A Walk through the Graveyard:

Which Insurance Companies Have to Leave the Market?

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Abstract

This paper analyzes insurance companies that left the market in 2003-2013. In a sample of 4,655 insurers, 146 of which failed, we find that technical efficiency negatively and business volatility positively correlates with failure probability. Firm growth has a U-shaped non-linear relationship with the failure probability. We classify insurers taken over by other firms as a special type of failure, because they show different symptoms from other failures (i.e. higher efficiency and profitability). Moreover, we document that the warning signals from failure indicators become stronger as the time to the failure event approaches. The findings are robust across the 2008 financial crisis. Our research relies on a large dataset, a long time period, a cross-country design, and is innovative in using new insurer failure models relying on business volatility measures and rare event logistic regressions.

Keywords

Business Failure Model, Insurer Insolvency Prediction, Technical Efficiency, Business Volatility, Merger and Acquisition, Financial Crisis

Introduction

The insurance industry is of significant economic importance to the stability and sustainability of the financial system and the global economy. In 2012, USD 27,000 billion in funds (12% of global financial assets) were managed and invested by the insurance industry (Swiss Re, 2014). Unlike other industries, the contingent nature of an insurance promise and the long-term contracts make safety particularly important and serves as motivation for regulation. Regulatory intervention and market discipline are expected in the insurance industry so that potential failures can be identified well in advance with early surveillance. Then the corresponding measures can be conducted to prevent such failures, and if failure is unavoidable, to minimize its consequences.

This paper analyzes such insurance failures. A first fundamental step of failure surveillance is to identify potential indicators of financially distressed insurers before their actual failures.[1] We empirically investigate such indicators in a global dataset consisting of 4,655 insurers from 65 countries over eleven years (2003-2013). In addition to the failure indicators, we are interested in the strength and validity of failure indicators depending on the time to failure (BarNiv and McDonald, 1992) and whether different types of failures show different symptoms. Moreover, the long-term dataset across the 2008 financial crisis allows us to investigate potential dynamic changes in the causes of insurer financial distress (Zhang and Nielson, 2015), in order to identify robust failure indicators across both crisis and non-crisis periods.

Most studies of insurer failure (insolvency) are country- or region-specific, focusing on, for example, the U.S. (Cheng and Weiss, 2012), German (Rauch and Wende, 2015), or selected Asian markets (Chen and Wong, 2004). Pasiouras and Gaganis (2013) provide the first piece of worldwide evidence but look at the general financial soundness of insurers instead of insurer failure. We broaden the geographical scope of the insurer failure models to the global market with the largest sample ever explored for this purpose.

Following Leverty and Grace (2010), we include the efficiency measure derived by data envelopment analyses (DEA) to predict the insurer failure. This measure is developed based on the optimization principle in microeconomics and fit for the purpose of solvency prediction. Firms that are not attaining the optimization (not fully efficient) will have to leave the markets driven by competition (Bauer, Berger, Ferrier,

[1] *Financial distress*, *insolvency*, and *failure* are used interchangeably to describe insurers experiencing liquidation, runoff, dissolution, etc.; sometimes, the term *retirement* is used as an umbrella concept to incorporate all situations of insurers leaving the market (BarNiv and McDonald, 1992). In this paper, we use the term *failure* in order to incorporate multiple types and scenarios of financial problems.

and Humphrey, 1998). DEA efficiency captures the management quality and the firm's overall operational efficiency, both of which are critical to the failure or success of the banking industry (Barr, Seiford, and Siems, 1993; Wheelock and Wilson, 2000). The DEA efficiency has been widely used as the failure predictor in the banking industry (e.g., Siems, 1992; Barr, Seiford, and Siems, 1994; Luo, 2003; Wheelock and Wilson, 2000) and in mixed manufacturing industries (e.g., Psillaki, Tsolas, and Margaritis, 2010; Li, Crook, and Andreeva, 2014).

We also propose a new indicator for insurer failure that have not been considered in earlier insurer failure models: the overall business volatility measured by standard deviations of return on equity (ROE) or return on assets (ROA). Moreover, we are the first to use rare event logistic regression (King and Zeng, 2001) which we present as a methodological alternative in our robustness tests.

By way of preview, the logistic business failure models show that the insurer's technical efficiency (business volatility) negatively (positively) correlates with its failure probability. We are also the first to document a U-shaped impact of growth on the failure probability, which mirrors findings from other insurance studies on underwriting discipline (Eling and Schmit, 2012; Harrington, Danzon, and Epstein, 2008). We classify insurers being acquired by other firms as a special type of failure and demonstrate that their symptoms of failure are different from other types of failures (confirming findings from the banking sector; see Wheelock and Wilson, 2000). Moreover, we illustrate the diminishing impact of failure indicators as the length of time prior to the failure event increases.

Our paper contributes to the general economic discussion on factors driving firm failure (Browne, Carson, and Hoyt, 1999; Rajan, Seru, and Vig, 2010) and on recent regulatory reforms regarding risk-based capital (RBC) (Klein, 2012; Kreutzer and Wagner, 2013). Moreover, our results have important policy implications such as a group of indicators consisting of both firm characters and market economics which can be used to predict an insurer's failure. Among these failure indicators, the regulators may pay additional attention to the long-term and fundamental measurements of a firm's management quality, efficiency, as well as its business volatility over time, which send early warning signals of unhealthy insurers.

The rest of the paper is organized as follows. In Section II, we develop our hypotheses. Section III is a summary of our data and methodology. In Section IV, we present our empirical analyses. In Section V, we discuss the robustness and predictability of our models. Finally, we conclude in Section VI.

Literature Review and Hypotheses Development

Regulators use various methods to safeguard insurers' financial strength and to protect policyholders from losses due to insurer failures. The solvency capital requirements (e.g. RBC, Solvency I/II) have always been a focal point of insurer failure studies. Cheng and Weiss (2012) focus on the insolvency predictability of U.S. RBC ratio in P&C insurance industry. In line with the expectation, they find that the RBC ratio is negatively correlated with the insolvencies of P&C insurers. However, studies also strongly suggest that the RBC system is not good at predicting insurer insolvency (Pottier and Sommer, 2002), particularly after the RBC system was formally implemented (Cheng and Weiss, 2012). This is because insurers would have adjusted their capital or operating behavior to avoid regulatory intervention (Cheng, 2008). Insurers may take real changes (such as raising new capital) or create illusory changes (such as financial statements manipulation, using fraudulent reinsurance transactions, or capital arbitrage instruments) (Cheng, 2008). Such illusory changes reduce the predictive power of RBC ratio and run counter to the regulatory intention to increase the stability and security of an insurer.

We are thus motivated to look for potential factors that are difficult to manipulate, not fully captured by the capital solvency requirements, and deeply reflect the management quality and business operation status of an insurer. This paper proposes two such indicators: DEA technical efficiency and business volatility. In Table 1, we review the insurer failure (insolvency) prediction literature published in the 21st century.[2] DEA technical efficiency measures the relative productivity of an insurer to its peers on an input-output quantity basis, which captures multi-dimensional inputs and outputs (Cummins and Weiss, 2013), and thus is less sensitive to short-term price fluctuations and more difficult to manipulate than other measures. Kao and Liu (2004) show that DEA technical efficiency is able to make forward-looking predictions in a timely manner. Xu and Wang (2009) demonstrate that DEA technical efficiency significantly improves the failure prediction accuracy regardless of the models used in the failure prediction[3]. In summary, Demyanyk and Hasan (2010) highlight the demand for more application of operations research techniques in analysis of financial failures and crises.

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[2] We refer to Chen and Wong (2004) for studies done in the 1990s and to BarNiv and McDonald (1992) for studies done in the 1970s and 1980s.

[3] Xu and Wang (2009) discuss some commonly used failure prediction models, such as vector machines, multiple discriminant analysis, and logistic regression. They conclude that technical efficiency works well no matter which model is used in failure prediction.

Microeconomic theory suggests that firms that do not succeed in maximizing the input-output ratio will be forced to exit the market (Samuelson and Nordhaus, 2009). Cummins and Rubio-Misas (2006) show that Spanish insurers exiting the market for reasons other than M&A are relatively inefficient and have relatively unfavorable financial performance characteristics. The insurance industry has also been aware that inefficient management practices cause insurer insolvencies (Ashby, Sharma, and McDonnell, 2003). Empirical studies document the negative impact of inefficient management practice in insurer solvency analysis and acknowledge the necessity and the difficulties in incorporating the efficiency factors (Kim, Anderson, Amburgey, and Hickman, 1995). Kim et al. (1995) and Zhang and Nielson (2015) proxy the efficiency by the expense ratio, suggesting that high expense ratio (inefficiency) positively correlates with the probability of P&C insurer insolvency.

Outside of the insurance industry, Siems (1992) shows that management quality, captured by DEA technical efficiency, is critical to a bank's survival. Miller (1996) notes that management-driven weakness (i.e. inefficiency) has a significant role in 90% of bank failures. Luo (2003) again documents the significantly negative correlation between the DEA technical efficiency and the probability of bank failures. Wheelock and Wilson (2000) show that DEA efficiencies reduce the probability of bank failures. In light of these empirical results, we offer Hypothesis 1A.

