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Document de Travail
Working Paper
2020-15

George Overton
Olivier de Bandt

EconomiX - UMR7235
Université Paris Nanterre
Bâtiment G - Maurice Allais, 200, Avenue de la République
92001 Nanterre cedex

UMR 7235

Email : secretariat@economix.fr

Why do insurers fail? A comparison of life and non-life insolvencies using a new international database *

Olivier de Bandt[1] and George Overton[1]

[1]*EconomiX, CNRS, Paris-Nanterre University*

May 7, 2020

Abstract

Plantin and Rochet (2007) document how insurers often engage in risk-shifting years before the materialization of a failure. This paper empirically examines this claim by testing the mechanisms of insurance insolvency, using a first-of-its-kind international database assembled by the authors which merges data on balance sheet and income statements together with information on impairments over the last 30 years. Employing different fixed effects logistic specifications and parametric survival models, the paper presents evidence, on top of the role of profitability as a leading indicator of failures, of the intrinsic asymmetries between the life and non-life insurance sectors. In the life sector, asset mix is highly significant in predicting an impairment, while operating efficiency plays no role. In the non-life sector, the opposite proves true.

Keywords: Insolvency Prediction, Insurance Default, Financial Crises

JEL Codes: G22, G01, G11

*Authors' emails: goverton2@gmail.com, odebandt@gmail.com. We thank Ed Toy at the National Association of Insurance Commissioners, Stefan Claus at the Bank of England and Keisuke Wagatsuma at the Financial Services Agency for their help in accessing data. All views expressed here belong solely to the authors.

1 Introduction

As highlighted in Plantin and Rochet (2007), the failure of insurance companies often takes place due to bad decision making—ranging from negligent to fraudulent—several years preceding an actual failure. This issue, which stems from the so-called "inversion of the production cycle" in insurance (whereby firms collect premiums in advance of the realization of risks and the disbursement of funds to customers), is problematic from a supervisory point of view. Indeed, when insurers do fail, insolvency is quite costly; the resolution of an insurance company is three to five times more expensive than that of other financial institutions (Grace, Klein, and Phillips, 2003). Can we effectively identify doomed insurers before it is too late?

While historically less exposed to systemic crises, it was an insurer (AIG) who was at the center of a $200 billion rescue package from the United States government in the immediate aftermath of the 2007-2008 financial crisis. Additionally, Dutch insurer Aegon required a $3.7 billion bailout from its government during the same period, while a dangerous wave of life insurance failures helped magnify financial shocks in Japan following the Lost Decade. Today, the question of insurance insolvency has regained relevance as undertakings face increased pressure and uncertainty in the low (or negative) interest rate environment. The International Association of Insurance Supervisors (IAIS) has continued its pursuit of a formula for the identification of Globally Systemically Important Insurers (G-SIIs); new methodologies were released in 2013 and 2016 (IAIS, 2016). Further, the emergence of new threats from climate change, which is projected to increase the frequency and severity of extreme weather events[1], has captured the attention of insurers and policymakers within the financial system.

Still, the debate surrounding the systemic contribution of insurance remains open. Harrington (2009) emphasizes the lack of systemic footprint in traditional insurance activities, while Mühlnickel and Weiß (2015) demonstrates the systemic significance of mergers, non-traditional financing activities and business line diversification. While insurance liabilities are less "runnable" compared with banking, insurance risks do nonetheless exhibit some correlation with economic cycles. In the property and casualty sector, risk protection decreases during recessions, potentially driving up claims from policyholders. In the life insurance sector, surrenders are affected by the macroeconomic environment (Geneva Association, 2012), increasing during adverse economic conditions (the emergency fund theory relates surrenders

[1] Several insurance defaults have been associated with natural catastrophes, such as Hurricane Andrew in the US in 1992.

to higher unemployment). In addition, upward shocks to long-term interest rates lead policyholders to look for higher alternative returns at times where insurers themselves face capital losses on their fixed income portfolios. In the presence of such behavior, microprudential intervention becomes more important to held stymie contagion effects from spreading across firms.

In 2018, the European Insurance and Occupational Pensions Authority (EIOPA) published a study (EIOPA (2018)) which utilizes questionnaire survey responses from 31 national supervisory authorities to understand the presumed cause of 180 cases of fragility or "near-misses" in different European jurisdictions. The mostly qualitative work documents how, in the non-life sector, the top declared risks involve the evaluation of technical provisions, corporate governance and management. In the life sector, the top three reported risks are management, investment risk and market risk—in line with the literature's emphasis on the linkages between life insurance and financial markets. Most events occur during or after the financial crisis of 2007-2008. Only 48% of cases represent failed firms, including firms that have been partially resolved.

An important contribution of the paper is the construction of an international database of insurance failures, to which we apply several empirical strategies. Our database is bigger than those produced by the insurance insolvency prediction literature. EIOPA (ibid.) contains 180 EU cases from 1999-2016, while Leverty and Grace (2012) contains 256 U.S. cases from 1989-2000. In comparison, our database includes 437 impairment cases in five big countries. Eling and Jia (2018) use a large insolvency database composed of both life and non-life insurers, but concentrates on Europe and includes several small countries with specific insurance systems (Denmark, Ireland, etc). We use our database to test a certain number of hypotheses on how these events take place, which helps predict future insurance failures on the basis of available financial data.

In the paper, we investigate several dynamics and intuitions provided by previous literature, including some case studies, regarding the relative importance of the asset and liability sides of an insurer's balance sheet for the sake of forecasting its default—and how this changes across sectors. We additionally contribute to the evaluation of the potential impact of supervision, in the sense that we measure the true predictive power of the indicators collected by supervisors vis-à-vis future defaults. We find evidence that while such indicators matter, their predictive power changes depending on the nature of the business at hand.

In addition to the construction of our database, the second major contribution of the paper to the literature is to confirm practitioners' view—which had never been clearly verified by the academic literature for failure prediction in insurance—that life and non-life sectors behave very differently, with portfolio choice having an important impact for life and operational efficiency in non-life. We are able to better highlight these differences by separating analysis by sector using a single, common database. Further, we find that macroeconomic variables do not play a very significant role beyond financial indicators, with the exception of interest rates, where an increase in interest rate negatively impacts life insurance stability over the 1985-2016 period in question.

Finally, we acknowledge that many different types of behavior may explain insolvencies. Nonetheless, investors and supervisors alike must condition their decision making on available financial reporting. Seminal academic work such as Altman (1968) and Shumway (2001) precisely attempt to shed light on how simple financial ratios can be used by such parties. Applying this empirical approach to insurance, we seek to use historical data to help understand the following questions:

- While the years directly preceding an insurance impairment will see lower net income levels, do losses occur suddenly through a huge, sudden spike in claims, or instead increase progressively?

- While an increase in premiums by an insurer may be a sign of better performance, increasing market shares may also reveal underpricing or "gambling for resurrection" for a low profitability firm. Do failing firms experience a spike in premiums prior to collapse?

- What is the relationship between reinsurance ceded and the stability of equity/own funds? Without knowing detailed information about reinsurance treaties, do ceded premiums lower the volatility of net income relative to written premiums?

- Governance problems within insurance firms, often mentioned as a major source of insolvencies, may appear in different ways: either involuntary underestimation of technical provisions and a late re-assessment of the situation, or high management costs and a high wage bill. These two different behaviors would materialize differently as the latter one would take place over a longer period, while the former one would be identified just before the crisis. Which case appears more prevalent?

- What is the relative weight of macroeconomic determinants in insurance failures, as opposed to purely idiosyncratic, firm-level characteristics?

The remainder of the paper is organized as follows: Section 2 reviews the existing literature, section 3 presents the novel dataset and some summary statistics, and section 4 outlines our expected results. Section 5 details our econometric approaches and expected results. Sections 6 reports our results and robustness checks, and 7 concludes.

2 Review of the literature

The early insurance insolvency literature dealt mainly with the predictive performance of regulatory ratios and ratings. Ambrose and Seward (1988) use a multivariate linear discriminant analysis approach in which A.M. Best ratings are combined with information given by financial statements. The authors find significant predictive power in the premiums-to-surplus ratio, the loss ratio and time spent settling claims; the expense ratio, return on equity (or, in some jurisdictions, "surplus" for insurers) and return on assets were not significant predictors. Cummins, Harrington, and Klein (1995) document the inadequacy of NAIC's RBC ratios, finding predictive power "very low" without additional regressors. Cummins, Grace, and Phillips (1999) later compare the accuracy of the next generation of indicators—NAIC's so-called Financial Analysis and Surveillance Tracking (FAST) audit ratio system—with the classic risk-based capital (RBC) prudential measures. The authors find that while the "FAST" system dominates RBC ratios, predictive power remains low overall without additional inputs.

The more recent literature on insurance insolvency is related to four considerations: (i) efficient management and corporate governance, (ii) industrial organization, (iii) the macroeconomic environment, risk appetite and portfolio choices, and (iv) profitability. We review the literature in each area.

First, different measures of "efficiency" or management quality have been proposed by academic studies. Leadbetter and Dibra (2008) show that management quality and risk appetite have been responsible for Canadian property-casualty insolvencies, although the authors posit that an adverse macroeconomic environment is often what pushes a company over the edge. Leverty and Grace (2010) examine two methods for measuring output in property-liability insurer efficiency studies. The authors find that efficient "value-added approach" firms are less likely to go insolvent, while firms characterized as efficient by the "flow" approach are generally more likely to fail. In a later study, Leverty and Grace (2012) find the managerial ability of CEOs to be inversely related to the amount of time a firm spends in distress, the likelihood of a firm's failure and the cost of failure. Zhang and

Nielson (2015) incorporate state-specific factors on a U.S. database of property-casualty failures, finding that insurers with low business-line diversification, fewer failed Insurance Regulatory Information System ratio tests and membership in a larger group are less likely to become insolvent. Most recently, Eling and Jia (2018) show how "technical efficiency" is associated with financial health across the entire European sector.

Second, higher market concentration has a demonstrated link with firm failure, particularly in the non-life industry. Browne and Hoyt (1995) find non-life insolvency to be significantly tied to market concentration—more insurers leads to slimmer margins and more failures—and further estimate the industry-wide combined ratio to have predictive power for insolvency. EIOPA (2018) documents a similar trend: most detections of non-life insolvency are small firms with low market share, which, the authors point out, mirrors the structure of the EU insurance market. Lastly, Cummins, Rubio-Misas, and Vencappa (2017) shows how increased competition throughout the EU pushes firms towards greater efficiency, improving the financial health of the sector.

Third, the health of insurance companies often fluctuates with the macroeconomic environment. The life insurance industry is widely understood to exhibit more interconnection with the macroeconomy, depending on the degree of liquidity of liabilities and the subsequent financial nature of the business. 37% of life insurers in EIOPA's 17-year study experienced their failure or near-miss in the 2007-2008 window (EIOPA, 2018). Browne, Carson, and Hoyt (1999) shows how life insurers are sensitive to long-term interest rates, personal income, unemployment, stock markets and also the number of insurers present in the industry. In addition to firm size, Chen and Wong (2004) finds asset returns to be a high-ranking factor explaining insurance company distress in both life and non-life sectors of the Asian insurance market. Still, the life sector is not the only one exposed to the macroeconomy; Lee and Urrutia (1996) finds that higher shares of fixed-income investments significantly decrease the probability of failure in the non-life industry.

