROA*, respectively. Notably, six variables to include *Leverage*, *CL*, *CS*, *PS*, *Stock*, and *StockHolding* are also included in the top ten SHAP values. Therefore, these variables are significant variables that can be used to explain reinsurance purchases using the SHAP and significant-test frameworks. We add year dummy variables to account for the panel data. The results indicate three significant variables: *CS*, *PS*, and

[7] https://github.com/fintechstanford/SFIT

StockHolding. The variables from Table 2 that are not significant after including year dummy variables are *Leverage*, *Stock*, and *CL.* Therefore, we can identify the change in results for the SFIT test when adding year dummy variables.

VI. Conclusions

This study employs an explainable AI (XAI) framework to explore the strategic determinants that affect reinsurance levels in the property and casualty industry. Unlike previous studies that use various econometric approaches to explain reinsurance purchases, we utilize the SHAP library coupled with DeepExplainer to analyze how features explain reinsurance purchases. The Shapley value approach provides new insights into reinsurance purchase behavior. First, the methodology does not assume that the relationship between dependent and independent variables is linear, as many other econometric methodologies do. Second, the SHAP library offers deeper insights into how each variable influences hedging decisions based on SHAP values. This allows us to examine how each characteristic of the independent variable affects hedging levels through observation levels.

The top ten most important variables that impact reinsurance purchases are product types (*commercial long-tail*, *commercial short-tail*, *personal short-tail*, and *personal long-tail*), leverage, brokerage expense position compared to peers, stock holding percentage in the portfolio, size, ownership structure, and number of companies in the industry. Additionally, we use significance tests from Horel and Giesecke (2019) for each variable. Six variables that are significant are also among the top ten SHAP values, including leverage, ownership structure, product types (*commercial long-tail, commercial short-tail, personal short-tail*), and stock holding percentage in the portfolio.

Stakeholders in the insurance industry can benefit from this study in several ways. First, managers and executives of insurers can explore how other insurers adjust their reinsurance purchasing decisions based on strategic variables, allowing them to refine their own strategic reinsurance purchases. Second, investors can gain a deeper understanding of how insurers use reinsurance when analyzing their investment choices. Risk management is influenced not only by financial decisions but also by competition between peers. Third, regulators can gain insights into how insurers adjust their reinsurance purchases based on various strategic decisions, recognizing that insolvency risks may come from factors beyond financial consideration alone. By leveraging computation power, it is now possible to implement alternative methods that complement classical econometric approaches, providing more comprehensive insights into financial studies.

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Appendix

Table A1. Product Types

Personal Short-tail (*PS*)	**Personal Long-tail (*PL*)**	**Commercial Short-tail (*CS*)**	**Commercial Long-tail (*CL*)**
Auto physical damage	Private passenger auto liability	Allied lines	Aircraft
Farmowners multiple peril		Boiler and Machinery	Commercial auto liability
Homeowners multiple peril		Burglary and Theft	Excess workers compensation
		Commercial multiple peril	Medical professional liability-claims-made
		Credit accident and health	Medical professional liability-occurrence
		Credit	Other liability-claims
		Earthquake	Other liability-occurrence
		Fidelity	Other property and casualty
		Financial Guarantee	Product liability-occurrence
		Fire	Product liability-claims
		Group accident and health	Reinsurance (assumed liability)
		Inland marine	Warranty
		International	Workers compensation
		Mortgage guarantee	
		Ocean marine	
		Other accident and health	
		Reinsurance (assumed financial)	
		Reinsurance (assumed property)	
		Surety	

Note: This table categorizes each line of business into each product type.