H1A: The probability of an insurer failure is negatively related to its technical efficiency.

Fahlenbrach, Prilmeier, and Stulz (2012) argue that a firm's risk culture and business model have a strong impact on its vulnerability to financial crisis. They show that a firm's performance in the 1998 financial crisis predicted its performance and chance of failure in the 2008 financial crisis. Their conclusion highlights the importance of long-term risk measurement in predicting insurer failure. Therefore, we consider business volatility to capture the risk aspect of insurers over a relatively long period (e.g. 5 to 11 years in our sample). Various business volatility measures have been used in insurance empirical research (see e.g. Eling and Marek, 2013). We introduce the standard deviations of ROE (ROA) to capture the long-term risk[4] of an insurer. By definition, higher risk leads to a higher probability of failure. Pasiouras and Gaganis (2013) capture the insurer's business volatility also by the standard deviation of ROAs. They use a three- and four-year rolling window to obtain the standard deviation, which we show a five-year rolling window standard deviation as an alternative to our

[4] ROE and ROA capture the overall volatility of insurance business. We also consider another volatility measurement, the standard deviation of the combined ratio, in the Section Robustness Test, which concentrates on the unexpected loss and expense of the insurance business.

long-term standard deviation in the robustness tests. They obtain Z-score using the standard deviation as the denominator of dependent variable, which derives the direct measurement of insurer soundness, however, cannot observe the correlation between the volatility and the probability of an insurer failure. We complement their findings by looking directly at the business volatility impact on the probability of an insurer failure. This leads us to Hypothesis 1B.

H1B: the probability of an insurer failure is positively related to its business volatility.

Kim et al. (1995) and Rauch and Wende (2015) empirically find that rapid premium growth is positively associated with insolvency and thus with the probability of failure based on the Solvency I measure. Rapid growth does not only impose pressure on the premium to capital ratios, but also endangers the underwriting quality and profitability of the insurer, thus a firm that grows too quickly may experience trouble (Zhang and Nielson, 2015) and self-destruct when other important objectives are neglected (Chen and Wong, 2004). However, a positive and reasonable growth indicates a healthy and active operation and reflects its attractiveness to policyholders and investors; such firms are more likely to stay financially stable (Zhang and Nielson, 2015). The philosophy of Solvency II also emphasizes not "punishing" the firm with a healthy growth, since growth does not necessarily suggest failure. Thus, we hypothesize a U-shaped relationship between insurer growth and its probability of failure, where firms with negative or extremely high growth are more likely to fail than firms that show healthy growth.[5] We extend the insurer growth measurement in the literature with the inflation-adjusted asset growth[6] and use the real growth of net premium written as a robustness test, the results of which are consistent with our core models (see Appendix 2). We thus present Hypothesis H1C.

H1C: There is a U-shaped correlation between an insurer's growth and its probability of failure.

In addition to the three indicators, there are other firm- and country-specific factors that might predict an insurer's failure. Table 1 summarizes the factors used in early insurer failure/insolvency models and demonstrates our selection of control variables. In line with the literature, we expect the probability of an insurer failure to be

[5] Other studies on underwriting discipline also highlight the non-linear link between growth and financial soundness. See, e.g., Eling and Schmit (2012), and Harrington, Danzon, and Epstein (2008).

[6] Compared with the premium growth, asset growth is less sensitive to the accounting premium allocation bias, i.e., more difficult to manipulate by the management when they need a growth story. Thus asset growth more accurately captures the real growth situation of a firm. Moreover, asset growth is consistent with the size measurement in the paper and has more valid observations than premium growth.

negatively associated with the mutual form of organization,[7] with a large firm, with high profitability,[8] and with a higher capital-to-asset ratio (BarNiv and McDonald, 1992; Zhang and Nielson, 2015). The likelihood of failure may also be influenced by the lines of business that an insurer operates (life, nonlife, or composite) and/or its legal structure (unaffiliated single firm or group). We also include five country-specific factors to control for the impact of industrial and economic environment in different markets (see Browne and Hoyt, 1995 for a comprehensive discussion of market and economic factors). We expect that the probability of an insurer failure negatively associates with economic growth (i.e. in boom times all insurers are less likely to fail). We expect the probability of an insurer failure to be positively associated with the market maturity, since an insurer in a mature market has more difficulty generating a large cash flow in a short period of time, thus saving itself from failure through the cash-flow underwriting[9]. A rapidly rising interest rate indicates a liquidity shortage in the market, which increases the probability of failure. According to Cheng and Nielson (2015), a high interest rate, different from a rapid rise in the interest rate, however, suggests that insurers could earn a higher return on new money, thus a higher interest rate is expected to relate negatively to insolvency. Inflation adversely influences administrative expenses, claims amounts, and real rates of return on fixed-income investments, hence increasing an insurer's likelihood of insolvency (Cheng and Nielson, 2015). Some research based on U.S. data also includes the industry loss ratio (combined ratio) and/or premium Herfindahl Index to capture the industry performance and market competition; however, such information is not widely available across countries and thus we are not able to use it.

Insurance companies have to leave the market for many reasons, a special type of which is mergers and acquisitions (M&A). In the insurance industry, M&A often indicates that a financially or operationally stronger company takes over a weak company, or an efficient insurer takes over and reforms an inefficient firm[10] (Cummins,

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[7] Following agency theory, Lamm-Tennant and Starks (1993) show that stock insurers write relatively more business in high-risk product lines.

[8] The capital market theory says high risk associates with high expected profit; however, here we measure the actual profit for each firm-year, thus, high actual profit indicates a health firm operation, thus less likely to fail in the same period or in a few years. This prediction is in line with other solvency prediction studies (see e.g. Zhang and Nielson, 2015).

[9] A mature client is less likely to switch insurer because of short-term price discounts, and there are fewer new business opportunities in a mature market than in an emerging market. The cash flow underwriting means that insurers are willing to cut prices (i.e., use a larger discount rate for losses in the premium) to gain market share and obtain assets to invest (Weiss, 2007); insurers increase supply when interest rates rise in order to obtain funds to invest (Cummins and Outreville, 1987).

[10] We also acknowledge that not all insurance M&A, which causes insurers to leave the market, should be regarded as financially distressed or failed (BarNiv and McDonald, 1992).

Tennyson, and Weiss, 1999). Being acquired is different from other types of failures, because acquired firms should possess leading-edge competencies that are viewed as attractive to the acquirers (Cummins et al., 1999; Wheelock and Wilson, 2000). However, the M&A targets may also have some problems similar to other types of failures thus making them less optimal to operate on a standalone basis. For example, an insurer taken over by others could be technical efficient or profitable (Cummins and Rubio-Misas, 2006), but not able to generate enough cash flow in a liquidity shortage period, thus making it vulnerable and thus more likely to be acquired. Cummins and Rubio-Misas (2006) empirically show that insurers participating in the M&A market as targets are not less efficient than non-M&A firms. Wheelock and Wilson (2000) also document that banks being acquired are as technical efficient as those banks that are not M&A targets. We thus phrase our second hypothesis as follows.

H2A: Insurers that are acquired by other firms have some problems similar to those with other types of failures, however, they are not necessarily less profitable.

H2B: Insurers that are acquired by other firms have some problems similar to those with other types of failures, however, they are not necessarily less technical efficient.

Early surveillance is desirable because it gives regulators ample time to evaluate weak insurers (Cummins, Harrington, and Klein, 1995) and take corresponding regulatory measures. BarNiv and McDonald (1992) summarize that the models' ability to identify insolvency is substantially reduced as the length of time prior to insolvency increases. Firm failure is not a sudden and unexpected event (Luoma and Laitinen, 1991) but a predictable one (otherwise, it would make no sense to develop and use business failure prediction models). Balcaen and Ooghe (2006) describe failure as the result of a process or path, which may consist of several phases, each characterized by specific behavior of certain indicators or specific symptoms. Moreover, the relative importance of failure indicators is not constant (Daubie and Meskens, 2002). Following these arguments, we examine the changes in the significance and magnitude of failure indicators' impact. We expect the correlation between the probability of an insurer failure and corresponding indicators to be weaker at first and then to become stronger as the time of the actual failure event approaches. In other words, the impact or the warning signals from failure indicators become stronger over time, yielding our Hypothesis 3.

H3: The warning signals from failure indicators become stronger as the failure event approaches.

Finally, we check whether the financial or economic crisis has any systematic impact on the identified failure indicators. In other words, are the failure indicators valid during the financial crisis? Do the failure indicators have the same impact during crisis and non-crisis periods? This question is important because only reliable failure indicators that are robust across financial crisis can alert regulators and managers before the crisis thus allowing them to take action to minimize the negative consequences of the crisis. Anyway, the financial crisis is the time that saw the most insurer failures (comparable to the situation in banking; see Demyanyk and Hasan, 2010) as shown in Table 3. Fahlenbrach et al. (2012) show that some indicators like leverage ratio and growth predict the bank's poor performance across the two financial crises. These indicators consistently explain why the same banks are prone to poor performance in both the 1998 and 2008 financial crises. We complement their findings by looking at whether our identified indicators are robust across the crisis and non-crisis periods. Are there some common reasons for insurer failures that matter in both the crisis and non-crisis periods? We thus phrase our fourth hypothesis as follows.