Unlike property-casualty insurance, however, life policyholders may be able to withdraw funds to invest elsewhere. Kim (2005) explains surrender as a function of several economic variables, finding that increases in the interest rate often lead to disintermediation.[2] Unemployment, GDP growth rates, seasonal effects and policy age appear important as well. Cheng and Weiss (2012) analyse the macroeconomic factors involved in non-life insolvency, ultimately reaffirming the relevance of interest rate changes and market concentration. Rus-

[2]Interestingly, in recent years, policyholders' sensitivty to the interest rate has seemed to diminish, implying substantial inertia in savers' behavior.

sell et al. (2013) also tests the sensitivity of life insurance surrender to macroeconomic variables, finding a positive correlation to interest rate levels and a negative relation with income levels and interest rate spreads.

Fourth and finally, the link between profitability and failure has been addressed by several authors in the literature. Eling and Jia (2018) show how, while ROE is weakly associated with health, its volatility positively correlates with the probability of failure. Bernard et al. (2016) use internal firm-level data from the French Prudential Supervision Authority to derive leading indicators of insurance distress. Although the econometric analysis yields few significant results, low levels of reserves and weak profitability appear to precede financial vulnerability.

3 Data & Descriptive Statistics

After explaining how the data were assembled to create a new international database on insurance impairments, we provide a few summary statistics.

3.1 Constructing an international database of insurance impairments

The data for this study has been gathered from a multitude of sources, including guaranty fund associations,[3] the National Association of Insurance Commissioners, the UK Prudential Regulation Authority (PRA), internal French Prudential Supervision Authority (ACPR) data, AM Best and Bloomberg. The failure events or, as we term them, "impairments" we have collected are strictly defined but include different types of events, ranging from the intervention of a local supervisor leading to the suspension of the insurance licence (which may only be temporary with a subsequent recovery) to routine liquidations and large-scale failures such as AIG. Simple profit warnings or supervisory interventions without actions limiting activity are not considered as impairments.

Indeed, there are different ways to define an insurance company failure from an economic point of view. The scope of financial troubles leading to a failure could range from market warnings, substantial losses, partial suspension of activities or withdrawal of agreement by the supervisor, with liquidation being the most extreme consequence. It is important to note that, as we have defined an impairment, some impaired firms in our database may

[3] Examples include the National Organization of Life and Health Insurance Guaranty Assocations (NOLGHA), Property and Casualty Insurance Compensation Corporation (PACICC), Assuris and Protektor.

eventually return to financial health, although in practice few do, and those who survive only do so thanks to a major restructuring or large-scale government bailout. We consider this definition helpful from a supervisory point of view, as it allows us to predict (and thus, hopefully, help prevent) any case that was destabilizing enough to prompt intervention, as opposed to just those cases which fit a specific legal definition (which changes considerably across jurisdictions). Indeed, only considering liquidating firms would ignore cases of firms which were acquired following a supervisory intervention.

Following collection from the sources mentioned above purely regarding the impairments, our database contained 1,607 cases across life and non-life sectors. These company-events are matched with available historical financial data for these companies. The latter data are also used to define a control sample of companies.

In order to be as comprehensive as possible, we used standard sources for historical financial data. This includes SNL Market Intelligence, the Prudential Regulation Authority (Bank of England) for UK cases, the Financial Services Agency for Japanese cases and the French Prudential Supervision Resolution Authority for French cases. We do not, however, have historical balance sheet and income statement data for all of the 1,000+ identified cases of impairments. Taking the intersection of these impairments with the available series of historical financial data, we were left with 495 "impairments" out of 8,893 total companies in our database. We next dropped countries in our control group (meaning, healthy companies) for which we did not have any impairments. This left us with a sample containing failures and non-failures for the US, France, the UK, Japan and the Netherlands.

Finally, we cleaned the database of abnormal values, notably by dropping companies below $1 million in total assets and trimming values outside of the 1.5 and 98.5 percentiles, similar to Eling and Jia (2018), and Cummins, Harrington, and Klein (1995), to correct for noise in our data which yielded economically implausible values in key ratios. The dataset remains quite extensive with well over 50,000 (company-year) observations. Our final database contains 287 property and casualty (PC) impairments and 150 life and health (LH) failures, totaling 437 across both, although we must note that the number of impairment cases (i.e. impaired companies) included in most regressions (notably our baseline regression) is 266. This loss of cases in our estimates is due a lack of correspondence between the available financial data of a firm in SNL and the year of its failure. To our knowledge, this figure remains the largest unique dataset of its type for large countries in an academic study with a global perspective.

Macroeconomic data on 10-year government bond yields and the output gap were taken from the OECD Economic Outlook database. Figures 1 and 2 show how the output gap and long-term interest rates have evolved through time in the countries in our sample. We adopt the output gap as a continuous measure of the macroeconomic cycle, while we use the long-term interest rate due to its linkages with the typical insurer's balance sheet.

3.2 Summary Statistics, Impaired vs. Healthy

Below, we report a few summary statistics regarding companies which at some point become impaired, as compared to the control group of companies who remain healthy in our database.

As shown in tables 1 through 4, financial ratios for impaired companies are on average quite different from those of healthy companies. Data on total assets has been converted in USD in table 1, while the data used for the ratios in tables 3 and 4 have been left in reported currency. A few striking conclusions can be drawn from these t-tests.

First, table 1 shows that failing companies generally tend to be smaller across all four countries, a stylized fact also shown in EIOPA (2018). We also confirm from our database the intuition that performance, as measured by ROA and ROE, is lower for firms which eventually fail. The latter group of companies exhibits more dispersion across all insurers in our study. Further, these performance measures are much less stable amongst firms that fail; indeed, the volatility of ROE is over twice as big for failing firms, even after trimming outliers as previously described.

Averaging over all periods, firms which fail appear to invest less in fixed income investments such as bonds, and slightly more in real estate. We also see that failing firms spend greater amounts in operating and administrative expenses, expressed as a share of written premiums.

While we have collected impairments as far back as 1975, the bulk of our balance sheet data for US firms begins in 1996 (our UK, Japanese and French data begin in 1986, 1987 and 1992, respectively). We choose to only report in these histograms cases for which we have available financial data, and therefore which will be included (depending on the specification) in our regression results. We report histograms for the failures by distinguishing between US and non-US cases in figures 3 and 4.

Figure 5 provides evidence of the cyclical nature of impairments, with spikes in the US in the mid 1980, in the early 1990 associated with Hurricane Andrew, and in 2001 following the September 11th attacks (see Cheng and Weiss (2012) for more on the role of hurricane exposure in the non-life industry). Many studies, as mentioned above, also relate these waves with the increasing entry into the sector at the time. There are also spikes in impairments around the 2007 Financial Crisis for US and non-US cases (as in EIOPA (2018), for the latter, using a more restricted dataset).

4 Expected Results

In order to explain insurance failures, we refer to "insurance ruin theory", as explained by Plantin and Rochet (2007), which leads to imposing capital requirements to ensure that equity E is such that

$$E \geq 2\sqrt{A_1^2\sigma_r^2 + R^2\sigma_x^2}$$

where A_1 is the risky asset in which the insurer invests the premiums collected, σ_r^2 is the standard deviation of the return on the risky assets held by the insurer, R the amount of reserves or technical provisions and σ_x^2, the standard deviation on the unit cost for the insurer (as percentage of reserves, which measure to what extent initial reserves may diverge from the ex-ante assessment). The insurer defaults if this condition is not met. Such an equation assumes independence between technical and financial risk. In addition, extending to different risks, as well as diversification across risks leads to a formula close to the US Risk Based Capital or the Solvency II definition of the Solvency Capital Required. In such a formula, defaults occur when equity is too low, if assets face capital losses in case of a sudden increase in interest rates, or if reserves are not properly assessed.

According to another approach, where a portfolio of N risks is introduced (see also Plantin and Rochet (ibid.)), the insurer fails if $E + N(1+\rho) \leq (\tilde{S}_1 + \tilde{S}_2 + ... + \tilde{S}_N)$, where ρ are the premiums collected on each of the N risks (they are assumed to be similar, without loss of generality, with mean normalized to one and standard deviation of σ)). Using Chebyshev's inequality, this leads to:

$$Pr(default) \leq \frac{N\sigma^2}{(E + N\rho)^2}$$

Defaults can therefore be avoided by increasing equity E, or N the number of risks, or tariffs ρ, or by decreasing σ through, e.g., reinsurance. However, such a formula does not take into account the risks associated with an uncontrolled increase in the size of the portfolio. Furthermore, moral hazard or adverse selection needs to be taken into account, in order to ensure that shareholders and managers implement the appropriate internal risk control, and do not "gamble for resurrection" if they do not have enough "skin in the game", or if their stakes decrease over time.

In our database, $Impairment_{jit}$ stands for an impairment of company j, in country i at time t. The determinants of impairments are individual financial indicators (balance sheet, P&L, etc) as well as macroeconomic variables (interest rates, output gap, as indicated above). Regarding financial variables, we use:

- Return on assets (Net income/Total assets)
- Return on equity (Net income/Total equity)
- Total assets (in log)
- Share of fixed-income instruments in total investments
- Loss ratio (Claims/Premiums)
- Portion of gross premiums ceded to reinsurers
- Operating expenses/Gross premiums
- Growth rate in gross written premiums

The values used for the log of total assets (to control for size) have been converted to USD. Since all other variables are ratios, values have been left in reported currency.

Below, we map the expected sign for each parameter estimated in our baseline empirical analysis.

Variable	Impact on impairments (+/−)	*Hypotheses*
ROA	(−)	Intuitively, an insurer running losses is more likely to become insolvent.
Size	(−)	Bigger firms (measured by the log of total assets) can better absorb shocks, and the law of large numbers should result in lower underwriting risk for larger firms.
Capital/Reserves	(−)	Firms with higher risk-based capital have a low failure rate.
DebtIns	(−)	Fixed-income assets are often held to maturity by insurers, and are generally considered less risky.
LossRatio	(+)	Higher loss ratios erode PC insurers' bottom lines and own funds; higher values indicate lower financial health.
Reins	(−)	Depending on the reinsurance treaty, ceding premiums to a reinsurer can serve to transfer risk, lowering an insurer's exposure.
OpExp	(+)	Cost-inefficient firms mismanage their resources and perhaps engage in risky behavior to attempt to remain competitive.
PremGrowth	(−/+)	(+) For longer lags, fast growing companies can lack underwriting prudence, and collect such volume precisely due to underpricing risks. An endangered firm may grow their business in order to gamble for resurrection. (−) On the other hand, in the short run, disreputable firms may struggle to collect premiums (e.g., following an A.M. Best downgrade), or may face surrenders, accelerating a failure.
IntRate	(−/+)	(−) level has a negative effect on failures: higher interest rate levels provide higher returns for long-term bonds popular among insurers; (+) changes or upward movements may lead to disintermediation for certain life insurance contracts, as policyholders surrender to exploit higher interest rates available elsewhere.
OutputGap	(−)	To the extent that insurance risks (or the market risk borne in their investments) are correlated with recessions, macroeconomic crises pose a threat to insurers; in addition, personal financial distress associated with higher unemployment may lead policy holders to surrender.

5 Econometric Approaches

The empirical analysis is based on logistic regressions where we explain the likelihood of default events using a set of economic and financial determinants. We additionally estimate duration models in which the explanatory variables (depending on parametric definition) either help extend or serve to reduce a company's survival time in the sample. As logistic and duration models are very close, the second one may be viewed as a robustness check of the former; see Allison (1984) for a review of survival analysis.