H4: The failure indicators identified are robust across financial crisis.

Table 1. Literature Review and Variable Constructs

		Pottier and Sommer (2002)	Chen and Wong (2004)	Leverty and Grace (2010)	Cheng and Weiss (2012)	Pasiouras and Gaganis (2013)	Zhang and Nielson (2015)	Rauch and Wende (2015)	This Paper
Sample	Number of insurers	1,780	341	1,119-1,403	1,700-2,000	1,742	2,163	108 (on average)	4,655
	Number of failure (insolvent) firms	31	not applicable; solvency ratios used to identify unstable firms	7-32	19-77	Not applicable; continuous dependent variable is used	98	Not applicable; continuous dependent variable is used	146
Dependent Variable	Measurement of Insolvency or Failure	Insolvent dummy	Financially unstable dummy	Failure dummy	Insolvent dummy	Z-score = (mean ROA + mean equity to asset ratio) / std. dev. ROA	Insolvent Dummy	Solvency I Ratio	Failure dummy
Inde-pendent Variables: Firm-level	Performance	Not included	operating margin, combined ratio, investment yield	Pure technical efficiency, scale efficiency, and allocative efficiency	Not included	Not applicable because ROA is integrated in the dependent variable	ROE and return on revenue	ROA and loss ratio	ROE, ROA, technical efficiency
	Growth	Not included	premium growth, surplus growth	Not included	Not included	Not included	Premium Growth	Premium growth	Asset growth and premium growth
	Size	Total assets	Total assets	Total assets	NPW	Total assets	Total assets	Total assets	Total assets
	Ownership	Mutual dummy	Not included	Mutual dummy	Mutual dummy	Stock dummy	Not included	Mutual dummy, public dummy	Mutual dummy
	Legal Structure	Not included	Not included	Not included	Not included	Single dummy	Group dummy	Not included	Single dummy
	LOB Structure	Not included	change in product mix (for life insurer only)	Not included	Hurricane exposure	Life dummy	LOB Herfindahl Index	LOB Herfindahl Index	Life dummy, Composite dummy
	Leverage or Solvency Ratio	RBC ratio	reserves to surplus (for life insurer only)	Not included	Inverse RBC ratio	Not applicable because equity to asset ratio is integrated in the dependent variable	Liability to Asset	Net premiums written to equity capital	Equity to asset
	Asset portfolio description	Not included	Change in asset mix (for life insurer only)	Not included	Bond portfolio duration	Not included	% of all asset classes	% of stock and real estate	Not included due to data limitation
	Other ratios or ratings that capture risk and other aspects	FAST ratios, AMB financial strength rating, Best capital adequacy ratio	Liquidity ratio	FAST financial ratios	FAST financial ratios	Not included	IRIS3, No. of failed IRIS ratios, cash flow to premium written, liquidity	Not included	Standard deviations of ROE, ROA
Country- or State-level if US studies	Economic environment	Not included	Not included	Not included	Not included	GDP growth	Stock return, unemployment rate	Not included	GDP growth
	Inflation	Not included	Inflation rate change	Not included	Inflation rate, unanticipated inf.	Inflation rate	Inflation rate, unexpected inf.	Not included	Inflation rate
	Interest rate	Not included	Interest rate and its change	Not included	Interest rate and its change	Not included	Government bond yield	Not included	Government bond yield
	Insurance development	Not included	Not included	Not included	Not included	Insurance penetration	Not included	Not included	Insurance penetration
	Insurance competition	Not included	Number of Insurers	Not included	Premium Herfindahl index by state	Not included	Not included	Not included	Not included due to data limitation
	Insurance industry loss performance	Not included	Not included	Not included	Industry combined ratio	Not included	State insolvency ratio; industry combined ratio; catastrophe loss	Not included	Not included due to data limitation
	Other factors	Not included	Not included	Not included	Not included	Overall quality of institutions; author constructed factors	Not included	Not included	Not included

Data and Methodology

Our sample is extracted from Best's Insurance Reports, Non-US version (A.M. Best, 2003-2013). It contains eleven years of data (2003 to 2013) and contains all insurers, but excludes entities that are branches, special purpose vehicles, captives, and firms that operate insurance as minor business (e.g., banks, manufacturers, and health care providers). The failure events include Ceased Operation, Dissolved, In Liquidation or Liquidated, In Runoff, Portfolio Transfer, Struck from Register, Surrendered License, Struck from Register, and being acquired by another firm.[11] We then define the observation as financially distressed if there is a failure event in the year or in the next two years (Cheng and Weiss, 2012), for example, firm *i* has a failure event in year *t*, then the firm-years (*i, t)*; (*i, t-1);* and *(i, t-2)* are identified as financially distressed observations.

To eliminate outliers, we trim the extreme values beyond 1% and 99% percentiles (Cummins et al., 1995; Loughran, 2005; Eling and Marek, 2014). This practice is necessary because some insurers with extreme values are startups that do not yet underwrite business or runoff insurers, which are not comparable to and not in competition with regular insurers.[12] The key ratios considered in this analysis are return on equity (ROE), return on assets (ROA), leverage ratio (total capital and surplus divided by total assets), and yearly real asset growth. Our final sample is an unbalanced panel consisting of 4,655 insurers and 29,581 firm-years, in which 614 firm-years (2.1%) are identified as financially distressed observations (i.e. to fail in the subsequent three years); 304 firm-years (1.0%) are observations with actual failure events; 146 insurers (3.1%) are failure insurers (i.e. insurers having a failure event during the entire sample period). Tables 2 and 3 present the summary statistics.

Beaver (1966) and Altman (1968) developed the business failure model, which was introduced into insurance studies by Trieschmann and Pinches (1973). McDonald (1993) compares different empirical approaches and promotes the logistic model to overcome problems in early multiple discriminant analyses. Davis and Karim (2008) show that, in the banking and financial crises, logistic regression performs best in a

[11] This broad classification of failures or insolvencies can be traced back to BarNiv and McDonald (1992), who group all failed insurers, voluntarily retired insurers, and insurers merged into other companies together as failure insurers.

[12] Trimming or winsorizing is the outlier treatment widely used in risk and insurance research (see e.g., Loughran, 2005; Berry-Stoelzle, Hoyt, and Wende, 2013). Given that this paper investigates the extreme cases, i.e. failure firms, we perform robustness tests with trimming at 0.5 and 99.5 percentiles and at 2 and 98 percentiles, the results of which are consistent with our core models. Different trimming method does not change our conclusions, however, with minor changes on the magnitude of coefficients, which demonstrate the robustness of our conclusions.

global early warning system. In the past 40 years, there have been many empirical investigations of insurer failure models; however, the topic remains important, because of the number of unpredicted insurers failures in recent years. In the 2008 financial crisis, the (almost) failure of three important (re)insurers[13] recall the academic investigation to analyze the failure reasons, better surveillance of the failure event, and minimize the consequences.

So far, most insurer failure studies focus on the U.S. insurance industry (see Zhang and Nielson, 2015 for a review) with a few country/region-specific studies outside the U.S. (see Rauch and Wende, 2015 for a review). However, whether those identified precursors are country-dependent or broadly applicable across markets has not yet been investigated. We use the data across 65 countries, 11 years, and 4,509 solvent and 146 insolvent insurers to re-examine the business failure models, which significantly increases the model's geographical scope of applicability in the insurance industry.

In Equation (1), we use logistic regression to detect the potential correlation between firm- and country-level indicators and the failure probability (Cheng and Weiss, 2012).[14] The dependent variable *Distressed* equals 1 if the observation is identified as financially distressed. We use two alternative firm *performance* measurements: accounting profitability (ROE or ROA) and DEA technical efficiency.[15] We measure insurers' technical efficiency by their relative productivity scores obtained from Data Envelopment Analysis (DEA, see Appendix 1 for a detailed discussion). We assume constant returns to scales (CRS) to estimate efficient production frontiers separately for each year between 2003 and 2013, as well as for each region: Europe and Rest of the

[13] The three cases commonly referred during the 2008 financial crisis are write-down of Swiss Re, government bailout of AIG, and insolvency of Yamato Life Insurance (Eling and Schmeiser, 2010).

[14] In "Results," we use standard logistic regressions, which are consistent with existing insurer failure studies. Then in the Section "Robustness Tests," we present the rare event logistic regression (King and Zeng, 2001) as an alternative methodology that has not yet been used in this context. The advantage of this methodology is that it corrects the coefficient bias and reduces the tendency of underestimates the probability of an event in standard logistic regressions due to rare events (King and Zeng, 2001). One disadvantage is, however, that it is difficult to obtain the standard deviation of coefficients' marginal effects, thus the interpretation of results are less straight forward than the standard logistic regression. For this reason we present the standard logistic regression as the main results and position the rare event logistic regression in the robustness tests.

[15] We do not include the DEA efficiency and the return measurement in one equation because DEA efficiency explains a part of the profitability, particularly for life insurers. See Greene and Segal (2004) for a detailed discussion regarding the relationship between efficiency and profitability. DEA technical efficiency does not only capture the management quality but also various environmental factors (Huang and Eling, 2013). Therefore, in later logistic regressions, we always control for the country-specific economic factors or the country-year fixed effects, thus the coefficient between DEA technical efficiency and the probability of failure largely reflects the impact of management quality and efficiency differences of each firm.

World[16]. The DEA approach is widely used in insurance management research (see e.g., Bates and Mukherjee, 2010; He, Sommer, and Xie, 2011; Leverty, 2012).

$$Distressed_{i,t} = \beta_0 + \beta_1 Performance_{i,t} + \beta_2 Business\ Volatility_i + \beta_3 Growth_{i,t} + \beta_4 Growth_{i,t}^2 + \beta_5 X_{i,t} + \beta_6 Y_i + \beta_7 Z_{c,t} + \varepsilon_{i,t} \quad (1)$$

Unlike the RBC ratio, which is evaluated on a yearly basis, our measurement of business volatility is a firm's standard deviation of ROEs (ROAs)[17] over years (Brighi and Venturelli, 2014; Elango, 2010; Eling and Marek, 2014; Lamm-Tennant and Starks, 1993)[18], which is robust across multiple years and thus better reflects the long-term stability and sustainability of an insurer's profitability. Specifically, we use two alternative standard deviations: 1) standard deviations of all years with available information (i.e. 5 to 11 years), and 2) rolling window 5-year moving standard deviations as a robustness test.

Growth is captured by the real (inflation-adjusted) yearly asset growth and by the real net premium growth as a robustness test (Appendix 2). X is a series of firm- specific and time-variant control variables, including firm size measured by real total assets and leverage ratio. Y is a series of firm-specific but time-invariant control variables, including the life insurer dummy, composite insurer dummy, mutual insurer dummy, and unaffiliated single firm dummy. Z is a series of country-specific and time-variant control variables, including insurance penetration, inflation, real GDP growth, interest rate, and percentage change in interest rate. We also show specifications with market and year-fixed effects to replace the country-level control variables to capture the market differences (Zhang and Nielson, 2015).

Instead of using the financial distress dummy in Equation (1), we use the dummy for actual failure event as the dependent variable, which equals 1 if the firm i has a failure event in year t. We separately conduct the regressions in the event year t, the prior year t-1, and the second prior year t-2, as shown in Equation (2) (s=0,1,2) (Zhang and

[16] One of the assumptions for DEA efficiency estimates is that firms employ similar technologies. It would be a strong assumption that all Non-US insurers employ similar technologies. Therefore, we group insurers in our sample into the two regions according to their domiciliary countries.

[17] The standard deviation of DEA technical efficiency is not applicable here, because the DEA efficiency scores are calculated on yearly and on relative-to-the-best basis. The standard deviation of efficiency scores over years does not capture the business volatility.

[18] Other business volatility measures are used in insurance studies, e.g., Eling and Marek (2014) measure asset, insurance product, and financial risks separately with different indicators. We use the standard deviation of ROE and ROA as an aggregate measure of the overall business volatility, which has not yet been used in the insurer failure assessment. We are not able to further decompose the volatility measure into separate operations within an insurer due to data limitations.

Nielson, 2015; Rauch and Wende, 2015). This approach is used as a robustness check to Equation (1) and directly tests Hypotheses 3 and 4. [19]

$$Failure\ Event_{i,t} = \beta_0 + \beta_1 Performance_{i,t-s} + \beta_2 Business\ Volatility_i + \beta_3 Growth_{i,t-s} + \beta_4 Growth^2_{i,t-s} + \beta_5 X_{i,t-s} + \beta_6 Y_i + \beta_7 Z_{c,t-s} + \varepsilon_{i,t} \quad (2)$$

[19] This two-step philosophy (i.e. first financial distressed dummy and then failure dummy) has been adopted in early studies of insurer failure, see e.g. McDonald (1993), and explored by subsequent studies (see Zhang and Nielson, 2015 for a review). This approach covers the whole process as insurance company having financial problems and then heading towards insolvency.

Table 2. Summary Statistics

	Unit	N	Mean	Std. Dev.	Min.	10th PCTL	Median	90th PCTL	Max.
Panel A: Failures									
Distressed	Dummy	29,581	0.021	0.14	0	0	0	0	1
Failure Event	Dummy	29,581	0.010	0.10	0	0	0	0	1
Panel B: Firm Specific Factors									
Technical Efficiency	1	29,581	0.77	0.19	0.075	0.49	0.82	0.98	1
ROE	1	29,581	0.095	0.18	-1.66	-0.057	0.096	0.28	0.88
ROA	1	29,371[a]	0.025	0.048	-0.26	-0.011	0.017	0.080	0.25
sdROE	1	29,581	0.13	0.10	0.0021	0.035	0.098	0.25	1.07
sdROA	1	29,449[a]	0.030	0.026	0.000017	0.0036	0.023	0.066	0.17
Real Total Assets	1,000	29,581	8,225,319	59,601,326	228.6	20,743	427,060	12,015,570	3,563,977,728
Growth	1	29,581	0.11	0.25	-0.55	-0.10	0.074	0.35	2.63
Leverage Ratio	1	29,581	0.28	0.22	0.0024	0.041	0.23	0.59	0.99
Life	Dummy	29,581	0.29	0.45	0	0	0	1	1
Composite	Dummy	29,581	0.17	0.38	0	0	0	1	1
Mutual	Dummy	29,581	0.16	0.37	0	0	0	1	1
Unaffiliated	Dummy	29,581	0.33	0.47	0	0	0	1	1
Panel C: Macroeconomic Factors									
Insurance Penetration	1	29,581	0.070	0.037	0.0044	0.021	0.069	0.12	0.19
Inflation	1	29,581	0.030	0.034	-0.15	0.0070	0.023	0.057	0.51
Real GDP Growth	1	29,581	0.021	0.032	-0.18	-0.014	0.021	0.058	0.18
Interest Rate	1	29,581	0.044	0.027	0.000100	0.019	0.040	0.071	0.32
Percentage Change in Interest Rate	1	29,581	-0.012	0.81	-0.98	-0.26	-0.047	0.19	41[b]

Notes: a. The smaller number of observations is due to missing values.

b. The extreme large percentage change of interest rate is because the denominator is close to 0.

Table 3. Failure events by year

Year	Number of firms with a failure event [a]	Number of firms without a failure	Failure Rate[b]
2003	29	2,042	1.40%
2004	23	1,981	1.15%
2005	16	1,591	1.00%
2006	16	2,101	0.76%
2007	23	2,834	0.81%
2008	33	2,837	1.15%
2009	42	3,080	1.35%
2010	51	3,576	1.41%
2011	33	3,570	0.92%
2012	25	3,431	0.72%
2013	13	2,234	0.58%
Total	304[a]	29,277	1.03%

Notes: a. One insurer may have multiple separate failure events over the sample period. Thus, the 304 events are from 146 firms. If we consider two years prior to the event and the event year as the distressful firm-years, the sample yields 614 distressful firm-year observations.
b. Failure rate equals the number of firms with a failure event in a year divided by total number of firms in that year.

Results

H1 Failure indicators of efficiency, volatility, and growth

Table 4 shows the marginal effects after logistic regressions with Equation (1). The result for efficiency (business volatility) can be seen by the negative (positive) coefficient between technical efficiency (standard deviation of ROE or ROA) and the dependent distressed dummy. The result for growth can be seen by the positive coefficient of linear and the negative coefficient of quadratic term in Table 4. The coefficient signs are in line with expectations. We see that insurers are more likely to fail if they are less technical efficient, more volatile, and exhibit a negative or extremely high growth. These conclusions are conditioning on other firm- and country-specific characters and robust to year- and market-fixed effects. The empirical evidence supports H1A-H1C.

Our finding in DEA technical efficiency-firm failure correlation is consistent with Siems's (1992), Wheelock and Wilson's (2000), and Luo's (2003) conclusions in the banking industry. The efficiency-failure correlation from the banking industry can thus also be confirmed for the insurance industry. [20] Our findings also complement

[20] We conduct additional tests with DEA cost efficiency, however, do not find a significant impact of cost efficiency on the probability of an insurer's failure. We explain this by the effect of input price fluctuation in the cost efficiency calculation. Such price fluctuation is short-term and exists both cross country wise and over years. We also notice that most DEA efficiency-business failure studies in banking and other industries use DEA technical efficiency instead of cost efficiency as the predictor to capture the management quality.

Kim et al.'s (1995) finding by showing that negative growth also indicates an unhealthy insurer.

Looking at the firm-specific control variables, we see that large insurers are unsurprisingly less likely to fail (confirming Cheng and Weiss, 2012). Mutual insurers are more stable than stock insurers. This is because mutual insurers usually operate more conservatively to maximize the interest of the policyholders and tend to be active in less risky business lines (see Lamm-Tennant and Starks, 1993). Life insurers are more vulnerable than nonlife and composite insurers during our sample period. This may reflect the low interest rate problems in many countries and the changing life product landscape (Berdin and Gründl, 2015). The legal structure and leverage ratio have little impact on the probability of business failure.