5.1 Fixed effect logitistic regression

In logistic regression, we assume the probability of an impairment can be written as follows:

$$p = \frac{1}{1+e^{-x}} = \frac{e^x}{1+e^x} \tag{1}$$

where x, in our case, is a linear combination of our explanatory variables. Rearranging, we have:

$$ln(\frac{p_{i,j,t}}{1-p_{i,j,t}}) = \beta_{i,t}\gamma_{i,t-k} + \delta_{i,t}\theta_{i,j,t-k} + \alpha_i + \alpha_t + \epsilon_{i,j,t-k} \tag{2}$$

where the log-odds of becoming impaired at date t become a linear function of our explanatory variables (with $k \geq 1$).

$\gamma_{i,t}$ represents a vector of macroeconomic factors for country i, such as the long-term interest rate, its first difference[4] and the OECD output gap. α_i is the country fixed-effect for country i, while α_t is the time fixed effect for year t . $\theta_{i,j,t}$ represents a vector of individual financial variables.

5.2 Survival Analysis

To proceed with the parametric estimation of a survival model, we first assume survival time T to follow a certain distribution:

$$S(t) = P(T > t) = \int_t^\infty f(u)du$$

[4]The slope of the yield curve being a linear combination of this lag and its level, we have omitted it from the regressions.

The baseline distribution $f(t)$ in our estimations will be the Weibull distribution (although we test others as robustness checks):

$$f(t) = \lambda p t^{p-1} exp(-\lambda t^p)$$

This will yield, respectively, the following survival function:

$$S(t) = exp(-\lambda t^p)$$

and the hazard function ($h(t) = \frac{-dS(t)}{dt}$) becomes in that particular case:

$$h(t) = \lambda p t^{p-1}$$

If $p = 1$, the model becomes the exponential function with constant risk over time. $p > 1$ means risk increases over time, while it decreases through time with $p < 1$.

There exist two families of such so-called parametric survival models: proportional hazards (PH) models and Accelerated Failure Time (AFT) models. In PH models, the covariates are assumed to have a multiplicative effect on the hazard function. PH regression thus estimates the effect of $exp(-x_j\beta)$ on the "hazard ratio", either accelerating or decelerating ($\lesseqgtr 1$) time to failure for each insurer:

$$h_i(t) = p t^{p-1} exp(\beta' \mathbf{x_j})$$

where x_j is a vector of covariates, β is a vector of regression coefficients.

In the AFT framework, the dependent variable is the (log of) the survival time:

$$log t_j = x_j \beta + z_j$$

where z_j is the error term with a specified density. A one unit increase in the covariates decelerate or accelerate the time to failure.

In our setup, we measure survival time as the number of one-year periods a firm has survived relative to its origin—assumed to be the year in which its historical data series begins. At each period, a firm will either experience a failure (in which case its terminal survival time becomes known), or it will be considered "censored", meaning that the observation window ended before the indivual experienced the event. This type of data is referred to as "right-censored." The likelihood function to be estimated for such data is written as follows:

$$L = \prod_{i=1}^{N} [f(T_i)]^{C_i} [S(T_i)]^{1-C_i}$$

Non-censored observations thus contribute directly to the chosen density $f(T_i)$, while censored observations intervene in the survival function $S(T_i)$, contributing the information that a firm's terminal survival time T_i is at least later than the current measurement period t. In this way, all information from both impaired and never-impaired firms are taken into account in the estimation procedure.

For parametric estimations of proportional hazards models, one typically reports hazard ratios instead of traditional coefficients; if the hazard ratio for a predictor is close to 1, then its effect is null. Hazard ratios are below one for variables which are "protective" or "healthy" (extend life), while values above are associated with increased risk. As with a logistic regression, all of the parameters are estimated taking the other predictors into account. Instead of hazard ratios, we here directly report traditional parameter estimates, which represent the increase in the expected relative hazard for each one unit increase in the predictor, holding other predictors constant. Positive coefficients therefore are associated with shorter survival in the sample, and vice versa.

Note that in the Accelerated Failure Time (AFT) specifications, the interpretation of coefficients changes considerably, since the dependent variable is no longer the hazard rate but the survival time. With this approach, positive coefficients *delay* failure (as opposed to increasing the hazard rate under the PH metric), while negative ones accelerate failure. It should also be emphasized that such estimates can accelerate or decelerate time to failure without necessarily affecting the hazard rate, which can yield certain intuitive advantages to the approach depending on the specification.

6 Discussion of Results

For our baseline logistic regression specifications, we include a single (interacted) country-year fixed effect, similar to Eling and Jia (2018), to account for the macroeconomic context of a given country. Firm-level fixed effects could not be used for this type of analysis as it would drop the entirety of our control sample (i.e., those firms which never experience a failure since there is no variation to be explained in y_{it} (meaning $Pr(Default)$)). We later explicitly include macroeconomic variables (the output gap and the interest rate) as robustness checks, and further show specifications using separate time and country fixed effects.

Further, we estimate predictive margins to evaluate our logit results in a more intuitive fashion. Instead of a covariate's effect on the log odds, this transformation gives us:

$$\frac{\partial Pr(Impairment = 1|X = x)}{\partial X_1} = \frac{\Delta P}{\Delta X_1}$$

or, the effect on the predicted probability following a discrete change in an explanatory variable.

This can be done in a number of ways. The approach we adopt is to plot incremental jumps (e.g., 2.5pp jumps in ROA, from -10% to +10%) in a given variable, and calculate marginal effects using different "predictive margins" for each of these values. Computationally, this consists of calculating a predicted probability of failure ($\hat{p}$) for each observation after universally replacing ROA by the given value, while leaving the rest of the observed values for other variables unchanged. In STATA, this is known as "average marginal effects." Values for $\hat{p}$ are then averaged across all observations, and a "predictive margin" for this ROA value is yielded. By differencing theses predictive margins obtained at two different given ROA values, we are able to understand the impact on the probability of failure due to a discrete change in this variable, keeping other variables at their observed values. For reference, we have additionally included such marginal effects where other covariates have been held at their *mean* values, which in practice does not severely impact our values.

Our analysis is split across the two sectors owing to their innate differences: tables 5 and 6 report our results for the non-life sector, while tables 7 and 8 report our life sector results. Separating the two sectors allows us to provide various contributions to the academic literature.

6.1 Non-life sector

In our non-life results (tables 5 and 6), the coefficient for operating efficiency is positive and significant across all specifications. This result confirms Zhang and Nielson (2015), who find a significantly higher expense ratio on a sample including 98 insolvent property and casualty firms, and Leverty and Grace (2012) who show how managers can be responsible for running inefficient (and thus more failure-prone) firms. Our result remains novel given the breadth of our data and the choice of variable to instrument for operating efficiency. Evaluated at the margin across all observed values, we find that a one standard deviation increase in our operating efficiency measure increases the probability of default by 0.15

percentage points (pp.). This absolute increase in $Pr(Default)$ should be understood as a deviation from the unconditional probability of 0.5pp (see graphs 8 and 9). Relative to this baseline probability, such an movement increases the probability of failure by 30%. When holding other covariates at their sample mean values, this amount drops slightly to 0.11pp.

Looking to the asset side, we see that the share of debt instruments in a firm's investment portfolio is far outside of statistical signifiance in the property and casualty sector. Overall this result underscores the relative importance of the liability side of the balance sheet in this sector; due to the faster production cycle and shorter liability duration, a firm's efficiency (in settling claims, for example) is of paramount importance for its survival. After splitting this sector off from the life sector, portfolio choice does not appear to play a significant role in predicting failure.

Unsurprisingly, after inclusion of our country and time fixed effects, our macroeconomic variables lose all significance: the long term interest rate is the only significant variable (see column (3)). Interestingly, we find weak evidence of *higher* levels of ceded premiums to reinsurance being associated with failure in the non-life sector. We interpret this as a self-selection effect, whereby less healthy insurers observe their risk levels, and attempt to share more of this risk with a third party. As demonstrated in our t-tests, reinsurance is more popular in the property-casualty sector than in the life sector, adding to the interest of this result.

Concerning profitability, ROA—used widely in the literature as a measure of firm performance—is strongly significant across all columns, as is ROE, for both approaches (logit or survival). At the margin, we find that a one standard deviation increase in ROA decreases the probability of default by 0.28 percentage points in absolute terms, or 0.23pp when holding other covariates at their means. Zhang and Nielson (2015) also use ROE as measure of profitability, similarly finding that higher levels help prevent failure, as the literature suggests for ROA. The loss ratio appears to matter weakly for survival (for a given level of ROA), implying that claims management and proper pricing helps survival. The significance of the loss ratio confirms the findings of Ambrose and Seward (1988) while challenging Lee and Urrutia (1996) with a much more complete and current dataset.

Finally, graphs 10 and 11 demonstrate the significance of these key variables through additional lags. In this sector, a profitability shock significantly increases the probability of failure as many as three years in advance, indicating a particularly sensitivity to productivity shocks which may prove hard to correct. The coefficient for operating efficiency only gains significance in the second year leading up to a failure, suggesting that managers can perceive and correct for inefficiencies before they prove fatal. In other words, a firm's profitability three years ago matters for their financial health, while misdeeds related to management are not necessary impactful in a permanent manner.

Our parametric survival model results are largely in line with our logit results: operating efficiency significantly predicts failure, asset mix is not important and strong firm performance (ROA, ROE and loss ratio) intuitively prevents insolvency.

6.2 Life sector

As previously stated, by dividing the two sectors, we are able to see emphasize their inherent differences. Our life sector results can be found in tables 7 and 8. The most striking difference from the non-life sector is the importance of asset mix: the higher the share of debt instruments in total investments, the lower the probability of failure. This confirms our prior intuition that the asset side—and subsequent exposure to financial cycles—plays a larger role for life insurers. At the margin, a one standard deviation increase in the share of debt instruments in a life insurer's portfolio decreases the probability of failure by approximately 0.23 percentage points (virtually unchanged when holding other covariates at the mean). Operating efficiency appears to play no role, in stark contrast to the results for the property and casualty sector.

In the life sector, we see that our firm profitability measures play a lesser role; ROA is more weakly significant in tables 7 and 8. At the margin, a one standard deviation increase in ROA decreases the probability of default by 0.24 percentage points (0.18 with other covariates at their means), compared with 0.28pp in the non-life sector. One explanation for this small contrast with the non-life sector is the fact that profits and losses in the life insurance sector can be smoothed out over several years,[5] implying less importance for the financial result of one given year. Non-life firms, however, have no such smoothing mechanism helping them to remain competitive in bad times. The duration of the liability side is typically much lower in this sector, as well, regardless of jurisdiction. Lastly, reinsurance appears to play no role in firm survival for life companies.

Additional lags plotted in graphs 14 and 15 exhibit a contrast with those of the non-life sector. Here, ROA is only meaningful at the first lag; the 2nd and 3rd are firmly outside of statistical significance. The stronger leading indicator in this sector is the portfolio composition variable, which retains significance up to three years prior. We interpret this as

[5] In France, the *Provision pour participation aux bénéfices* allows insurers to distribute investment profits to policyholders up to eight years after their realization.

a confirmation that profits and losses are more easily smoothed in the life insurance industry due to its longer liability duration, lessening the importance of past ROA shocks.