In respect of the market indicators, the insurer is more likely to fail if the insurance penetration is high, the interest rate is increasing, and the economic growth is low. These findings are within expectation in the sense that high insurance penetration indicates a matured insurance market in which the new business opportunity is limited and long-term client-insurer relationship is more valued thus the cash-flow underwriting cannot help to save an insurer from immediate failure. A similar story applies when the interest rate is fast increasing in the market indicating a liquidity shortage. Unsurprisingly, a low economic growth also harms the insurance industry. The inflation and the absolute level of interest rate are not the major drivers for insurer failure. The yearly dummies in Columns 4-6 show that insurers are more likely to be financial distressed in 2009 and 2010, which reflects the significant financial crisis impact on the insurance industry.

Comparing our results with Zhang and Nielson's (2015), both papers support that a strong economy reduces the likelihood of an insurer's failure. Moreover, neither paper finds evidence that the inflation adversely affects the insurers, which can be explained by that the insurers successfully capture the inflation in their pricing (Zhang and Nielson, 2015). Both papers also show that the probability of insurer failure depends on its domiciliary location through the market fixed effects, thus suggesting the importance of market environment on insurers' insolvency. Comparing our results with the banking studies, Demirguec-Kunt and Detragiache (1998) show that bank crises are more likely in countries with low GDP growth, high real interest rates, and high inflation rates. We show that the insurance industry is less sensitive to inflation and to the absolute value of interest rate but more sensitive to the sharp increase of interest rate. The difficulty in asset and liability management in insurance industry may explain such sensitivity to interest rate changes (Zhang and Nielson, 2015).

Table 4. Hypothesis 1

Specifications	Logistic Regressions			Logistic Regressions with Market-Year Fixed Effects			
Variables	Distressed (1 if any failure event in the year or the next two years)						
Technical	-0.0112***			Technical	-0.00143**		
Efficiency	(0.00329)			Efficiency	(0.000630)		
ROE		-0.00568**		ROE		-0.000974**	
		(0.00232)				(0.000464)	
ROA			-0.0266***	ROA			-0.00479**
			(0.00966)				(0.00220)
sdROE	0.0200***	0.0176***		sdROE	0.00276***	0.00249**	
	(0.00482)	(0.00507)			(0.00104)	(0.00108)	
sdROA			0.0672***	sdROA			0.0112**
			(0.0247)				(0.00559)
Growth	-0.0117***	-0.0110***	-0.0105***	Growth	-0.00235***	-0.00229***	-0.00233***
	(0.00225)	(0.00226)	(0.00228)		(0.000487)	(0.000499)	(0.000532)
Growth^2	0.0107***	0.0104***	0.00999***	Growth^2	0.00198***	0.00191***	0.00196***
	(0.00187)	(0.00188)	(0.00190)		(0.000373)	(0.000382)	(0.000408)
lnAsset	-0.00178***	-0.00186***	-0.00187***	lnAsset	-0.000339***	-0.000352***	-0.000373***
	(0.000314)	(0.000314)	(0.000310)		(6.71e-05)	(6.75e-05)	(7.24e-05)
Leverage Ratio	0.00160	-0.00103	-0.00392	Leverage Ratio	-0.000850	-0.00130*	-0.00174**
	(0.00333)	(0.00333)	(0.00372)		(0.000707)	(0.000710)	(0.000796)
Life	0.00722***	0.00400***	0.00436***	Life	0.00126***	0.000826***	0.000938***
	(0.00190)	(0.00154)	(0.00156)		(0.000360)	(0.000308)	(0.000329)
Composite	-0.00145	-0.00231	-0.00207	Composite	-0.000585*	-0.000712**	-0.000712**
	(0.00190)	(0.00181)	(0.00184)		(0.000336)	(0.000328)	(0.000354)
Mutual	-0.0145***	-0.0149***	-0.0151***	Mutual	-0.00266***	-0.00273***	-0.00296***
	(0.00113)	(0.00111)	(0.00112)		(0.000240)	(0.000240)	(0.000247)
Unaffiliated	-0.000798	-0.00123	-0.00132	Unaffiliated	0.000245	0.000210	0.000216
	(0.00135)	(0.00133)	(0.00132)		(0.000306)	(0.000310)	(0.000330)
Insurance	0.216***	0.223***	0.223***	Year03	-0.00120***	-0.00124***	-0.00132***
Penetration	(0.0145)	(0.0147)	(0.0147)		(0.000313)	(0.000315)	(0.000333)
Real GDP	-0.114***	-0.106***	-0.108***	Year04	-0.00143***	-0.00146***	-0.00158***
Growth	(0.0210)	(0.0212)	(0.0214)		(0.000283)	(0.000286)	(0.000301)
Interest Rate	0.0344	0.0511*	0.0501*	Year05	-0.00181***	-0.00183***	-0.00197***
	(0.0280)	(0.0280)	(0.0283)		(0.000236)	(0.000241)	(0.000251)
Percentage Change	0.000636*	0.000631*	0.000630*	Year06	-0.00148***	-0.00147***	-0.00156***
in Interest Rate	(0.000348)	(0.000348)	(0.000342)		(0.000269)	(0.000277)	(0.000292)
Inflation	-0.0441	-0.0426	-0.0387	Year07	-0.00145***	-0.00144***	-0.00153***
	(0.0338)	(0.0341)	(0.0338)		(0.000260)	(0.000267)	(0.000282)
				Year08	-0.00116***	-0.00121***	-0.00127***
					(0.000262)	(0.000263)	(0.000282)
				Year09	0.000869*	0.000852*	0.000876*
					(0.000447)	(0.000452)	(0.000478)
				Year11	-0.000822***	-0.000845***	-0.000870***
					(0.000280)	(0.000283)	(0.000304)
				Year12	-0.00123***	-0.00124***	-0.00132***
					(0.000258)	(0.000263)	(0.000280)
				Year13	-0.00208***	-0.00211***	-0.00224***
					(0.000236)	(0.000240)	(0.000251)
Market FE	No	No	No		Yes	Yes	Yes
Pseudo-R^2	0.091	0.090	0.088		0.170	0.170	0.169
Observations	29,581	29,581	29,307		29,581	29,581	29,307

Notes: We present the marginal effects of logistic regressions with robust standard errors provided in parentheses; *, **, *** denote the significant differences of the regression coefficients from 0 at the 10%, 5%, and 1% levels, respectively.

H2 M&A

Table 5 presents results from Equation (1) for two subsamples (i.e. M&A and other types of failures). Among all the distressed observations, there are 184 firm-years (127 firms) falling into the subsample of M&A (i.e., being acquired), and 430 firm-years (195 firms) falling into the subsample of other types of failures. In the M&A subsample, the coefficients for technical efficiency and profitability are insignificant, suggesting that insurers being acquired by other firms may possess technologies and reasonable profitability that are attractive to their acquirers. This result echoes the findings in Cummins and Rubio-Misas (2006) who document that M&A targets are not less efficient than non-M&A insurers. Wheelock and Wilson (2000) also found that M&A targets are not less technical efficient than firms that are not targets. Our evidence shows that only insurers exiting the market for reasons other than M&A exhibit inefficiency and other unfavorable financial performance characteristics. Cummins et al. (1999) explain such phenomenon in the life insurance industry as that acquirers may be motivated to select more efficient firms in an effort to acquire competencies in a changing market. Milbourn, Boot, and Thakor (1999) use a similar competency acquisition argument in their banking studies.

Another important difference between M&A targets and other types of failure firms pertains to the leverage ratio. Similar to Wheelock and Wilson (2000) for the banking industry, we document that all else being equal, the less capitalized (lower equity-asset ratio) an insurer is, the greater the probability that it will be acquired, suggesting the acquisition of some insurers just before they become insolvent. This finding is also in line with BarNiv and Hathorn's (1997) evidence that insurers are more likely to acquire financially troubled insurers. However, M&A targets and other types of failure insurers do have common problems, which explain why M&A should also be considered as a type of failure. These problems are the high business volatility, negative growth, small size, and poor economic environment. Our results support H2A and H2B.

Table 5. Hypothesis 2

Subsamples	Mergers and Acquisitions			Other Types of Failures		
Variables	Distressed (1 if any failure event in the year or the next two years)					
Technical Efficiency	0.00327			-0.0117***		
	(0.00199)			(0.00246)		
ROE		0.000566			-0.00593***	
		(0.00136)			(0.00166)	
ROA			0.00837			-0.0299***
			(0.00589)			(0.00690)
sdROE	0.00541**	0.00566**		0.0131***	0.0104***	
	(0.00247)	(0.00254)		(0.00372)	(0.00403)	
sdROA			0.0342***			0.0270
			(0.0131)			(0.0185)
Growth	-0.00576***	-0.00594***	-0.00569***	-0.00630***	-0.00561***	-0.00512***
	(0.00159)	(0.00165)	(0.00157)	(0.00169)	(0.00172)	(0.00175)
$Growth^2$	0.00290*	0.00286	0.00278*	0.00648***	0.00612***	0.00575***
	(0.00163)	(0.00175)	(0.00166)	(0.00139)	(0.00140)	(0.00143)
lnAsset	-0.000398**	-0.000376**	-0.000346**	-0.00120***	-0.00130***	-0.00133***
	(0.000176)	(0.000179)	(0.000169)	(0.000233)	(0.000235)	(0.000234)
Leverage Ratio	-0.00597***	-0.00541***	-0.00837***	0.00572**	0.00278	0.00249
	(0.00205)	(0.00209)	(0.00220)	(0.00232)	(0.00236)	(0.00266)
Life	-0.000742	5.00e-06	0.000182	0.00705***	0.00348***	0.00355***
	(0.000724)	(0.000702)	(0.000686)	(0.00158)	(0.00123)	(0.00125)
Composite	-0.00203***	-0.00183**	-0.00161**	0.000469	-0.000434	-0.000406
	(0.000712)	(0.000731)	(0.000719)	(0.00162)	(0.00153)	(0.00155)
Mutual	-0.00463***	-0.00461***	-0.00460***	-0.00874***	-0.00927***	-0.00940***
	(0.000589)	(0.000597)	(0.000593)	(0.000885)	(0.000858)	(0.000862)
Unaffiliated	-0.000746	-0.000666	-0.000772	1.51e-05	-0.000484	-0.000451
	(0.000741)	(0.000750)	(0.000709)	(0.00100)	(0.000985)	(0.000997)
Insurance Penetration	0.00146	0.00159	-0.000109	0.178***	0.188***	0.190***
	(0.00816)	(0.00808)	(0.00782)	(0.0118)	(0.0121)	(0.0121)
Real GDP Growth	-0.0560***	-0.0580***	-0.0562***	-0.0412**	-0.0329*	-0.0334*
	(0.00913)	(0.00926)	(0.00922)	(0.0170)	(0.0172)	(0.0175)
Interest Rate	0.0149	0.0109	0.00809	-0.00151	0.0156	0.0154
	(0.0135)	(0.0137)	(0.0134)	(0.0217)	(0.0222)	(0.0225)
Percentage Change in Interest Rate	-0.000581	-0.000526	-0.000353	0.000426*	0.000423*	0.000426*
	(0.000934)	(0.000928)	(0.000804)	(0.000223)	(0.000223)	(0.000222)
Inflation	-0.0377***	-0.0377***	-0.0364***	-0.00339	-0.000279	0.00374
	(0.0121)	(0.0119)	(0.0113)	(0.0276)	(0.0275)	(0.0272)
R^2	0.076	0.074	0.078	0.116	0.120	0.111
Observations	29,581	29,581	29,307	29,581	29,581	29,307

Notes: We present the marginal effects of logistic regressions with robust standard errors provided in parentheses; *, **, *** denote the significant differences of the regression coefficients from 0 at the 10%, 5%, and 1% levels, respectively.

H3 Time Aspects

Table 6 presents the marginal effects after logistic regressions with Equation (2). Three groups of specifications are for time lags equal to 0, 1, and 2. We see that the coefficient signs of our primary explanatory variables, *performance*, *business volatility*, and *growth*, are the same as those in Table 4, which again confirm our H1A-H1C. Moreover, the results show decreasing significant levels and decreasing magnitude of the marginal effects from t to t-2 for almost all explanatory variables,[21] which suggests that the earlier the time to the failure event, the less significant and the smaller magnitude of the precursors' impact. The results support H3. Zhang and Nielson (2015) show, as a byproduct, the macroeconomic factors with 2-year lags are less significant than factors with 1-year lag. Chen and Wong (2004) show the opposite in Asian P&C insurance industry, where 2-year lag indicators have a stronger impact on solvency than 1-year lag indicators; for Asian L&H insurers, there is no systemic trend. It remains an open question whether the models' ability to identify insolvency is substantially reduced as the length of time prior to insolvency increases (BarNiv and McDonald, 1992). And if this is true, what is the optimal lag that the researchers, managers, and regulators should use to predict the insolvency? Our results are more in line with Zhang and Nielson's (2015) and support the hypothesis that the warning signals from failure indicators become stronger as the time approaches to the failure event.

This finding is important to regulators and insurer managers because 1) it clarifies that the insurer failure is a gradual process rather than a sudden event; 2) in this case, regulators and managers can monitor the development of failure indicators from one period to the next, thus the decisions or actions can be supported by the dynamic evidence in addition to static ratios. In other words, it justifies the actions of regulators and managers when the failure indicators are getting worse.

[21] For firm growth, the impact with two-year lag is weaker than no lag scenario, however, slightly stronger than one-year lag scenario. All other coefficients support H3.

H4 Financial Crisis

Table 7 presents the results from Equation (2). The specifications include the crisis dummy (1 if the failure event occurs in 2008, 2009, or 2010) and its interactions with primary explanatory variables. The time lag s equals 0. For almost all specifications, the crisis dummy is positively correlated with the probability of an insurer failure, which suggests the 2008 financial crisis indeed has a significant and negative impact on insurance industry. If we look at the failure indicators identified earlier -- profitability, technical efficiency, growth, and business volatility -- their correlations with the failure probability remain unchanged. Their interactive terms with the crisis dummy are insignificant, suggesting our identified indicators are robust across crisis and non-crisis periods. The results support H4.

This results are important because the financial crisis had a significant negative impact on the insurance industry (see also the summary statistics from Table 3), where the crisis periods, 2003-2004 and 2008-2010, saw more percentage of failure events than the booming period. Demyanyk and Hasan (2010) argue that the financial crisis is the time that had the most failures in financial service firms. Eling and Schmeiser (2010) summarize the financial crisis' impact to insurance industry in terms of decreasing asset values due to investment activities or underwriting losses for certain lines of business. Therefore, it is critical to find the failure indicators work during both the financial crisis and non-crisis periods. Our selected indicators, namely technical efficiency and business volatility, are proved robust.

Table 6. Hypothesis 3

Variables	Failure Event (1 if any defined failure event occurs in the year)								
Specifications	No time lag: independent variables are at t			One year lag: independent variables are at t-1			Two years lag: independent variables are at t-2		
Technical Efficiency	-0.00812***			-0.00484***			-0.00158		
	(0.00162)			(0.00152)			(0.00123)		
ROE		-0.00350***			-0.00178**			-0.00121**	
		(0.00105)			(0.000758)			(0.000613)	
ROA			-0.0192***			-0.0118***			-0.00508**
			(0.00468)			(0.00377)			(0.00250)
sdROE	0.0109***	0.00937***		0.00553***	0.00501**		0.00236	0.00178	
	(0.00232)	(0.00251)		(0.00199)	(0.00214)		(0.00159)	(0.00175)	
sdROA			0.0361***			0.0189*			0.0119*
			(0.0123)			(0.00999)			(0.00649)
Growth	-0.00434***	-0.00390***	-0.00366***	-0.00147*	-0.00109	-0.00107	-0.00187**	-0.00171**	-0.00175**
	(0.00109)	(0.00112)	(0.00114)	(0.000845)	(0.000845)	(0.000841)	(0.000749)	(0.000716)	(0.000711)
$Growth^2$	0.00338***	0.00322***	0.00290***	0.00103	0.000887	0.000762	0.00109*	0.000962*	0.000952*
	(0.000893)	(0.000904)	(0.000924)	(0.000700)	(0.000693)	(0.000689)	(0.000581)	(0.000558)	(0.000545)
lnAsset	-0.000667***	-0.000742***	-0.000722***	-0.000366***	-0.000412***	-0.000407***	-0.000299***	-0.000302***	-0.000294***
	(0.000158)	(0.000164)	(0.000163)	(0.000132)	(0.000137)	(0.000135)	(0.000100)	(0.000102)	(9.94e-05)
Leverage Ratio	0.00425***	0.00230	0.000638	0.00360***	0.00246**	0.00176	0.00182**	0.00143	0.000951
	(0.00147)	(0.00154)	(0.00177)	(0.00115)	(0.00115)	(0.00127)	(0.000912)	(0.000885)	(0.000940)
Life	0.00654***	0.00362***	0.00397***	0.00476***	0.00285***	0.00307***	0.00313***	0.00238***	0.00251***
	(0.00122)	(0.000886)	(0.000906)	(0.00115)	(0.000791)	(0.000814)	(0.00105)	(0.000791)	(0.000826)
Composite	8.07e-05	-0.000529	-0.000469	-0.000149	-0.000455	-0.000415	0.00202	0.00181	0.00192
	(0.00111)	(0.00104)	(0.00105)	(0.00100)	(0.000940)	(0.000934)	(0.00127)	(0.00120)	(0.00124)
Mutual	-0.00485***	-0.00528***	-0.00534***	-0.00322***	-0.00346***	-0.00346***	-0.00245***	-0.00249***	-0.00247***
	(0.000620)	(0.000620)	(0.000624)	(0.000531)	(0.000555)	(0.000560)	(0.000422)	(0.000435)	(0.000428)
Unaffiliated	-0.000102	-0.000438	-0.000331	0.000890	0.000644	0.000718	0.00118**	0.00111*	0.00117**
	(0.000648)	(0.000645)	(0.000656)	(0.000626)	(0.000606)	(0.000600)	(0.000600)	(0.000572)	(0.000561)
Insurance Penetration	0.113***	0.121***	0.124***	0.0702***	0.0755***	0.0758***	0.0409***	0.0420***	0.0412***
	(0.00960)	(0.0102)	(0.0103)	(0.00847)	(0.00913)	(0.00921)	(0.00825)	(0.00847)	(0.00851)
Real GDP Growth	-0.0327***	-0.0282**	-0.0285**	-0.0279***	-0.0256***	-0.0256***	0.00350	0.00456	0.00458
	(0.0112)	(0.0115)	(0.0117)	(0.00776)	(0.00798)	(0.00789)	(0.00708)	(0.00708)	(0.00694)
Interest Rate	-0.000845	0.0106	0.0105	-0.00839	-0.00204	-0.000586	-0.00705	-0.00359	-0.00331
	(0.0143)	(0.0150)	(0.0153)	(0.0129)	(0.0140)	(0.0140)	(0.00970)	(0.0101)	(0.00968)
Percentage Change in	-0.000316	-0.000337	-0.000341	-1.25e-05	-1.83e-05	-9.65e-06	-9.87e-06	-1.03e-05	-1.19e-05
Interest Rate	(0.000779)	(0.000819)	(0.000850)	(0.000120)	(0.000115)	(0.000106)	(3.78e-05)	(3.69e-05)	(3.68e-05)
Inflation	-0.00995	-0.00716	-0.00573	-0.000541	0.00108	0.000244	-0.00168	-0.000501	-0.00140
	(0.0173)	(0.0181)	(0.0181)	(0.0119)	(0.0127)	(0.0127)	(0.00883)	(0.00837)	(0.00828)
R^2	0.159	0.151	0.151	0.157	0.149	0.153	0.165	0.165	0.170
Observations	29,581	29,581	29,307	22,826	22,826	22,629	18,812	18,812	18,665