In summary, we broadly understand these differences to imply a heavier relative importance of market risk in the life industry, compared to the relatively larger factors of underwriting risk and efficient claims management in non-life. This result confirms that life insurance—a sector with a longer liability-side duration—is ultimately more exposed to macroeconomic conditions, while providing a simple intuition that has not directly been addressed in the literature; Cheng and Weiss (2012) explore bond portfolio duration but not fixed-income instruments as a portion of the total asset mix. This is also purely a study of non-life insurers, and thus unable to highlight this marked difference regarding insolvency across these different business lines. Finally, as for the non-life sector, most of our country-year fixed effects are significant (particularly in crisis years), reflecting the importance of country-specific macroeconomic conditions across all sectors.

As a means of model selection, we utilize the Akaike Information Criterion (AIC) as well as Receiver Operating Characteristic (ROC) curves. The ROC curves tell us, for a given level of sensitivity (or, rate of true positives) what rate of false positives (1-specificity) we must tolerate. For example, in the property-casualty logit with contemporaenous lags, a threshold of our indicator (the $\hat{p}$ of our estimation) which catches $\sim$90% of true insolvencies must come at the expense of a false alarm $\sim$25% of the time. While this underlines the difficulty of insolvency prediction, our AUC is in line with, although slightly higher than, the current literature ($\sim$0.87, against $\sim$0.86 in Eling and Jia (2018)).

The area under the curve (AUC) in ROC analysis serves as a measure of how good our estimated model is at discriminating between failures and non-failures. An AUC of 0.5 represents a model which is no better than a random guess, while an AUC of 1 corresponds to a flawless predictor. Including both the cases of false positives and false negatives (Type I and Type II errors), an AUC of 0.87 would correspond to a model which yields an 87 % chance of successfully distinguishing between impaired and non-impaired firms.

6.3 Further Analysis and Robustness Checks

We have included three additional tables as a means to both explore additional dimensions and reaffirm the robustness of our previous results. We first provide, in tables 9 and 10, additional lags for our explanatory variables. While this serves as a robustness check, it also helps us understand the timeline of a failure and gives an idea of the predictive power of these ratios through time. In the property and casualty sector, profitability (as measured by ROA) remains important up to three annual lags in advance of a failure, reflecting the fragility of this sector to profitability shocks. Operating efficiency remains significant two years in advance, but loses significance in the third year. This may suggest that premiums fall and costs begin climbing as a firm begins to fail. In the life sector, profitability plays less a factor in the second and third years leading up to a failure, while portfolio composition never loses significance. This outlines the long-term nature of life insurance; indeed, a life insurance firm, with liability duration of ten or more years, may survive a profitability shock so long as their investment income does not falter. Non-life insurers, however, may struggle to recover from a bad surprise to the liability side, given the quicker speed at which they must settle their claims.

Lastly, in table 11, we test various alternative specifications. Given the relatively strong presence of smaller firms in our database, we tested whether our results could be driven by these small, somewhat idiosyncratic players (e.g., mutual insurers) whose broader pertinence could be questioned. By excluding firms below \$10 and \$20 million threshods, we show that our results in tables 5 through 8 are robust to size. Further, given that we work mainly with ratios relative to levels of premiums, one may worry that our results are driven by a large drop or hike in the denominator of these ratios. By controlling for premium growth, our key ratios (operating efficiency in non-life, and debt instruments in life) remain significant.

7 Conclusion

In this article, we present evidence of the intrinsic differences between the life and non-life insurance sectors using a unique dataset of so-called "impairments" manually assembled by the authors. Applying logistic regression and parametric survival analysis to a dataset containing 150 life failures and 287 property and casualty failures in five different countries, we show that the asset side plays a determinant role in predicting life failures, while the liability side (and the income statement) are the most important criteria for non-life insurers. Asset mix (as captured by the part of fixed income instruments in the total investment portfolio) significantly predicts failure for life insurers, while operating efficiency (operating and administrative expenses over total written premiums) appears to play no role at all. The opposite is true in the non-life sector: asset mix—highly significant in the life sector estimates—appears to play no role at all in non-life, while operating efficiency is significant across all specifications. Lastly, we show that higher shares of premiums ceded to reinsurance are associated with *less* healthy non-life firms, a surprising result that is little explored in the literature.

We understand this stark contrast to be a consequence of the differences in balance sheet structure between the two sectors. Life insurers can spread profits and losses out over the course of several years, in line with their longer liability structure. Depending on the branch of activity, non-life insurers may have much shorter liability structures, meaning mismanagement (or, one or two bad years) may be enough to sink the firm. Most importantly, these insurers have no smoothing mechanism to remain profitable in bad years, leaving them vulnerable to profitability shocks.

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8 Figures

Figure 1: Output gaps (deviations of actual GDP from potential GDP as a % of potential GDP, by country. **Source:** OECD.

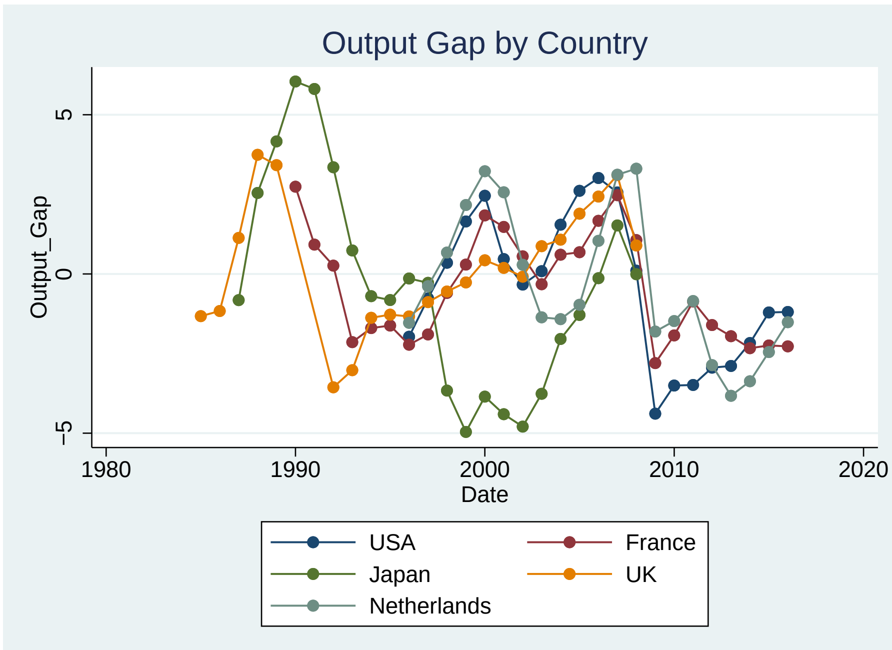


Figure 2: Long-term interest rates (government bonds maturing in ten years) by country. **Source:** OECD.