Notes: We present the marginal effects of logistic regressions with robust standard errors provided in parentheses; *, **, *** denote the significant differences of the regression coefficients from 0 at the 10%, 5%, and 1% levels, respectively.

Table 7. Hypothesis 4

Variables	Failure Event (1 if any defined failure event occurs in the year)								
Crisis	0.00228	0.00153**	0.00166**	0.00255**	0.00254**	0.00226**	0.00279*	0.00297*	0.00296*
	(0.00233)	(0.000737)	(0.000758)	(0.00115)	(0.00115)	(0.00111)	(0.00158)	(0.00165)	(0.00164)
Technical Efficiency	-0.00782***			-0.00808***			-0.00806***		
	(0.00189)			(0.00160)			(0.00159)		
ROE		-0.00322**			-0.00344***			-0.00342***	
		(0.00138)			(0.00103)			(0.00103)	
ROA			-0.0154***			-0.0190***			-0.0188***
			(0.00550)			(0.00457)			(0.00457)
sdROE[a]	0.0108***	0.00934***		0.0127***	0.0116***		0.0108***	0.00929***	
	(0.00230)	(0.00251)		(0.00282)	(0.00291)		(0.00229)	(0.00248)	
sdROA[a]			0.0352***			0.0427***			0.0356***
			(0.0123)			(0.0136)			(0.0122)
Growth	-0.00402***	-0.00359***	-0.00332***	-0.00404***	-0.00361***	-0.00334***	-0.00483***	-0.00461***	-0.00435***
	(0.00108)	(0.00113)	(0.00114)	(0.00108)	(0.00112)	(0.00114)	(0.00143)	(0.00150)	(0.00154)
$Growth^2$	0.00315***	0.00299***	0.00266***	0.00313***	0.00296***	0.00266***	0.00345***	0.00345***	0.00313***
	(0.000891)	(0.000908)	(0.000929)	(0.000888)	(0.000903)	(0.000927)	(0.00107)	(0.00109)	(0.00113)
Technical Efficiency *crisis	-0.000731								
	(0.00249)								
ROE*crisis		-0.000314							
		(0.00175)							
ROA*crisis			-0.00672						
			(0.00728)						
sdROE*crisis				-0.00483	-0.00563				
				(0.00435)	(0.00440)				
sdROA*crisis						-0.0163			
						(0.0170)			
Growth*crisis							0.00230	0.00275	0.00275
							(0.00209)	(0.00218)	(0.00221)
$Growth^2$*crisis							-8.04e-05	-0.000473	-0.000314
							(0.00202)	(0.00200)	(0.00213)
Firm and country specific control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.161	0.153	0.153	0.161	0.153	0.153	0.161	0.153	0.153
Observations	29,581	29,581	29,307	29,581	29,581	29,307	29,581	29,581	29,307

Notes: We present the marginal effects of logistic regressions with robust standard errors provided in parentheses; *, **, *** denote the significant differences of the regression coefficients from 0 at the 10%, 5%, and 1% levels, respectively. a. There is potential look-ahead bias when using all-year standard deviations to test the crisis hypothesis, since people would not know the results after crisis when they were in the crisis. However, considering the significant costs to use the moving standard deviation (discussed in detail in the robustness test) and considering the consistency with other hypotheses, we decide to use the all-year standard deviations in our core models and conduct a robustness tests with the 5-year moving standard deviations, the results of which support our conclusions.

Robustness Tests

We conducted the following five tests to check the robustness of our conclusions. The results are listed in Appendix 2.1-2.5. All results are consistent with our conclusions, unless otherwise stated in this section.

First, we introduce a new technique, rare events logistic regression, into the business failure models. One common problem in the business failure studies is that the failure events are rare compared to the non-failure observations. This is also true in our sample, considering the failure events (distressed observations) only take 1.0% (2.1%) of our sample. The literature has used, for example, matched pair sampling to address this issue, however, which was less than optimal (see Balcaen and Ooghe, 2006, for a review). The rare events logistic regressions were developed by King and Zeng (2001). The application of this innovative approach enables us to correct the coefficient bias and reduces the tendency of underestimates the probability of an event in standard logistic regressions due to rare events (King and Zeng, 2001). This technique may serve as a new test for future application of business failure models.

Second, we use the rolling window five-year moving standard deviations of ROEs and ROAs as the measurement of business volatility (risk) to replace the standard deviations of all available years. The advantage of moving standard deviations is that they capture the most recent and thus the most relevant profit volatility information. However, the tradeoff is that we have to omit all observations from 2002 to 2006, and exclude the observations if there is any ROE or ROA missing in the most recent five years. Moreover, the smaller number of observation also decreases the reliability of standard deviations. Third, we use the real growth of net premiums written instead of real asset growth for all model specifications. Fourth, instead of the 1 and 99 percentile trimming, we trim the key ratios at 0.5 and 99.5 percentiles and at 2 and 98 percentiles.

Fifth, we separately use the subsamples of life and nonlife insurers and re-conduct the regressions with Equation (1). For both life and nonlife insurers, the DEA technical efficiency (business volatility) is negatively (positively) correlated with the likelihood of firm failure, suggesting the two failure indicators of efficiency and volatility are robust across life and nonlife insurers. However, for life insurers, the high growth seems always helpful to reduce the probability of failure (i.e. we find a negative linear link rather than a non-linear one). This is probably because the claim payment of life insurance is usually many years later than the premium payment, and thus the cash-flow underwriting can easily save the firm in the short term without the immediate effect of claims. Moreover, failed life insurers are not necessarily less profitable than survivors and there are differences in the impact of macroeconomic factors on life and nonlife insurers. In general, we believe that life insurance is more heterogeneous than other kinds of insurance, because there are more country-specific regulations and cultural influences in life insurance (Chui and Kwok, 2009; Biener, Eling, and Jia, 2015).

Sixth, we use the combined ratio as alternative performance indicator and the standard deviation of combined ratios over years as alternative volatility measure. The results confirm Hypotheses 1, 2, and 4. Regarding Hypothesis 3, the results do not show weakened impact of combined ratio and its standard deviation over time, but the impacts are at similar levels for estimations of no time lag, one-year lag, and two-year lags. This inconsistency may be explained by that the combined ratio only capturing the underwriting performance and its volatility but not the investment side of the insurance business. In contrast, ROE and ROA capture the comprehensive operation of an insurance company.