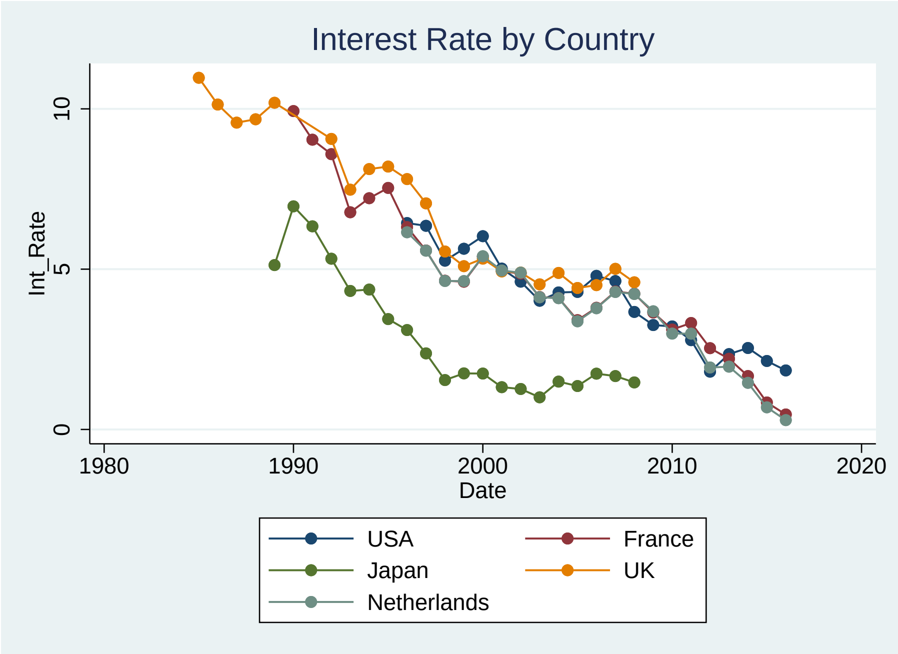


Figure 3: Histogram of impairments in the United States

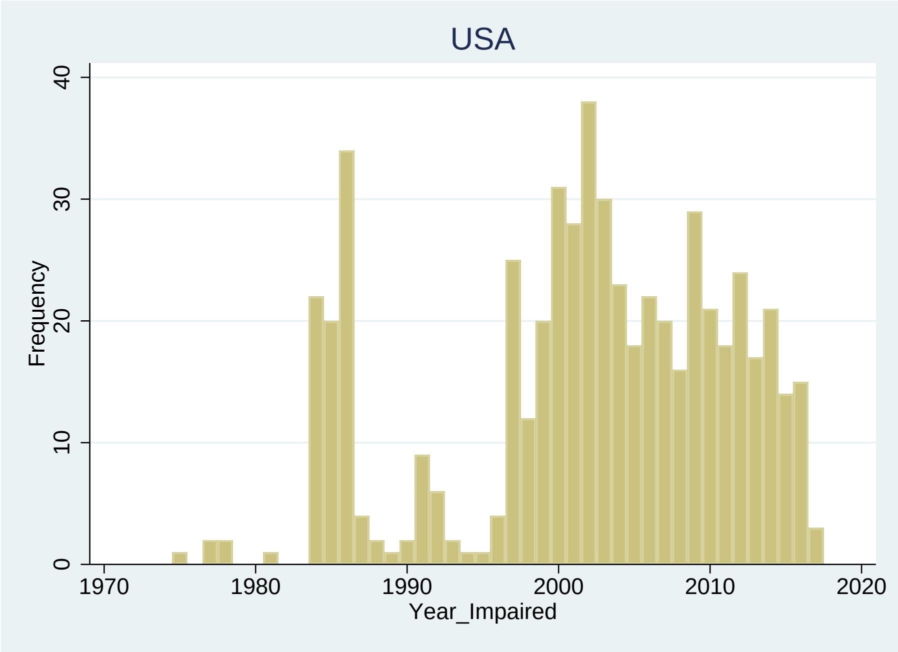


Figure 4: Histogram of impairments in Japan, France and the UK

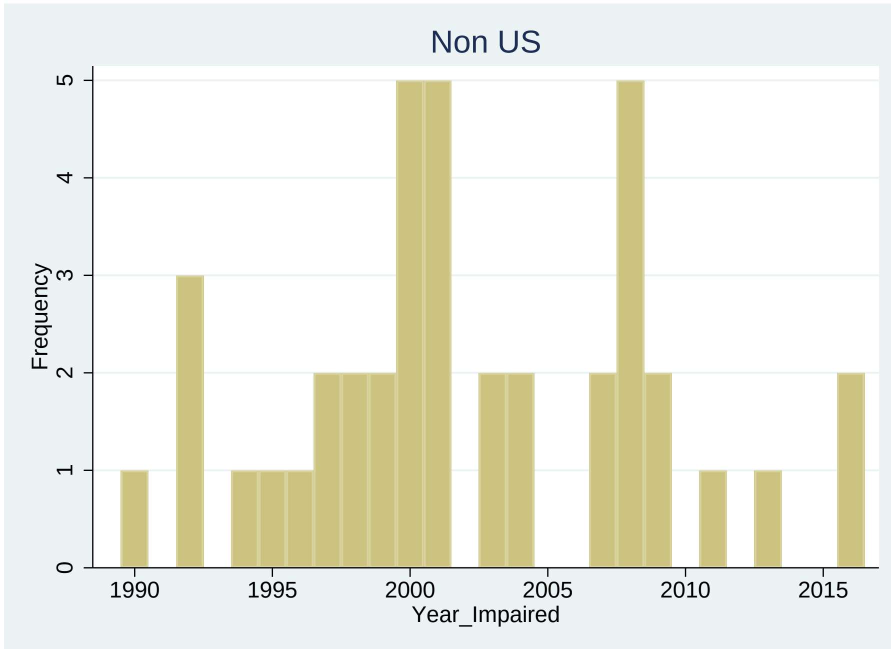


Figure 5: Histogram of life versus Non-Life Impairments

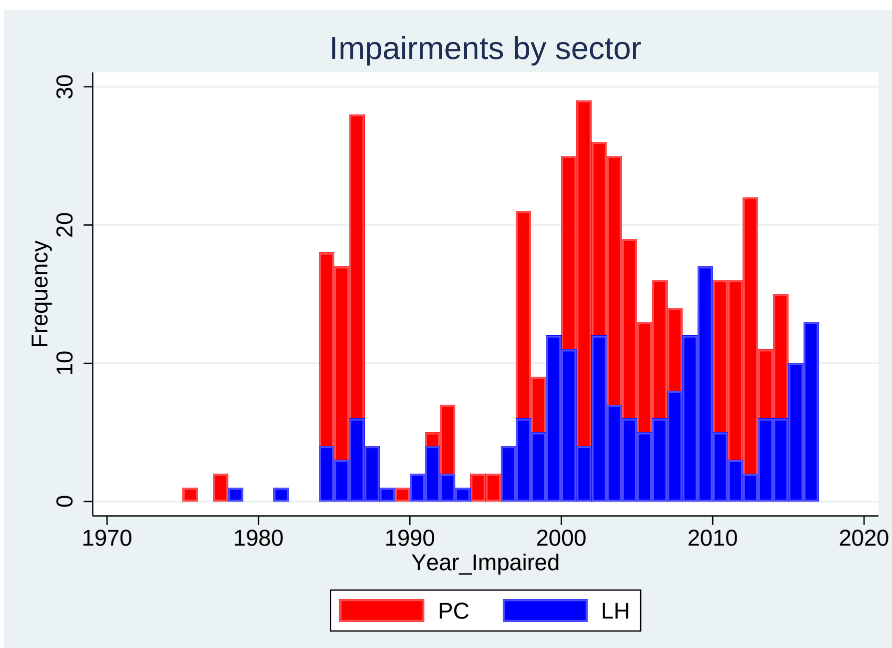


Figure 6: Receivership Operating Characteristic (ROC) curves in the property-casualty sector, by specification (1-7).

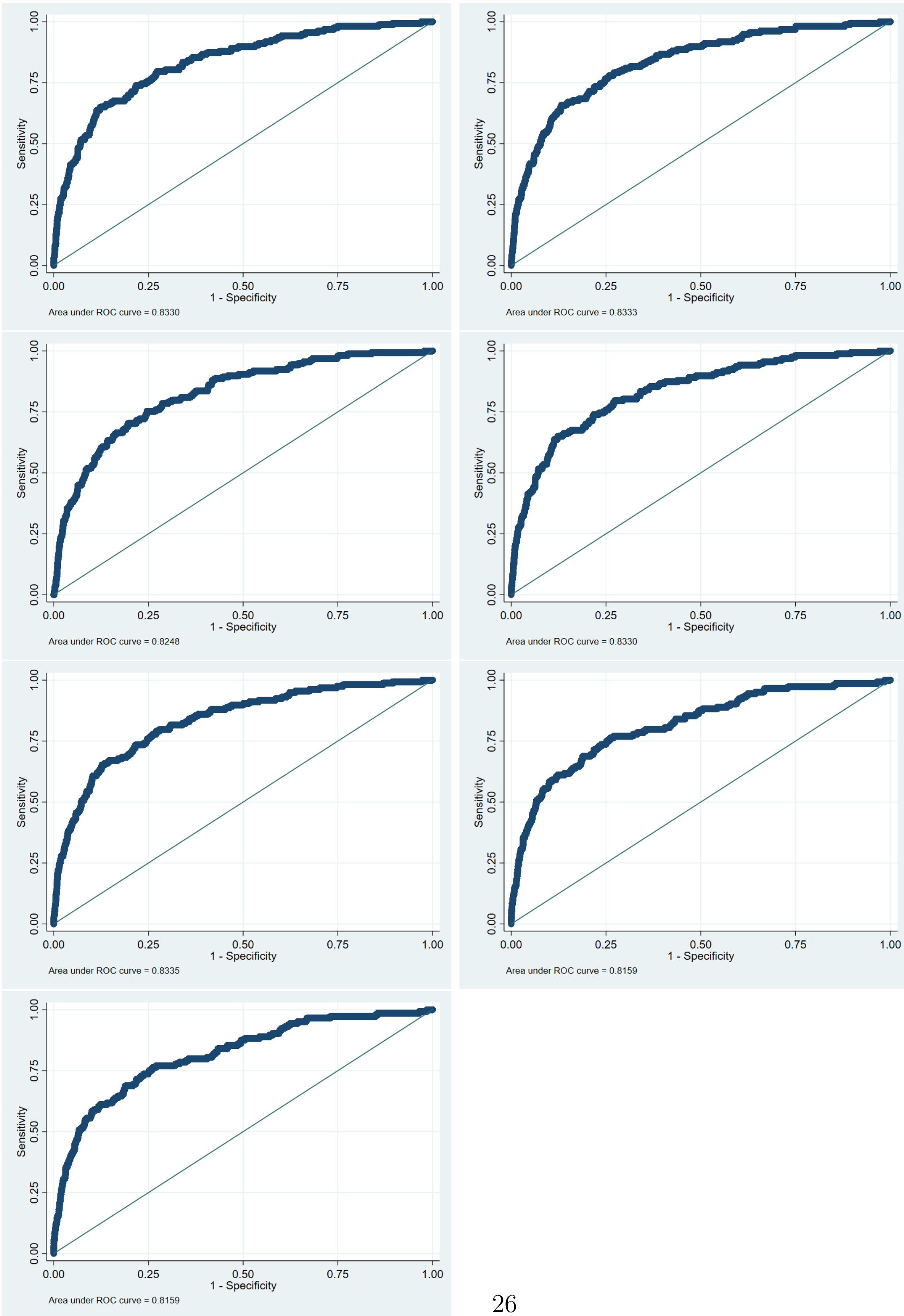


Figure 7: Receivership Operating Characteristic (ROC) curves in the life sector, by specification (1-7).

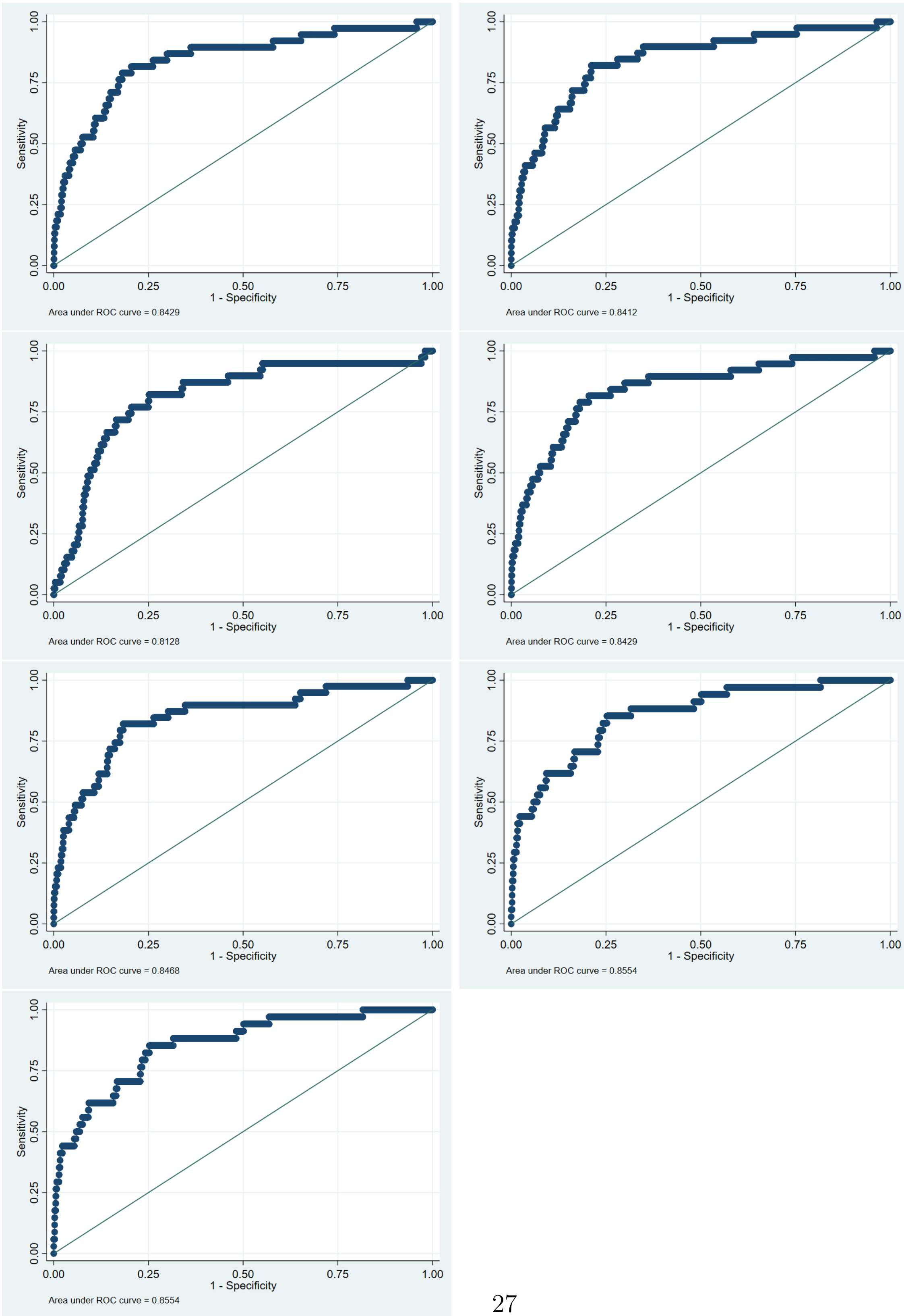


Figure 8: Predictive Margins: ROA (Non-life)

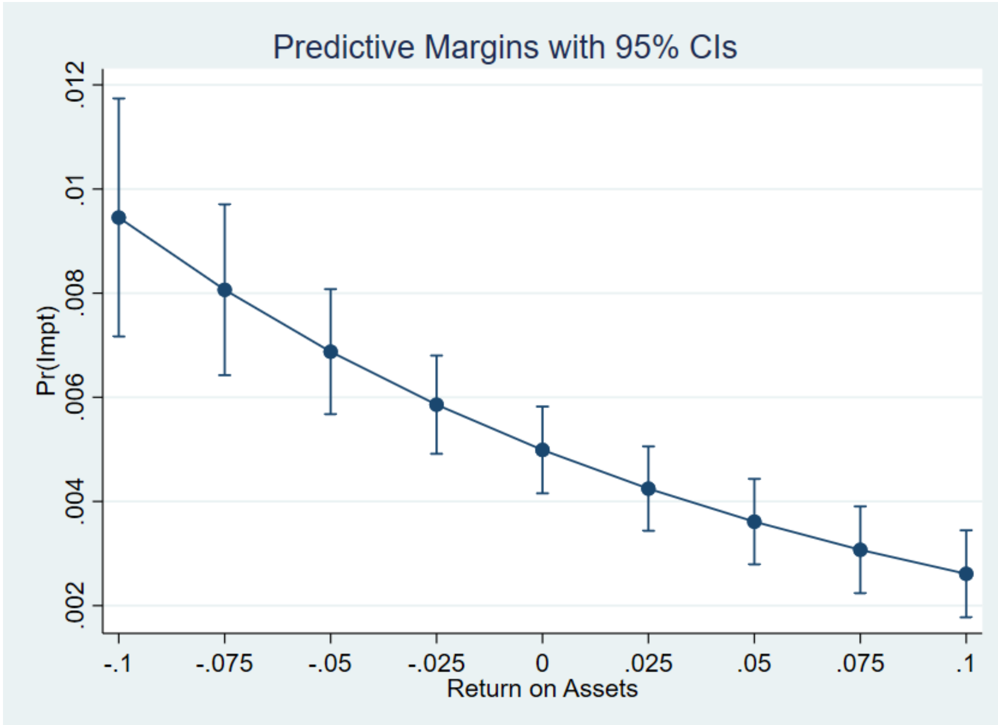


Figure 9: Predictive Margins: Operating Inefficiency (Non-life)

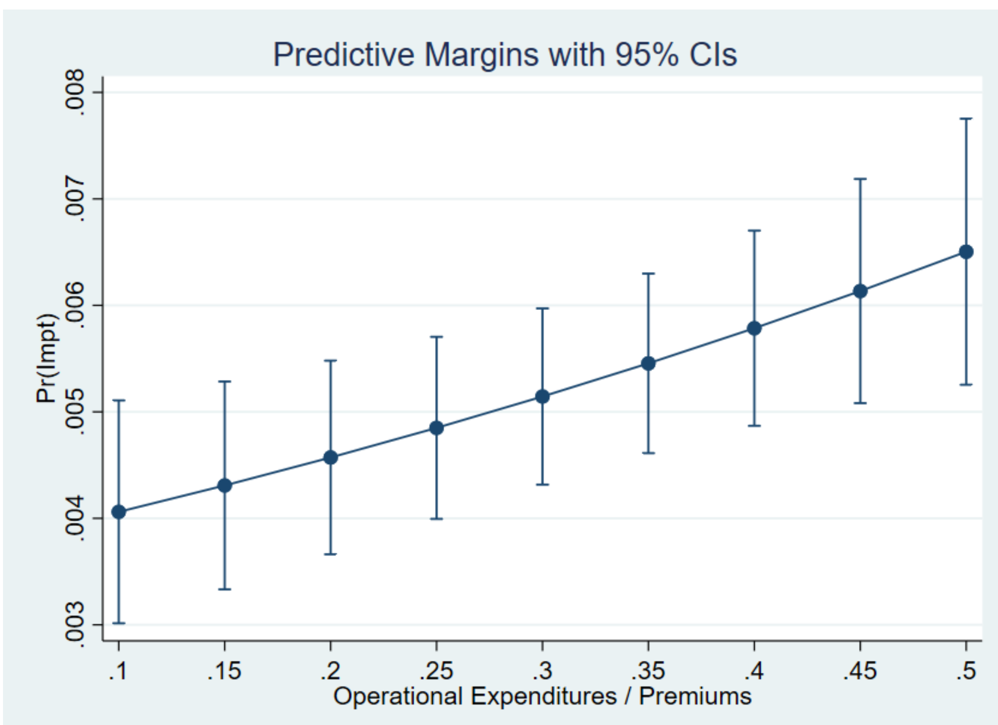


Figure 10: Additional Lags: ROA (Non-life)

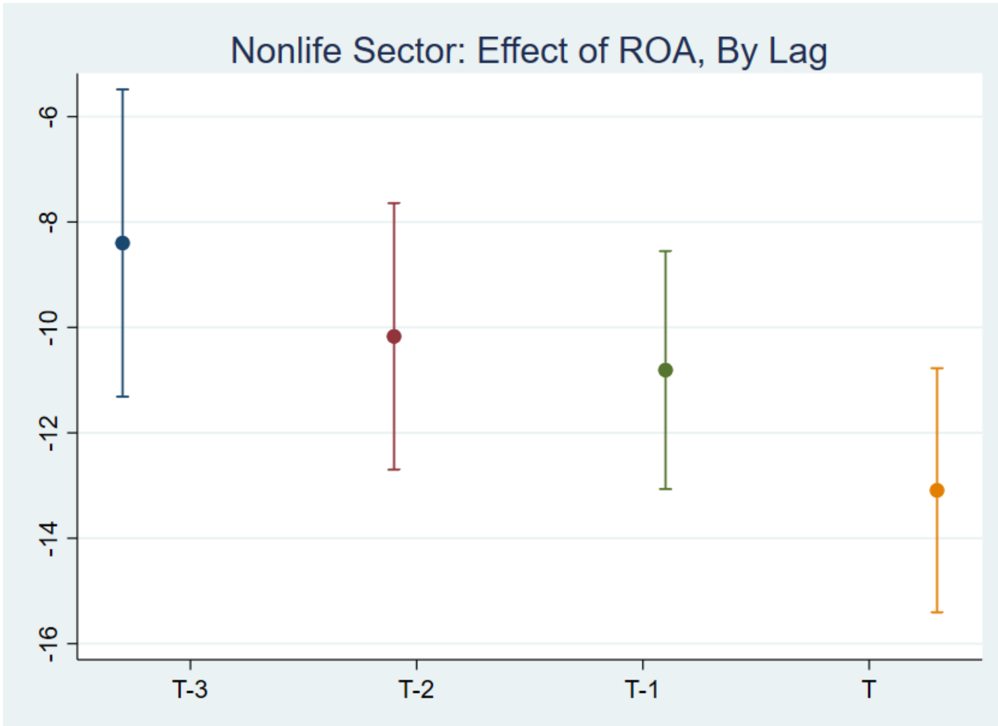


Figure 11: Additional Lags: Operating Inefficiency (Non-life)

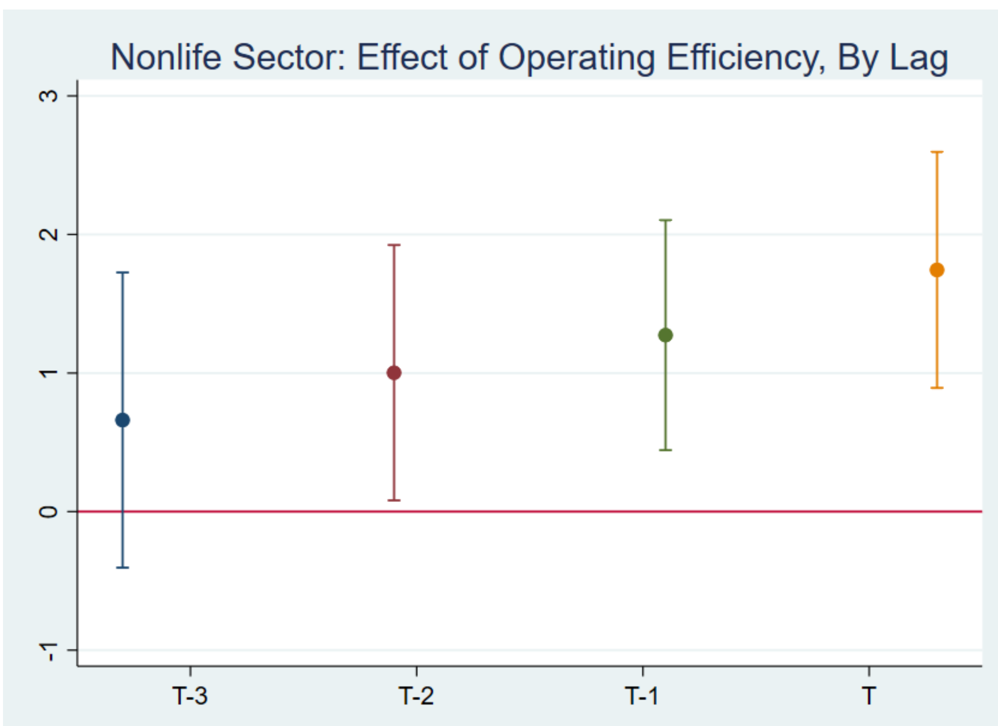


Figure 12: Predictive Margins: ROA (Life)

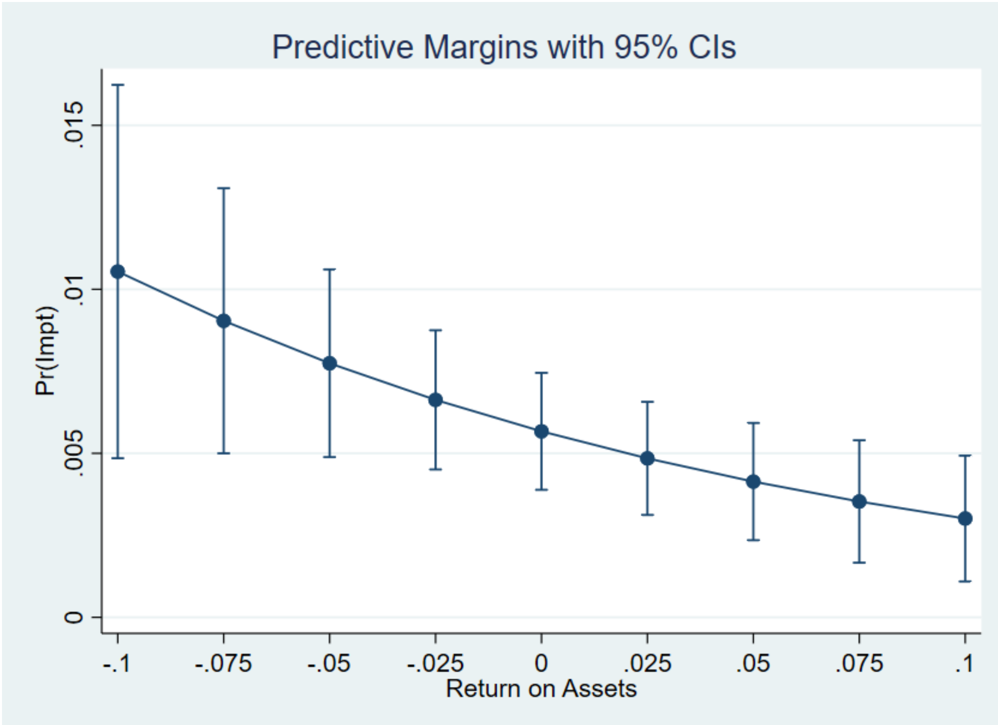


Figure 13: Predictive Margins: Portfolio Composition (Life)