Discussion

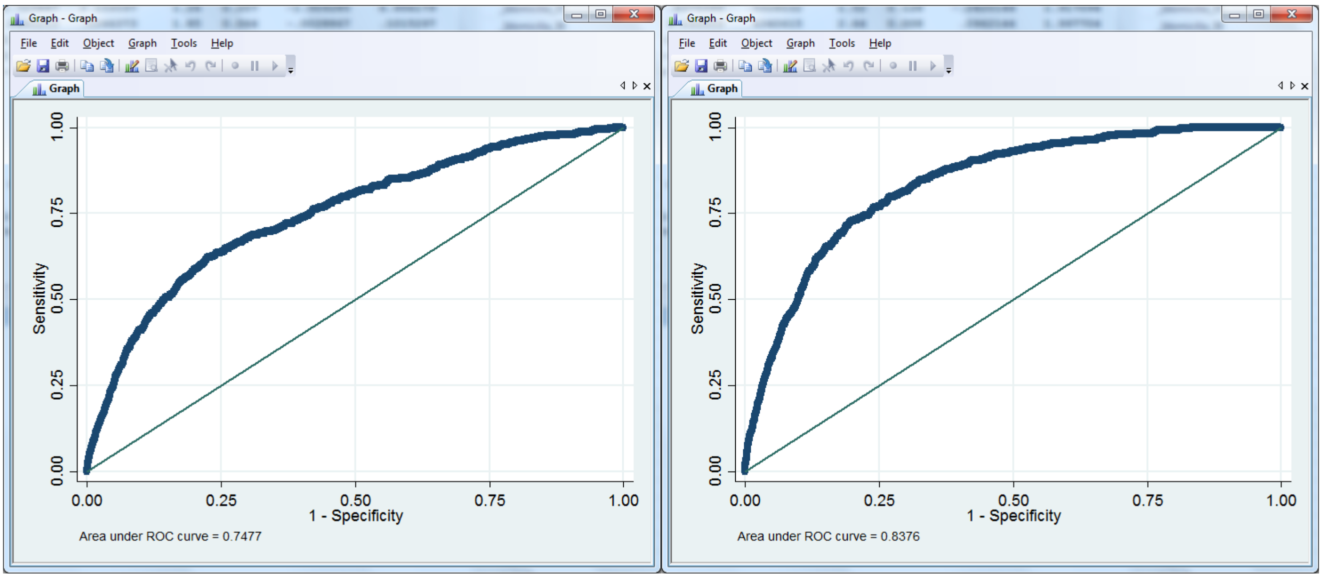
The predictive power of a business failure model is one focus in insolvency prediction studies (see BarNiv and McDonald, 1992; Zhang and Nielson, 2015 for reviews). It was highlighted very early that the criteria for selecting the cutoff points and the base year prior to insolvency have a substantial effect on the failure prediction (BarNiv and McDonald, 1992). We thus perform the Receiver Operating Characteristic (ROC) analyses for Equation (1), which reflects the Type I and Type II error trade-off for a logistic prediction model at different cutoff point. The results are shown in Table 8 and Figure 1. The predictability of our model is comparable to Chen and Wong (2004) and Cheng and Weiss (2012), but slightly lower than Zhang and Nielson (2015). The lower predictability is because of two reasons. (1) Our studies in the cross-country setup embed more market-specific information that we are not able to control. We see that the market fixed-effects model improves model predictability from 0.75 to 0.84 in respect of the area under ROC curve. The tradeoff between Type I and Type II errors are significantly improved by including market fixed effects, indicating that although international uniformed standard may have some advantages, the country- specific differences are also critical. This observation echoes the findings in Pasiouras and Gaganis (2013), who highlight the importance of country-specific institutional factors in predicting insolvencies. A similar approach has been justified by Cummins et al. (1995). (2) There are some firm- and/or state-specific ratios or other factors that are available only for the U.S. market, but not for the rest of the world, thus which are not included in our models (e.g. RBC ratio, industry combined ratio).

We compare the predictability of our model in Equation (1) with "classical models," in which we remove the technical efficiency, business volatility, and the square term of growth; and with "solvency ratio model," which only contains solvency ratio (defined as net premiums written divided by total capital and surplus) as the independent variable. The ROC analyses show that the predictive power of our model is 0.752, measured by the area under ROC curve, which is significantly larger than the classical model (0.743) and solvency ratio model (0.729).[22]

Table 8. Tradeoff between Type I and Type II Errors

Type II error rate	Type I error rate					
Fixed Effects	No			Market/Year		
Performance Indicator	TE	ROE	ROA	TE	ROE	ROA
5%	78%	78%	78%	55%	57%	55%
10%	67%	68%	69%	43%	43%	43%
15%	57%	58%	58%	32%	32%	33%
20%	47%	48%	48%	29%	28%	28%
25%	41%	41%	41%	23%	23%	22%
30%	32%	33%	34%	17%	18%	18%
ROC Area	0.752	0.750	0.748	0.840	0.840	0.839
Standard Error of ROC Area	0.010	0.011	0.011	0.007	0.007	0.007
Pseudo-R-Square	0.091	0.090	0.088	0.173	0.172	0.172
Observations	29,581	29,581	29,307	29,581	29,581	29,307

Figure 1. ROC Curve



Notes: The left chart shows ROC curve for Equation (1) and the right chart shows ROC curve with market and year fixed effects after respective logistic regressions. Any point on the ROC curve indicates how the probability of correctly predicting a 1 (y-axis) is traded off against the probability of correctly predicting a 0 (x-axis).

It is also worth discussing whether the pursuit of high predictability is the right target for the insurer failure models. A high predictability is good, but comes at the cost of

[22] Chi-squire statistic 22.94 with p-value 0.00 to reject the H0 that the three areas are equal to each other.

too many factors, which may prevent practical applications. We encourage focusing on the ineffectiveness of current solvency regulatory system, and identify indicators that may be overlooked by the current system, thus make a marginal contribution to the system. In particular, we try to find some general indicators with a worldwide application, instead of country-specific indicators. Therefore, targeting at a high R^2 by adding more control variables may not be helpful for regulators.

Empirical studies have acknowledged that insurers shall respond to the regulation in-force. For example, the implementation of RBC system indeed increases the capital adequacy and the financial health of the insurance industry (Cummins et al., 1995; Cheng and Weiss, 2012). Introducing new regulatory factors is expected to have the same effects. The insurer may therefore have an additional incentive to improve its management quality and efficiency. Particularly, since the technical efficiency is a relative measurement of firm productivity, it motivates insurers to learn from their peers and to explore the best technology available in the market, thus this regulatory standard can have strong promotion effects on technology progress including both the risk management and the operation management. We, therefore, recommend to regulators and managers that in addition to the risk-based capital requirements, the technical efficiency and long-term business volatility must also be considered and accounted in one way or another, which has also a significant impact on an insurer's failure or success. In addition, firm growth is an important indicator of failures.

Conclusion

We use an international dataset capturing the largest number of failure events ever analyzed in the insurance literature and covering a long time period across crisis and non-crisis years. This research is also original in that we introduce the business volatility measure into the insurer failure assessment and test the robustness of business failure models with the new technique of rare event logistic regression.

Based on our empirical results, we propose three failure indicators, which are robust across countries and regions, and across crisis and non-crisis periods. We document the negative correlation between DEA technical efficiency and the probability of an insurer failure. The business volatility impact on failure probability suggests that risk should play an important role in the regulatory framework, which echoes the recent trend of regulatory development, i.e., from premium-based to risk-based standards. We also reshape the growth impact on failure probability by showing a U-shaped nonlinear relationship, which suggests that both negative growth and extremely high growth are dangerous and unsustainable. These results might be very useful for regulators, analysts, insurance managers and academics interested in studying insurance failures.

Our findings also have other important business and regulatory implications. The results show that the insurer failure is a gradual process, not a sudden event. Regulators and managers can thus monitor the development of failure indicators over time in order to identify early warning signals and respond accordingly. It demonstrates the possibilities to continuously monitor whether the actions work by observing the trends of key failure indicators. These trends should also be reliable across countries and financial crises.

Insurers leave the market for all kinds of reasons, among which are poor management, macroeconomic environment, and risky operations. Our statistical approach helps to identify potential failure indicators. However, the use of such a model to diagnose and solve the problems of each insurer is limited. The case study-qualitative empirical approach (O'Brien, 2006; Bluhm, Harman, Lee, and Mitchell, 2011) may provide an alternative perspective to analyze insurer insolvency other than the failure prediction models. The case study can dive into the deeper aspects of each failure case. We thus believe that a combination of quantitative failure model and qualitative case study analyses can provide the best outcomes in insurer failure analysis.

Appendix 1

DEA process to derive technical efficiency

The DEA model applied allows us to compute the Shephard (1970) input-oriented distance functions, which are reported in terms of their reciprocal Farrell (1957) input efficiency measures. The resulting measure of technical efficiency is the representation of the firm distance to the best-practice efficient frontier and bounded between 0 and 1.

The inputs and outputs used to obtain the technical efficiency scores follow common practice of DEA analyses in insurance (see Eling and Luhnen, 2010; Cummins and Weiss, 2013 for reviews). We use the three input quantities labor (i.e., approximate number of employees), equity capital (i.e., capital and surplus, in real values at 2013), and debt capital (i.e., total liabilities, in real values at 2013). Labor is approximated by operating expenses divided by the annual wage for the insurance sector in country-years. We use annual wages (in real values at 2013) for the insurance sector in country-years as the price for labor. The wage information is obtained from the ILO Main Statistics and October Inquiry database.[23] The input of business services and materials is integrated into the input of labor, which is a common practice in insurance DEA analyses, due to data limitation.

Two output quantities are used, loss and total invested assets (all in real values at 2013). With respect to loss quantity, we use net benefits paid plus net reserve changes for life insurers and smoothed loss (Cummins and Xie, 2008) for nonlife and composite insurers. The benefits paid plus reserve changes are suitable for life insurance, since reserves reflect the accumulation of unpaid cash values (Cummins and Weiss, 2013). The smoothed loss is particularly suitable to measure the risk bearing output of nonlife insurance, because the actual loss of nonlife insurance is highly volatile over years. The two outputs represent insurers' two major functions: risk pooling and financial intermediation. Premiums instead of benefits are sometimes applied as an output. The rationale for using premiums is that they represent the business volume generated by insurers. However, Yuengert (1993) points out that the premiums represent price times the quantity of outputs, instead of output quantity only.

[23] To fill missing wages, we adjust the nearest available data point of ILO annual wage to the previous or later years by using changes in general price levels represented by the consumer price indices (CPI).

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