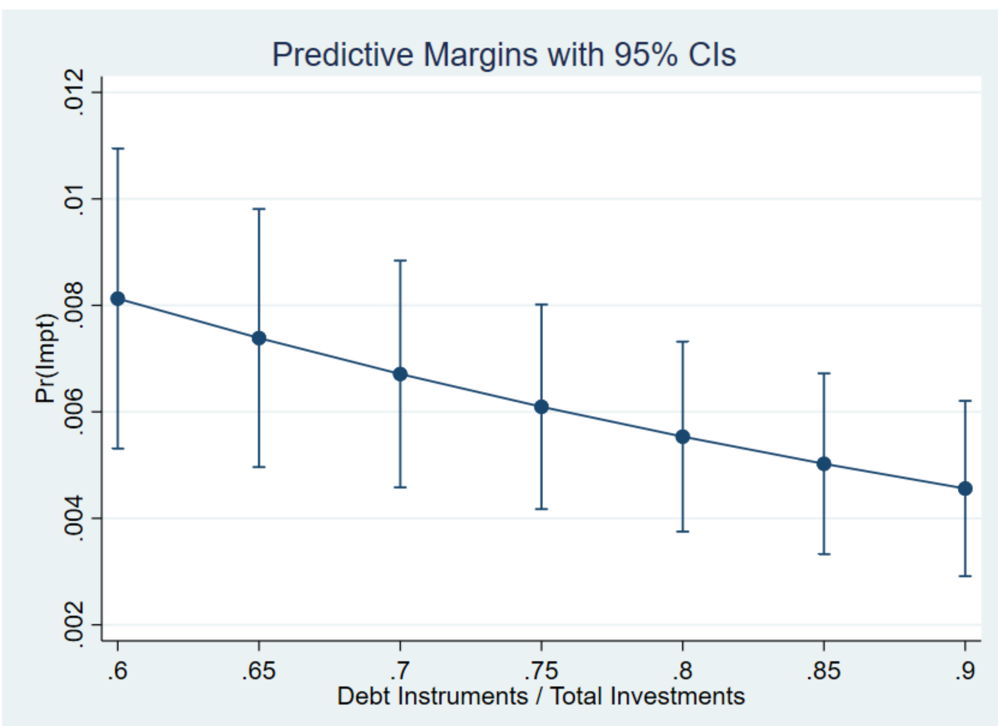


Figure 14: Additional Lags: ROA (Life)

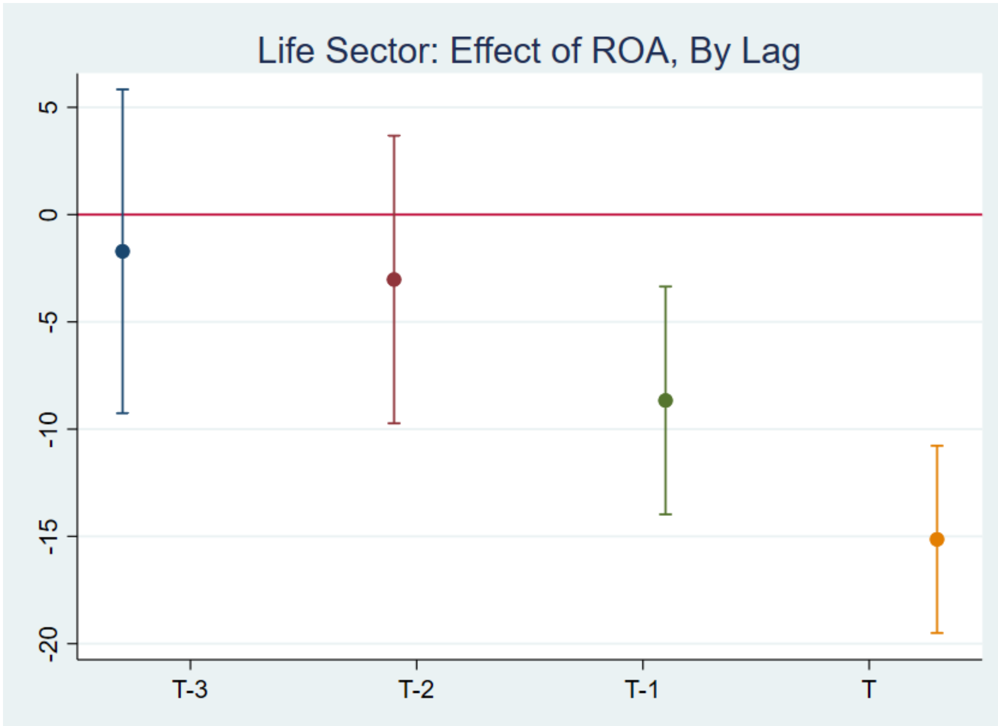
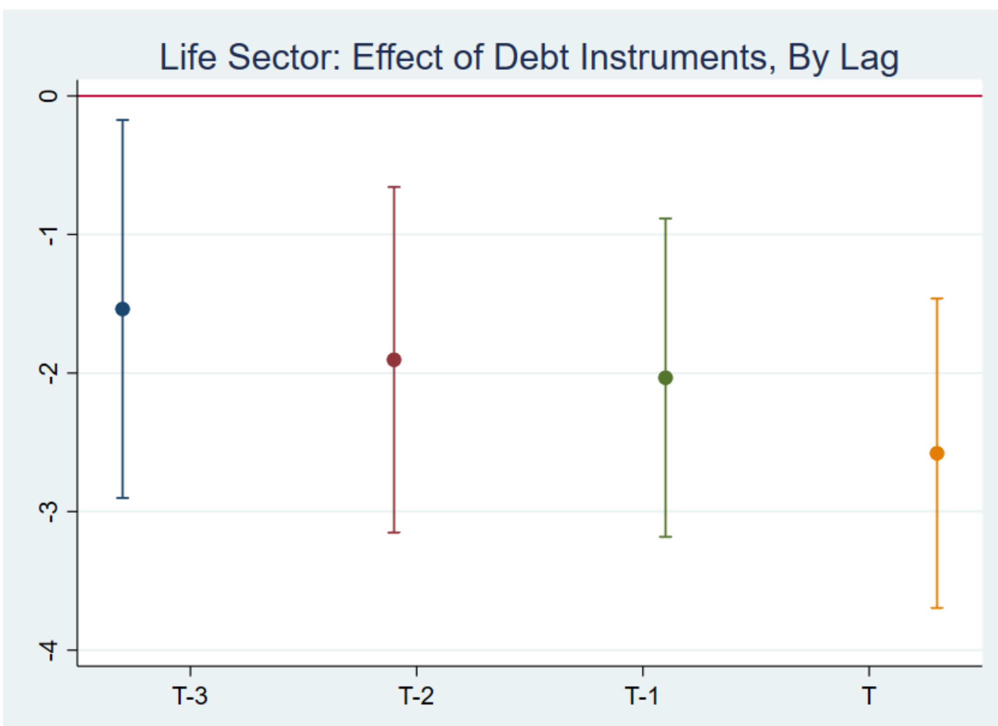


Figure 15: Additional Lags: Portfolio Composition (Life)



9 Tables

Table 1: Summary statistics with T-test between impaired and healthy firms (All countries). Full sample is an unbalanced panel which is comprised of 4,382 observations for impaired firms, and 74,442 for our control sample of healthy firms.

	(1) *Impaired*		(2) *Healthy*		(3) *Difference*	
	mean	sd	mean	sd	b	t
Avg T.A.	8,901,655	106,712,144	2,757,562	19,395,094	-6,144,093	(-0.94)
Avg T.A. (US)	253,330	1,232,399	1,640,363	12,322,283	1,387,033***	(7.93)
Avg T.A. (Other)	79,579,349	319,303,561	47,402,836	85,691,903	-32,176,513	(-0.54)
Observations	266		6431		6697	

Amounts above have been converted to USD for an even comparison.

Table 2: Comparison of financial ratios between impaired and healthy firms (All countries)

	(1) *Impaired*		(2) *Healthy*		(3) *Difference*	
	mean	sd	mean	sd	b	t
ROA	-0.02	0.05	0.02	0.05	0.04***	(13.03)
ROE	-0.04	0.16	0.04	0.13	0.09***	(8.60)
ROA Volatility	0.06	0.04	0.05	0.04	-0.02***	(-6.45)
ROE Volatility	0.19	0.11	0.13	0.10	-0.06***	(-9.10)
Loss Ratio	0.50	0.22	0.42	0.20	-0.08***	(-4.95)
Reinsurance Ceded (PC)	0.35	0.21	0.32	0.24	-0.03	(-1.77)
Reinsurance Ceded (LH)	0.12	0.18	0.17	0.19	0.04	(1.60)
Debt Investments	0.77	0.26	0.85	0.22	0.08***	(4.75)
Equity Investments	0.17	0.21	0.17	0.26	-0.00	(-0.13)
Real Estate Investments	0.07	0.15	0.03	0.11	-0.04***	(-4.41)
Operating Efficiency (PC)	0.38	0.17	0.36	0.25	-0.02	(-1.19)
Operating Efficiency (LH)	0.33	0.31	0.36	0.46	0.02	(0.60)
Observations	266		6608		6874	

Table 3: Summary statistics of financial ratios with T-tests between impaired and healthy firms (USA)

	(1)		(2)		(3)	
	Impaired		***Healthy***		***Difference***	
	mean	sd	mean	sd	b	t
ROA	-0.01	0.05	0.02	0.05	0.03***	(35.57)
ROE	-0.01	0.14	0.04	0.14	0.05***	(22.51)
ROA Volatility	0.06	0.04	0.05	0.04	-0.01***	(-11.87)
ROE Volatility	0.16	0.11	0.13	0.10	-0.03***	(-18.18)
Loss Ratio	0.45	0.19	0.42	0.20	-0.04***	(-10.03)
Reinsurance Ceded (PC)	0.32	0.22	0.31	0.23	-0.02***	(-3.85)
Reinsurance Ceded (LH)	0.14	0.19	0.17	0.18	0.03***	(5.35)
Debt Investments	0.81	0.25	0.84	0.22	0.06***	(14.69)
Equity Investments	0.15	0.22	0.17	0.26	0.00	(1.08)
Real Estate Investments	0.05	0.14	0.03	0.11	-0.04***	(-14.61)
Operating Efficiency (PC)	0.37	0.18	0.37	0.25	0.01*	(2.01)
Operating Efficiency (LH)	0.42	0.41	0.35	0.45	-0.04**	(-2.93)
Observations	4365		119483		127552	

Table 4: Summary statistics of financial ratios with T-tests between impaired and healthy firms (Non-US)

	(1)		(2)		(3)	
	Impaired		***Healthy***		***Difference***	
	mean	sd	mean	sd	b	t
ROA	-0.00	0.02	0.00	0.04	0.03***	(35.57)
ROE	0.06	0.12	0.05	0.14	0.05***	(22.51)
ROA Volatility	0.03	0.03	0.01	0.02	-0.01***	(-11.87)
ROE Volatility	0.11	0.09	0.11	0.12	-0.03***	(-18.18)
Loss Ratio	0.74	0.13	0.67	0.16	-0.04***	(-10.03)
Reinsurance Ceded (PC)	0.30	0.23	0.20	0.18	-0.02***	(-3.85)
Reinsurance Ceded (LH)	0.08	0.15	0.07	0.12	0.03***	(5.35)
Debt Investments	0.57	0.30	0.79	0.23	0.06***	(14.69)
Equity Investments	0.35	0.25	0.18	0.19	0.00	(1.08)
Real Estate Investments	0.24	0.31	0.17	0.32	-0.04***	(-14.61)
Operating Efficiency (PC)	0.27	0.10	0.45	0.21	0.01*	(2.01)
Operating Efficiency (LH)	0.22	0.18	0.26	0.22	-0.04**	(-2.93)
Observations	454		3250		127552	

Table 5: Logistic regression estimates (Property-casualty sector)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
ROA_{t-1}	-10.86***	-10.81***	-10.52***	-10.86***	-10.88***		
	(-9.37)	(-9.39)	(-9.28)	(-9.37)	(-9.42)		
ROE_{t-1}						-3.531***	-3.531***
						(-9.16)	(-9.16)
$DebtIns_{t-1}$	-0.245	-0.346	-0.617	-0.245	-0.316	-0.374	-0.374
	(-0.72)	(-1.04)	(-1.95)	(-0.72)	(-0.94)	(-1.08)	(-1.08)
$LossRatio_{t-1}$	1.192**	1.153**	1.515***	1.192**	1.129**	0.897	0.897
	(2.73)	(2.67)	(3.63)	(2.73)	(2.61)	(1.93)	(1.93)
$Reins_{t-1}$	1.766***	1.743***	2.070***	1.766***	1.712***	1.789***	1.789***
	(3.83)	(3.84)	(4.64)	(3.83)	(3.75)	(3.77)	(3.77)
$OpExp_{t-1}$	**1.287****	**1.273****	**1.388*****	**1.287****	**1.267****	**1.420****	**1.420****
	(3.02)	(3.01)	(3.30)	(3.02)	(2.98)	(3.25)	(3.25)
$10YRIntRate_{t-1}$			0.518***	2.819	-0.147		3.558
			(6.88)	(0.33)	(-0.08)		(0.41)
$\Delta 10YRIntRate_{t-1}$			-0.0185	-1.132	0.0289		-1.473
			(-0.17)	(-0.37)	(0.03)		(-0.48)
$OutputGap_{t-1}$			-0.0207	2.173	-1.368		3.020
			(-0.50)	(0.18)	(-0.97)		(0.25)
Country-Year Fixed Effect	Yes	No	No	Yes	No	Yes	Yes
Year Fixed Effect	No	Yes	No	No	Yes	No	No
Country Fixed Effect	No	Yes	No	No	Yes	No	No
Firm Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
AIC	1,726.5	1,736.5	1,771.1	1,726.5	1,739.7	1,626.0	1,626.0
Pseudo R2	0.146	0.142	0.122	0.146	0.144	0.137	0.137
Observations	28,772	28,901	32,025	28,772	28,901	28,656	28,656

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 6: Parametric survival analysis estimates with time-varying covariates (Property-casualty sector)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Size	-0.106*	-0.163**	-0.177**	-0.087	0.065*	-0.106*	0.065*
	(0.054)	(0.059)	(0.058)	(0.053)	(0.033)	(0.050)	(0.031)
DebtIns	-0.709*	-0.993**	-0.789*	-0.751*	0.395	-0.642	0.395
	(0.342)	(0.380)	(0.380)	(0.334)	(0.217)	(0.353)	(0.222)
Reins	2.951***	3.014***	3.157***	2.901***	-1.859***	3.019***	-1.859***
	(0.424)	(0.477)	(0.461)	(0.419)	(0.293)	(0.380)	(0.272)
OpExp	**1.497***	**1.271**	**1.187*	**1.359***	**−0.861***	**1.399***	**−0.861***
	(0.405)	(0.476)	(0.467)	(0.398)	(0.258)	(0.343)	(0.220)
LossRatio	2.150***	2.158***	2.395***	2.212***	-1.386***	2.251***	-1.386***
	(0.387)	(0.455)	(0.431)	(0.377)	(0.256)	(0.352)	(0.228)
OutputGap	0.030	0.064	-0.078	-0.043	0.064*	-0.104*	0.064*
	(0.141)	(0.152)	(0.053)	(0.054)	(0.030)	(0.044)	(0.026)
IntRate	0.564**	0.527**	0.736***	0.367***	-0.477***	0.775***	-0.477***
	(0.172)	(0.188)	(0.108)	(0.085)	(0.046)	(0.097)	(0.044)
ROA	-12.019***			-12.364***	7.493***	-12.173***	7.493***
	(1.118)			(1.100)	(0.997)	(1.088)	(0.865)
ROE		-3.995***	-3.882***				
		(0.373)	(0.358)				
Model	Cox PH	Cox PH	PH	PH	AFT	PH	AFT
Distribution			Weibull	Exponential	Weibull	Weibull	Weibull
Cluster?	No	No	No	No	No	Firm	Firm
AIC	1,560.96	1,256.73	762.07	901.30	885.74	885.74	885.74
Observations	33,363	33,183	33,183	33,363	33,363	33,363	33,363

Table 7: Logistic regression estimates (Life sector)

	(1)	(2)	(3)	(4)	(5)	(6)
ROA_{t-1}	-8.973**	-8.700**	-9.029***	-8.973**	-9.015**	
	(-3.28)	(-3.20)	(-3.81)	(-3.28)	(-3.29)	
ROE_{t-1}						-3.686***
						(-5.82)
$DebtIns_{t-1}$	$-\mathbf{2.193}^{***}$	$-\mathbf{2.167}^{***}$	$-\mathbf{2.445}^{***}$	$-\mathbf{2.193}^{***}$	$-\mathbf{2.195}^{***}$	$-\mathbf{1.790}^{**}$
	(-3.78)	(-3.79)	(-4.59)	(-3.78)	(-3.79)	(-2.83)
$Reins_{t-1}$	-0.411	-0.000736	-0.252	-0.411	-0.356	-0.755
	(-0.45)	(-0.00)	(-0.30)	(-0.45)	(-0.39)	(-0.73)
$OpExp_{t-1}$	0.00687	0.0418	0.172	0.00687	0.0162	0.153
	(0.02)	(0.10)	(0.45)	(0.02)	(0.04)	(0.34)
$10YRIntRate_{t-1}$			-0.0428	-0.568	9.952	
			(-0.25)	(-0.56)	(0.92)	
$\Delta 10YRIntRate_{t-1}$			-0.134	0.282	-15.65	
			(-0.56)	(0.32)	(-1.36)	
$OutputGap_{t-1}$			0.0980	0.296	-0.0377	
			(1.14)	(1.31)	(-0.07)	
Country-Year Fixed Effect	Yes	No	No	Yes	No	Yes
Year Fixed Effect	No	Yes	No	No	Yes	No
Country Fixed Effect	No	Yes	No	No	Yes	No
Firm Controls	Yes	Yes	Yes	Yes	Yes	Yes
AIC	437.4	448.9	492.9	437.4	447.4	378.6
Pseudo R2	0.158	0.159	0.073	0.158	0.175	0.201
Observations	6,751	6,892	10,215	6,751	6,892	6,637

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 8: Parametric survival estimates with time-varying covariates (Life sector)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Size	0.072	0.006	0.094	0.027	-0.050	0.094	-0.050
	(0.072)	(0.089)	(0.071)	(0.086)	(0.040)	(0.074)	(0.051)
DebtIns	$\mathbf{-2.752}^{***}$	$\mathbf{-3.301}^{***}$	$\mathbf{-2.595}^{***}$	$\mathbf{-3.320}^{***}$	$\mathbf{1.393}^{**}$	$\mathbf{-2.595}^{***}$	$\mathbf{1.393}^{*}$
	(0.528)	(0.642)	(0.532)	(0.649)	(0.534)	(0.567)	(0.615)
Reins	-0.016	-0.392	-0.193	-0.436	0.104	-0.193	0.104
	(0.837)	(1.128)	(0.846)	(1.126)	(0.453)	(0.811)	(0.438)
OpExp	0.344	0.227	0.329	0.262	-0.177	0.329	-0.177
	(0.330)	(0.410)	(0.331)	(0.410)	(0.189)	(0.338)	(0.199)
OutputGap	-0.003	0.252	-0.007	0.321^{*}	0.004	-0.007	0.004
	(0.183)	(0.301)	(0.102)	(0.153)	(0.054)	(0.108)	(0.058)
IntRate	-0.314	-0.973	0.266	-0.471	-0.143	0.266	-0.143
	(0.403)	(0.589)	(0.319)	(0.253)	(0.136)	(0.336)	(0.141)
ROA	-13.248^{***}		-13.617^{***}		7.308^{**}	-13.617^{***}	7.308^{**}
	(1.969)		(1.848)		(2.401)	(1.591)	(2.427)
ROE		-2.484^{**}		-2.508^{**}			
		(0.787)		(0.770)			
Model	Cox PH	Cox PH	PH	PH	AFT	PH	AFT
Distribution			Weibull	Exponential	Weibull	Weibull	Weibull
Cluster?	No	No	No	No	No	Firm	Firm
AIC	417.25	260.70	280.30	195.17	280.30	280.30	280.30
Observations	11,100	10,894	11,100	10,894	11,100	11,100	11,100

Table 9: Additional lags (Property-casualty sector)

	(T-3)	(T-2)	(T-1)	(T)
ROA	-8.399***	-10.17***	-10.81***	-13.09***
	(-5.65)	(-7.89)	(-9.39)	(-11.08)
DebtIns	-0.751*	-0.422	-0.346	-0.626
	(-2.09)	(-1.20)	(-1.04)	(-1.72)
OpExp	0.661	1.002*	1.273**	1.744***
	(1.22)	(2.13)	(3.01)	(4.01)
Country FE and Year FE	Yes	Yes	Yes	Yes
Firm Controls	Yes	Yes	Yes	Yes
Pseudo R2	0.084	0.110	0.142	0.216
Observations	23,012	25,064	28,901	30,185

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 10: Additional lags (Life sector)

	(T-3)	(T-2)	(T-1)	(T)
ROA	-1.712	-3.028	-8.665**	-15.14***
	(-0.44)	(-0.89)	(-3.20)	(-6.80)
DebtIns	-1.538*	-1.904**	-2.034***	-2.579***
	(-2.21)	(-2.99)	(-3.47)	(-4.52)
OpExp	0.378	0.579	0.0548	0.394
	(0.86)	(1.55)	(0.13)	(1.05)
Country FE and Year FE	Yes	Yes	Yes	Yes
Firm Controls	Yes	Yes	Yes	Yes
Pseudo R2	0.111	0.143	0.147	0.205
Observations	5,725	7,009	6,889	8,473

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 11: Robustness checks

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
ROA_{t-1}	-8.504***	-7.840***	-8.054***	-8.429***	-6.134*	-6.134*	-5.045
	(-10.60)	(-5.46)	(-4.73)	(-4.63)	(-2.32)	(-2.32)	(-1.85)
$DebtIns_{t-1}$	-0.716**	-0.111	-0.436	-0.480	-1.961***	-1.961***	-2.098***
	(-3.27)	(-0.27)	(-0.92)	(-0.98)	(-3.42)	(-3.42)	(-3.54)
$OpExp_{t-1}$		1.819***	2.410***	2.111**	0.0689	0.0689	0.121
		(3.33)	(3.68)	(2.93)	(0.17)	(0.17)	(0.28)
$PremGrowth_{t-1}$				-0.139			-0.114
				(-0.95)			(-0.58)
Country FE and Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Size	All	Above 10M	Above 20M	All	Above 10M	Above 20M	All
Sector	All	PC	PC	PC	LH	LH	LH
Firm Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R2	0.139	0.206	0.237	0.239	0.159	0.159	0.165
Observations	55,127	22,165	18,213	16,832	7,387	7,387	7,294